Skills England

What Works for AI Upskilling in the UK: Research evidence, analysis and methodology

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The opinions expressed in this report are those of the author and do not necessarily reflect the views of the Department.

1.0 Introduction

This report forms part of the SKAI programme, Skills for AI: What Works for AI Upskilling in the UK. The programme translates national evidence on AI skills into four connected outputs: employer guide, supporting case studies, insight briefing based on research, and a research evidence, analysis and methodology report. This report sets out the evidence and methodology underpinning three associated outputs: the Employers' Guide, Supporting Case Studies, and insight briefing based on research.

It provides a transparent account of how the evidence was collected, analysed and validated, and explains how key findings and analytical frameworks, including the PRIMES approach, were developed. The report is intended for policymakers, analysts and researchers who require a detailed understanding of the robustness of the evidence and how the findings can be applied across sectors and workforce contexts.

The report is produced through the British Academy Policy-Led Innovation Fellowship in partnership with Skills England. It builds on the 2025 report *AI Skills for the UK Workforce*, and shifts the focus from diagnosis to delivery by providing evidence on what works for AI upskilling across sectors.

According to The Alan Turing Institute, AI can be defined as machines that can perform cognitive functions we associate with human minds such as:

- reasoning
- learning
- interacting
- problem-solving
- exercising creativity

In this research, AI skills are defined as "the competencies and abilities required to develop, implement, manage, and interact with AI systems effectively". These skills are grouped into three categories: technical, responsible/ethical and non-technical AI skills.

The first report established a baseline of AI skills needs and introduced practical tools for employers. This includes the AI Skills Framework, the Employer AI Skills Adoption Pathway, and an Employer AI Adoption Checklist. Together these tools help organisations assess their current position, identify skills gaps, and plan workforce AI upskilling.

This report responds to demand from employers, training providers, and policymakers for clear, actionable insights on how AI skills can be developed across diverse workforce groups. The evidence includes 23 workshops, ten case studies and a survey of 536 responses.

Scope of the report

This report examines AI skills development across three types of training:

- **Formal training** including higher education, further education and training delivered by training providers

- **Employer-led training** including in-house training programmes and workplace-based learning linked to specific roles or tasks

- **Informal learning** including community-based or voluntary provision, and self-directed learning and everyday use of AI tools

Together, these training environments shape who can access AI training, how skills are developed in practice and whether learning is recognised and applied at work.

Evidence base and contribution

The report contributes to UK Government ambitions to build a productive, confident, and inclusive workforce that can take advantage of AI-enabled transformation. In particular, the findings align with the AI Opportunities Action Plan's commitments to:

- develop a clearer understanding of current and emerging AI skills needs and gaps across sectors, based on national survey data and multi-sector workshop evidence

- expand access to high-quality AI skills training through evidence-based, scalable, and inclusive delivery approaches, including the PRIMES training principles

- strengthen lifelong learning systems by identifying effective models of employer-led and provider-supported AI training and capability-building

- ensure AI opportunities are accessible across diverse workforce groups, supported by ten case studies demonstrating the impact of training on workforce capability, job quality, and organisational performance

2.0 Methodology

Part 1: Workshops

This report uses a triangulated research design, combining qualitative and quantitative data to ensure robustness, reliability, and policy relevance. The qualitative component was created through a structured programme of stakeholder workshops, designed to capture diverse perspectives on AI skills, training provision, and organisational readiness across sectors.

The research comprised 6 initial scoping workshops and 17 sector-based workshops, resulting in a total of 23 workshops involving close to 150 organisations. Participants included a broad range of stakeholders, including skills leads, policymakers, training providers, SME owners, academics, industry practitioners, and AI specialists. This ensured that the findings reflect multiple perspectives across policy, practice, and research.

All workshops were conducted online and lasted approximately 2.5 hours. A consistent design was used across sessions, focusing on obtaining both experiential insights and practical examples of AI skills development, training challenges, and effective approaches.

The workshop protocol, including guiding questions and discussion structure, was reviewed by experts from Skills England prior to delivery. Revisions were made in response to their feedback to ensure clarity, relevance, and alignment with policy priorities.

Participants were selected using goal-directed sampling to ensure the inclusion of individuals with relevant expertise and experience. Selection criteria included:

- domain expertise in AI, skills development, or workforce transformation
- professional roles linked to training design, delivery, or policy
- relevance to one or more of the six stakeholder groups identified as central to the research

All workshops were recorded with participant consent and professionally transcribed. The data were analysed using an iterative, reflexive thematic analysis approach following Braun and Clarke (2012; 2021). This method was selected for its ability to support rich, contextualised interpretation of complex qualitative data across diverse stakeholder groups.

The analysis followed Braun and Clarke's six-phase process: familiarisation with the data, initial coding, theme development, theme review, theme definition, and reporting. Coding and theme development were conducted iteratively, allowing patterns to emerge across workshops while remaining sensitive to sector-specific differences.

To enhance rigour and reliability, several measures were implemented. These included iterative coding and theme refinement, constant comparison across stakeholder groups and sectors, and alignment of emerging findings with evidence from other data sources used in the study. This approach ensured that the findings are both grounded in the data and robust across different contexts.

Part 2: Case study interviews

To complement the workshop findings, a set of in-depth case studies was developed to examine effective AI training approaches in practice. Case study organisations were identified through the workshop programme (except Cast Consultancy), where participants highlighted examples of successful or promising AI upskilling initiatives within their organisations.

Selection of case studies was therefore evidence-led and based on demonstrated practices discussed during the workshops, ensuring alignment with the research focus on "what works" in real organisational contexts. Follow-up invitations were extended to a subset of organisations representing different sectors, organisational sizes, and approaches to AI training.

Each case study was developed through a semi-structured interview lasting approximately one hour, conducted online via Microsoft Teams. Interviews focused on understanding the organisation's AI training journey, key challenges, interventions, and observed outcomes.

Interviews were recorded with consent and transcribed for analysis. A structured case study template was used to ensure consistency, covering challenge, intervention, implementation and outcomes.

To improve accuracy, each case study went through a validation process. Drafts were reviewed by the author, a Skills England expert and the participating organisation to confirm factual accuracy and fair representation.

Part 3: Survey

The survey provides a strong and policy-relevant quantitative evidence base, drawing on 536 responses from organisations across the UK. It was designed to complement the qualitative research with systematic, organisation-level evidence on AI adoption and skills, addressing gaps that could not be captured through the literature reviews, workshops and roundtables. Underlying data from this survey can be downloaded here.

Data collection was conducted using Amazon Mechanical Turk (MTurk), an online crowdsourcing platform which can be used to administer surveys. Individuals browse among available tasks and complete them in exchange for a fee set by the requester. Screening procedures ensured respondents were based in the UK and held senior or decision-making roles within their organisations, including business owners, managers, and senior professionals. The sample includes a strong representation of SMEs and covers organisations across all ten priority sectors.

The survey sample is strongly aligned with organisational decision-making contexts. Respondents were predominantly business owners and senior managers (over 75%), with substantial representation of SMEs, including medium (50%), small (29%), and micro-organisations (11%). The sample spans all ten priority sectors, including health and social care (22%), professional and business services (19%), financial services (16%), advanced manufacturing (12%), creative industries (10%), life sciences (6%), construction (5%), digital and technology (5%), clean energy (3%), and defence (1%).

The dataset shows consistent patterns across key areas such as barriers to training, priority support mechanisms, and gaps in provision. These findings provide clear and actionable insights aligned closely with Skills England's focus on employer demand,

workforce capability, and practical delivery models. Strong signals on issues such as cost, flexibility and capacity constraints reinforce the policy relevance of the findings.

Several measures were implemented to ensure data quality, reliability, and validity. These included screening questions, attention checks, and completion time thresholds to identify and exclude low-quality responses. Additional checks were conducted to identify inconsistent or duplicate responses.

While the sample is not fully representative of the UK economy, with a higher concentration of London-based and AI-engaged organisations, this is also a strength in providing focused insight into firms actively navigating AI adoption and skills development. However, the sample size does not support robust sector-level analysis.

The analysis used descriptive statistics to identify clear patterns across the dataset, supporting transparency and interpretability for policy use.

The survey findings were triangulated with qualitative evidence from workshops and case studies. This combined approach strengthens the overall evidence base and supports its use in informing Skills England's policy and programme development.

Survey respondents also identified with a range of groups currently under-represented in digital and AI employment. The largest proportions reported being working parents (41%), women (32%), and individuals from ethnic minority backgrounds (31%). Smaller proportions identified with low-income backgrounds (16%), disabilities (10%), and LGBTQIA+ groups (7%), while 25% preferred not to respond.

AI use was well established across the sample, with 97% of organisations reporting current use. Over half (56%) reported daily or near-daily use and a further 31% reported weekly use, indicating that the findings reflect organisations with active and ongoing engagement with AI tools.

RESULTS SHOULD BE INTERPRETED WITH CAUTION

This report presents key insights on AI skills from national workshops. As with all qualitative research, there are a few considerations to keep in mind when reading the findings. The data captures a moment during rapid changes in AI technologies and skills needs, but some regional and less-represented voices may be underrepresented. Workshop discussions provided rich and experience-based insights but are not designed to be statistically representative. Thematic analysis was carried out rigorously, though interpretations may still carry an element of subjectivity. These qualitative insights are further supported by findings from a national employer survey, enabling triangulation across data sources and strengthening the overall evidence base. However, quantitative data on AI skills remains limited.

The case studies were based on qualitative interviews and provide in-depth, practice-based insights into effective approaches to AI skills development but are illustrative rather than representative of all organisations or sectors.

Participant quotes included in this report are anonymised and, in some cases, paraphrased or constructed as composite quotations to reflect the dominant themes and repeated sentiments expressed across workshops. This approach supports anonymity and clarity while preserving the intent and voice of contributors.

Taken together, these insights offer a meaningful contribution to ongoing efforts to address AI skills inequality. The findings provide a strong basis to inform future policy development, programme design, and stakeholder engagement in a context of rapid AI adoption and growing impacts on job roles, skills requirements, and workforce inclusion.

3.0 Barriers to AI Upskilling

This section builds on the barriers identified in AI Skills for the UK Workforce report. It deepens that analysis by examining the barriers across different workforce groups, types of training, and levels of employer readiness to adopt AI.

3.1 Barriers experienced by different workforce groups

Learning to use AI at work is challenging for many workers. AI tools change quickly, and workers are not always sure what is safe, allowed, or useful in their job. Some groups face additional barriers and are at a greater risk of being left behind.

Common barriers include limited access to reliable devices or broadband, limited time to learn because of work or caring responsibilities, and few opportunities to practise AI use with support. Training is often not designed for different needs and is frequently marketed towards those who already feel confident with technology. These patterns are strongly reflected in survey findings. Employers identify cost (42%), lack of representation of relevant training provision (42%), and fear of failing in technical areas (32%) as the most significant barriers to participation. In addition, 28% report limited digital skills within the workforce, reinforcing the scale of capability constraints. People with fewer opportunities to develop digital skills may lack confidence and be less likely to engage with AI training.

Learners are more engaged when training connects AI to real tasks, values, and lived experience. However, AI training is often framed in technical or corporate language. This can feel disconnected from many job roles. Where groups do not see themselves represented in the training or marketing, they are less likely to be engaged.

Importantly, these barriers often intersect. Individuals may belong to more than one group facing disadvantage, meaning their experiences of exclusion can be compounded. For example, an older worker on a lower income may also have had fewer opportunities to develop digital skills and limited access to training through their organisation. Recognising this intersectionality is important for designing AI upskilling approaches that are inclusive, flexible, and responsive to diverse needs.

This section focuses on group-level patterns. It also links to wider barriers in training provision and employer readiness. Many issues mirror broader digital skills barriers but are intensified by the pace of AI development.

Low-income learners

Low-income learners face barriers linked to access, time, and digital infrastructure. Many have limited paid or flexible time for learning because of work and caring duties.

Training often assumes learners can use a desktop device and focus without interruption. This is not always realistic for many learners due to a range of factors, including low income, limited access to reliable devices and broadband, and competing work or caring responsibilities. Some rely on mobile-only access, which many courses do not support. In some households, access to devices is shared or unstable.

Many already use free AI tools informally, but this learning is rarely recognised or built into formal training pathways, limiting progression.

Women

Women face barriers linked to confidence, and representation. Lack of confidence can also reduce engagement. This is often linked to previous exclusion from digital or technical learning.

Women are more likely than men to have had fewer opportunities to develop digital skills, and this gap may widen as AI training is often aimed at those already confident with technology. Women also reported limited visibility of facilitators or role models with similar backgrounds. Weak provision of AI training linked to return-to-work transitions disproportionately affects women.

Disabled learners

Disabled learners face barriers where training is not designed with accessibility in mind. Awareness of inclusive design varies across providers, and accessibility standards are applied inconsistently. Many learning platforms still lack basic accessibility features.

Some training formats rely on speed, visual complexity, or timed interaction excluding learners with different needs. Although many disabled learners already use AI tools in enabling ways, this experience is often not recognised or used as a starting point in training.

Younger workers

Younger workers face higher exposure to job disruption without clear upskilling pathways.

While many have strong general digital skills, these do not always translate into confidence using AI at work, particularly where guidance and structure are limited. Understanding of responsible and professional AI use is often low, highlighting the need for structured, employer-led AI training in entry-level roles. Access to AI-related careers advice is inconsistent.

Older workers

Older workers face barriers linked to pace, confidence, and assumptions about capability. Training can move too quickly, be jargon heavy or assume prior digital fluency. This can discourage participation.

Older workers may be reluctant to ask questions in mixed-experience settings. Training can also underuse existing sector knowledge, even though this experience is valuable when applying AI responsibly. Age-based assumptions can affect inclusion and progression.

Older learners engage more confidently when training is task-based and well-paced. It also helps when training recognises everyday interactions with AI as valid entry points.

SME employees

SME employees face barriers linked to scale, recognition, and limited access to structured and practical training and development support.

Skills developed through informal practice are not always recognised or recorded. Many SMEs struggle to move from pilot use of AI to wider adoption. This is often due to limited time and lack of internal capacity. Employees may also lack time to engage with longer courses.

Many SME employees are already using AI tools creatively. However, their skills often remain invisible and unsupported within formal training systems.

3.2 Training ecosystem barriers

In an effective system, AI training would adapt quickly to meet workplace needs. In practice, several factors limit the relevance, quality and consistency of current provision.

Curricular lag

Updating formal qualifications, apprenticeships, and occupational standards is slow. This means AI content often falls behind what people are already doing at work. Training can then feel outdated or disconnected from real tasks and decisions.

Rapid change in AI technology

AI tools are changing quickly, which makes it difficult for training providers to keep content up to date. Many programmes still focus on specific tools rather than transferable skills. As AI moves beyond basic generative use, workers need more judgement and oversight skills.

Trainer constraints

There is a limited supply of trainers with both AI capability and relevant sector experience. Workshop evidence suggests that strong demand for AI expertise in industry reduces the availability of experienced practitioners for training and education roles. Some trainers may not have recent experience using AI tools in practice. Smaller training providers and further education colleges may not have the time or money to update their courses.

Limited contextualisation
Many AI courses are generic and do not reflect the realities of different sector job roles. Engagement is lower when training examples do not align with learners' responsibilities. This is a particular problem in sectors where safety, regulation, and ethical decision-making are essential for good use of AI.

Fragmentation and uneven quality

AI training provision is growing quickly, but quality remains inconsistent. Employers and learners struggle to identify which training is trusted, relevant, and worth investing in. The lack of shared benchmarks or minimum standards reduces confidence and limits uptake. This challenge is reflected in one case study within this report. LinkedIn Learning has created structured AI capability frameworks to help organisations move from fragmented experimentation to consistent learning pathways.

Survey evidence further highlights gaps in provision, particularly in flexibility and accessibility (51%), clear AI skills frameworks (35%), and practical, contextualised learning (34%). This suggests that current training systems are not aligned with employer needs.

3.3 Barriers to employer AI adoption

Employer readiness strongly influences whether AI training is prioritised, accessed and embedded in practice. Even where training is available, AI is unlikely to be used effectively without the systems, governance and leadership needed to support it.

Low data and digital maturity

Without strong basic data systems, AI tools cannot be used effectively or safely. Many organisations still lack clean data systems that can be linked. This is particularly the case in SMEs and in parts of the public and third sectors.

This challenge is illustrated in one case study in the report. Airbus linked AI upskilling to wider data infrastructure and operational systems to build internal capability at scale.

Limited governance and assurance

Many employers are unsure what good and safe AI use looks like, who is responsible for it, and how to manage the risks. Worries about data protection, bias, and legal liability can make organisations less willing to invest in AI training. In regulated industries, unclear guidance from regulators further slows AI adoption and training.

The KPMG case study highlights how these challenges can be addressed through organisation-wide governance arrangements and integrated learning models that connect AI training with professional standards and day-to-day client work.

Weak strategic clarity

AI is often ad hoc rather than guided by a clear organisational strategy. Training is not always linked to improving productivity, service quality, or other business goals, which limits leadership support and investment. Without strong support from leaders, learning AI skills usually stays optional, informal, and uneven across different teams.

Difficulty assessing impact

Many employers find it difficult to measure whether AI training improves performance or

outcomes. This makes it harder to justify investment or to expand successful initiatives. Training is likely to be deprioritised when benefits are unclear, difficult to evidence, or seen as short-term.

Time and resource constraints

Many companies struggle to give employees paid time for training, especially SMEs and frontline services. Day-to-day work pressures make it hard for staff to take part in learning, even when the training would be useful. This means not everyone gets the same chance to train, which leads to widening skill gaps.

4.0 Sector-Specific Deep Dives and Training Needs Priorities

Across all ten sectors, organisations are using AI in similar ways. Generative AI is now common in day-to-day work, while more advanced and agentic AI is still at an early stage. Many organisations struggle to build AI skills consistently across different capability areas. Technical skills are the hardest to support, cited by two-thirds (67%) of respondents to our survey, due to their complexity and resource requirements.

Nearly a third (32%) also report difficulties developing ethical and responsible AI skills, despite their importance for trust and safe use.

Fewer organisations report challenges with delivering non-technical skills (10%). However, capabilities, such as judgement, problem-solving, and collaboration, are critical to effective AI use.

This suggests a gap between current skills development and what organisations need. More work is needed to understand these challenges and how employers and workers can be better supported. This section explores these issues through sector-specific deep dives. Each looks at:

- the problems AI skills could help address
- how AI is currently used
- related training needs

Together, these examples show how AI challenges vary across sectors and organisations.

4.1 Construction

Key challenges AI upskilling can help address in construction

The construction sector has several long-term problems that AI training could help solve, if the skills taught match real work tasks and everyday practical limits.

Key challenges for construction include:

- uneven productivity and projects running over budget, often caused by poor planning, weak coordination, and reactive decisions.
- health and safety risks on site, where people often work under time pressure and with information that is incomplete or unclear
- uneven quality and compliance made worse by complex subcontracting and different standards across projects
- low digital skills and basic data systems, especially in small companies, which makes it hard to use data and digital tools effectively

- skills shortages and limited capacity, creating more pressure on project management, supervision, and delivery

AI tools can be used to help address these challenges, but only if workforce skills are developed to ensure they are used consistently, safely, and effectively.

Current context and AI use

AI use in construction is significantly behind other major sectors and adoption is uneven. It is mostly concentrated in design, planning, surveying, and commercial functions, with very limited use in on-site and trade-based work. Compared to sectors like manufacturing, defence, or life sciences, construction has lower digital maturity, weaker data foundations, and less formal governance around AI use.

The sector is highly fragmented, with extensive subcontracting and a large proportion of SMEs. Many organisations continue to rely on paper-based processes and disconnected digital systems. These conditions limit the ability to scale AI use safely and consistently and contribute to informal, uneven approaches to skills development.

As a result, AI skills in construction are frequently developed through trial and error rather than structured training. There is limited shared understanding of what effective, safe, and responsible AI use looks like across roles, projects, and organisations.

Training needs priorities linked to construction workflows

AI training in construction must work within project-based, safety-critical, and highly fragmented environments. The priority is not advanced AI capability, but shared, practical competence across roles and organisations.

Training should therefore prioritise:

- showing how AI can be used on-site, including safety reporting, incident documentation, tender preparation, and programme coordination
- clear guidance on when AI outputs can inform decisions and when human judgement must override them, particularly in safety and compliance contexts
- making it easy to access and relevant for organisations with low digital maturity, especially SMEs and subcontractors
- specific content for different roles, including site staff, supervisors, project managers, and commercial teams
- covering issues of data quality, information sharing, and governance across project partners

There is great potential for AI to help the construction industry to improve its productivity, quality and safety. To do so, the sector needs to agree clear standards and shared expectations that its workforce can be trained to.

4.2 Creative Industries

Key challenges AI upskilling can help address in the creative industries

Tailored AI upskilling could help the creative sector to tackle some long-standing problems in the industry. Key sector challenges that AI upskilling could help address include:

- uneven productivity, particularly among freelancers and micro-organisations.
- precarious work and income instability, with many creative jobs characterised by short contracts, project-based work, and limited progression pathways
- barriers to entry and progression for early-career workers and those from under-represented backgrounds. For example, informal recruitment practices and reliance on unpaid or low-paid work
- limited resource available for administration, funding applications, and strategic development, especially in small organisations and cultural institutions
- limited opportunities to develop digital and AI-related skills alongside creative practice

Effective AI upskilling can help creative organisations use tools to work more efficiently, reduce administration and strengthen their teams - while still supporting the values and ways of working that matter to the sector.

Beyond access to tools and training, there is a growing need to support workers and organisations in understanding where and how AI can add value in practice, including building confidence, supporting wellbeing, and developing the judgement needed to use AI effectively in rapidly evolving work contexts.

This is illustrated in one of the case studies in this report, where Vertis Media developed in-house AI capability through workflow integration and continuous learning, enabling the firm to adapt to AI disruption and expand its services.

Current context and AI use

The use of AI in the creative industries is growing but is uneven across subsectors. Film, music, gaming, advertising, and visual effects are making extensive use of generative AI and automation tools. Areas including theatre, heritage, crafts, and smaller cultural organisations, are adopting AI more cautiously. This is due to problems with funding, legal uncertainty, and ethical concerns.

Many creative workers begin using AI tools without formal training or clear guidance. AI capabilities are increasingly embedded into standard creative software through routine updates. Individuals start to use them without a full understanding of how systems work, what data they use, or how AI use affects ownership, attribution, and commercial value.

AI is influencing not only creative production but also distribution, marketing, and audience engagement. Recommendation systems, analytics, and automation tools shape how creative work is promoted, priced, and consumed.

The workforce is highly fragmented and with many people working as freelancers. These people work without formal organisational structures, including employer-led training programmes. They rely on informal learning, peer networks, and vendor-led resources.

This is also reflected in one of the case studies in this report, where Congregation explores emerging AI skill needs and future workforce scenarios, helping organisations and sector actors anticipate and prepare for longer-term transformation.

Training needs priorities linked to creative workflows

To be effective, AI training in the creative industries must reflect freelance work, project-based production, and rules on authorship and value. Training that treats AI as a generic productivity tool is unlikely to be used.

Training should prioritise:

- integration into specific creative types of work, including production, editing, design, marketing, and distribution
- copyright, ownership, consent, and attribution as core learning content, not optional extras
- support for freelancers and micro-organisations through short, affordable, and flexible learning routes
- neutral guidance that helps creatives navigate fast-changing tools without bias towards specific commercial products
- transparency with clients and collaborators about AI use

Many workers are outside formal employer structures, making trusted intermediaries such as cultural organisations, professional bodies, and unions essential for coordinating training and guidance. Their role has become more critical as sector-level support has reduced.

4.3 Health and Social Care

Key challenges AI upskilling can help address in health and social care

Improving AI skills would reduce administrative burden, support decision making, and improve safety and quality in health and social care. However, training would need to reflect how care is delivered, how staff work, and the rules that protect patients. Key challenges include:

- high staff workloads. This can lead to stress and burnout and leaves less time for seeing and supporting patients. It also leaves reduced time for training
- staff spend a lot of time on paperwork. This takes doctors, nurses, care workers, and managers away from giving direct care

- information is often kept in different systems that do not link well, especially between health and social care. This makes it harder to give joined-up care and make good decisions

- strong safety and quality rules. In places where mistakes can have serious consequences, extra checks and rules are needed

- many staff do not have good digital skills, especially in social care or smaller organisations. This makes it harder to use digital and AI tools well

To address these problems, teams need more than just access to AI tools. They need the right skills to use AI safely, build trust, and support good, person-centred care.

Current context and AI use

AI adoption is increasing across health and social care, but the two parts of the sector face very different positions and risks.

Health services

In health settings, AI use is more formalised and structured. Most adoption is in administrative and clinical support tasks, such as documentation, transcription, summarisation, reporting, and service auditing. Larger health organisations are more likely to pilot AI tools. It helps that they can rely on controlled digital environments, supported by established IT, data, and clinical governance.

There is a clear expectation that AI outputs are checked by qualified professionals and do not replace clinical judgement. Training focuses on using AI safely within current systems, knowing what AI cannot do, and making sure people stay responsible for decisions.

This is illustrated in one of the case studies in this report. NHS primary care settings adopted AI incrementally through local experimentation supported by training, improving efficiency while maintaining clinical oversight.

Social care services

In social care, AI use varies across settings and occupations. Some parts of adult social care, including local authorities, larger providers and regulated professions, have more structured approaches, governance arrangements and digital capability. However, in some direct care settings, AI use may be more informal and less consistently supported by clear organisational guidance, particularly where providers have limited digital infrastructure or staff have fewer opportunities for formal training. In this environment, there is often a lack of clear organisational guidance on how AI tools should be used in practice. This can create uncertainty for staff about appropriate use, particularly in tasks such as drafting care plans, assessments, or communication with families.

This uncertainty may create risks around accuracy, data protection, consent, and compliance with existing rules. It can also create inconsistencies in how AI is used across organisations.

Training needs priorities linked to sector workflows

Training needs in health and social care differ between formal, regulated health settings and highly fragmented social care environments.

Training should prioritise:

- for health: structured training embedded within existing systems. It must be aligned with processes on clinical governance, verification, and escalation
- for direct care occupations in social care: widening adoption of low-threshold training, including practice-based guidance for staff working with limited digital infrastructure
- clear, shared rules on acceptable AI use to reduce unsafe informal practices
- inclusion of managers and senior leaders responsible for governance, risk, and assurance
- formats that fit shift-based, time-pressured work and high staff turnover

The health and social care sectors must prioritise having clear baseline expectations for AI competence to reduce uneven practice and risk across providers and care settings.

4.4 Advanced Manufacturing

Key challenges AI upskilling can help address in manufacturing

AI upskilling can help address some of the persistent operational and workforce challenges in advanced manufacturing. Key challenges for the sector include:

- productivity pressures and tight margins. Small process gains matter but firms often lack knowledge and time to identify where AI can add value beyond small steps in automation
- unplanned downtime and inefficiencies in maintenance. Predictive approaches could improve reliability of manufacturing technology, but this requires workers able to use AI tools and interpret outputs
- quality variation. AI could support inspection, monitoring, and process control, but only if staff can check the outputs and apply appropriate oversight in quality-critical settings
- adoption gaps among SMEs. Smaller organisations are less likely to prioritise skills and investments due to uncertainty about what AI means in practical manufacturing terms and lack of time and resource to explore its potential.
- data infrastructure and confidence. This includes concerns about data quality, security, and use of commercially sensitive information

Addressing these challenges requires not only access to AI tools, but also the development of workforce capabilities. This can help organisations to identify high-value operational use cases, integrate AI safely into production processes, and maintain human oversight for quality, safety, and accountability.

Current context and AI use

AI use in manufacturing is more advanced and structured than in many other sectors, but adoption remains uneven. Larger manufacturers are increasingly using AI for predictive maintenance, quality control, production planning, supply chain optimisation, and process monitoring. In contrast, SMEs often rely on isolated tools or supplier-led solutions, with limited internal capability to scale or govern AI use.

Manufacturing has relatively strong foundations in automation, data collection, and operational technology. AI can learn from data, adapt over time, and influence operational decisions. This means that alongside technical capability, skills related to judgement, oversight, and responsible use are essential.

AI skills development in manufacturing is often driven by operational needs rather than formal training pathways. Skills are frequently developed on the job, with limited consistency, recognition, or progression across roles and organisations.

Training needs priorities linked to manufacturing workflows

To be most effective, AI training in manufacturing must be grounded in production environments, operational technology, and quality-critical workflows, rather than office-based or generic AI examples.

Training should prioritise:

- operational use cases such as predictive maintenance, quality inspection, process monitoring, and production planning
- differentiation between operator, technician, engineer, and managerial roles
- skills for interpreting and validating AI outputs in quality and safety critical contexts
- alignment with existing competence frameworks, apprenticeships, and CPD routes
- delivery models that fit shift patterns and continuous operations

Training that connects AI capability to real production decisions will help to bridge the gap between experimentation and scalable operational use.

4.5 Defence

Key challenges AI upskilling can help address in defence

AI upskilling has the potential to help address operational and workforce challenges in the defence sector. To do so, training must align with security requirements, assurance standards, and real operational contexts. Key challenges include:

- making decisions in complex, high-risk situations, where information is often unclear, time-sensitive, and spread across many teams and systems
- dealing with staff shortages, especially in technical and specialist roles, which puts pressure on current teams and reduces flexibility
- managing the loss of skills and knowledge when experienced staff retire or leave, taking important expertise with them
- working effectively in secure, tightly controlled environments, where systems and data cannot be easily changed or shared
- balancing the need for speed and innovation with the need to keep safety, accountability, and mission success at a high standard

Upskilling in AI could enable personnel to use AI tools as trusted decision support, strengthening analysis and oversight, supporting knowledge transfer, while operating effectively within secure and highly assured defence environments.

Current context and AI use

AI use in the defence sector is increasing but remains cautious and uneven. Activity is often focused on pilots, simulations, data analysis, logistics, and decision support rather than large-scale use. Security, assurance, and interoperability requirements shape both how AI tools are used and how skills are developed.

The sector has long experience with automation and complex digital systems. New AI systems that can learn and adapt increase the need for oversight, verification, and professional judgement alongside technical capability.

Training needs priorities linked to defence workflows

Open or generic training provision is often inappropriate for defence. AI training for the sector must operate within secure physical and data environments.

Training should prioritise:

- scenarios linked to real defence tasks and systems
- building skills in checking AI outputs, supervising AI use, and using good professional judgement as well as technical knowledge
- clear learning pathways that separate basic AI understanding from specialist or leadership skills
- consideration of procurement, commissioning, and leadership roles which are all involved in deciding how to use AI
- development routes that match a person’s level of responsibility, authority, and risk

Good defence training supports new technology while keeping to strong rules on safety and accountability. This ensures AI helps people make better decisions without weakening control or operational integrity.

4.6 Digital and Technology

Key challenges AI upskilling can help address in digital and technology

The digital and technology sector is experiencing rapid AI-driven change in job roles and workflows. AI upskilling can help address several immediate and emerging challenges, provided training keeps pace with technology change and is aligned with real job redesign needs. Key challenges include:

- some employers report fewer entry-level opportunities and slower early-career progression, linked to reduced demand for routine junior tasks not just those affected by AI
- qualifications and apprenticeships lagging behind the fast-changing workplace AI use
- changing skills needs from “pure coding” towards oversight, verification, and communication of AI processes
- new skills needed beyond programming, including applied analytics, data interpretation, and simulation
- confusion about what effective AI training looks like and variable quality across provision. This makes it difficult for employers and learners to identify good training and progression pathways

Workers in this sector need new skills to work effectively alongside AI. Roles and entry pathways need to be redesigned. Verification and responsible use are important to enable confident use of AI.

Current context and AI use

AI adoption is reshaping ways of working and job roles across the digital and technology sector. Some entry-level coding and testing tasks are declining as automation grows, but the fall has wider causes than AI alone. At the same time, there is growing demand for skills that support human oversight, verification, and communication. Prompt writing and interrogation are now essential skills in the sector.

Organisational readiness varies widely. Large organisations may face constraints linked to legacy systems and complex or outdated IT infrastructure. SMEs may adopt AI more quickly but can lack internal governance, mentoring, and assurance processes. There is also concern about uneven quality across training provision and a lack of clear pathways that help employers and learners understand what good AI skills training looks like.

Training needs priorities linked to digital and technology workflows

In the digital and technology sector, AI training must respond to rapid role redesign and shifting career pathways, particularly at entry and early-career levels.

Training should prioritise:

- task-based learning linked to real development, testing, analytics, and delivery workflows
- verification, evaluation, and oversight skills to counter over-reliance on AI-generated outputs
- differentiated pathways for baseline literacy, specialist expertise, and leadership roles
- support for educators and trainers whose own AI capability shapes training quality
- short, modular formats that keep pace with rapid technological change

Clear progression routes are essential to avoid AI hollowing out early-career pathways and to sustain long-term workforce development.

This is illustrated in one of the case studies in this report. LinkedIn Learning supports structured progression from awareness to applied AI capability aligned with evolving job roles.

4.7 Life Sciences

Key challenges AI upskilling can help address in life sciences

The life sciences sector faces several long-standing and structural challenges that AI upskilling has the potential to help address, provided skills development is aligned with regulated environments, scientific standards, and established workflows across research, manufacturing, and regulatory functions. Key challenges include:

- high assurance and validation requirements, where scientific integrity, reproducibility, and traceability are essential, placing strong demands on staff time and expertise
- heavy regulatory and documentation requirements, including preparing, reviewing, and maintaining regulatory submissions, quality records, and compliance documents across multiple regimes
- quality review and rework pressures, especially in manufacturing and quality functions, where investigations and corrective actions can be time-consuming
- skills shortages and competition for specialist talent, limiting productivity, innovation, and the ability to scale or attract investment
- inconsistent practices and standards across organisations and functions, reducing efficiency and increasing duplication of effort
- the need to balance new digital capabilities with core scientific and technical expertise, ensuring that tools support rather than replace professional judgement

Addressing these challenges requires more than access to AI tools. Staff also need training to use AI in controlled and accountable ways across research, manufacturing, and

regulatory work. This helps them check outputs, maintain standards, and reduce rework. It also ensures AI supports decisions rather than replacing professional judgement.

Current context and AI use

AI use in the life sciences sector is expanding rapidly across research, development, manufacturing, and regulatory functions. Adoption is most advanced in data-intensive areas such as genomics, drug discovery, laboratory automation, clinical analytics, and medicines manufacturing. AI is also increasingly used to support documentation, reporting, regulatory monitoring, and trial analysis.

Life sciences operate within highly regulated environments with sensitive data, strict validation requirements, and strong expectations of scientific integrity. As a result, AI is primarily used as a decision-support technology rather than an autonomous decision-maker. Human interpretation, verification, and accountability remain essential at all stages of use.

Workshop evidence highlighted important differences within the sector. In discovery and research settings, AI is used to explore, prioritise, and analyse large datasets. In manufacturing and scale-up contexts, AI is more tightly controlled and focused on quality, consistency, and process optimisation. These differences shape both skills needs and training priorities.

Training needs priorities linked to life sciences workflows

AI training in life sciences must reflect highly regulated, scientifically grounded environments where validation, traceability, and auditability are essential.

Training should prioritise:

- baseline AI literacy and responsible use across all roles
- contextualised technical pathways aligned to research, manufacturing, or regulatory functions
- strong emphasis on validation, documentation, and compliance requirements
- development of leadership capability to oversee AI adoption within regulated workflows
- flexible delivery models suited to laboratory, production, and clinical research settings

Trusted brokerage and quality assurance are particularly important given the complexity of the training landscape and the high consequences of inappropriate AI use.

4.8 Professional and Business Services

Key challenges AI upskilling can help address in professional and business services

The professional and business services sector is experiencing rapid integration of AI into client-facing and regulated workflows. AI upskilling can help address structural and professional risks, provided training strengthens governance, assurance, and judgement capabilities alongside technical use. Key challenges include:

- inconsistent assurance and governance capability, particularly around auditability, accountability, and defensibility in regulated contexts
- liability and accountability blind spots, especially where AI is adopted without sufficient understanding of professional obligations
- uneven AI capability between large firms and SMEs, with smaller firms relying more heavily on informal or self-directed learning
- fragmented training provision and limited clarity about what “good” AI training looks like in regulated professional environments
- tension between rapid AI development and slower professional accreditation and qualification cycles

Addressing these challenges requires AI upskilling that strengthens professional judgement, governance capability, and structured progression pathways within regulated service delivery environments.

Current context and AI use

AI adoption in professional and business services is largely framed as augmentation rather than automation, with emphasis on “human and AI” workflows. Enterprise generative AI tools (for example co-pilot-type systems) are widely used as entry points into adoption.

AI capability is increasingly treated as an assumed professional competence rather than a specialist-only skill. Larger firms are developing internal build capability, particularly for sensitive or proprietary data environments, while SMEs demonstrate more variable structured provision.

Adoption decisions are shaped by professional regulation, client trust, and assurance requirements. Governance structures are recognised as needing to evolve alongside AI deployment.

Training needs priorities linked to professional and business services workflows

AI training in professional and business services must reflect regulated, client-facing environments where accountability and defensibility are central.

Training should prioritise:

- baseline AI literacy for all staff, combined with strong emphasis on responsible use and governance
- critical thinking and professional judgement to interrogate AI outputs before client delivery

- auditability, defensibility, and explainability capability in regulated contexts
- tiered, role-appropriate pathways from foundational literacy to advanced technical build capability
- practical, hands-on formats (e.g. prompting workshops) embedded within everyday workflows
- scalable and modular provision capable of reaching large workforces while remaining relevant to SMEs

Effective AI upskilling in this sector must reinforce trust, accountability, and professional standards while enabling confident and productive integration of AI into client service models.

This is illustrated in one of the case studies in this report. KPMG embedded AI capability into professional workflows through structured, organisation-wide learning and governance.

4.9 Clean Energy

Key challenges AI upskilling can help address in clean energy

The clean energy sector is undergoing rapid transformation driven by decarbonisation targets, infrastructure modernisation, and increasing system complexity. AI upskilling can help address several structural and operational challenges, provided training aligns with regulated, safety-critical environments and real engineering workflows. Key challenges include:

- high assurance and validation requirements in safety-critical environments, where modelling errors carry operational and public risk
- heavy regulatory and planning burdens requiring transparent, explainable, and defensible modelling
- uneven AI adoption between large firms and SMEs, with smaller organisations facing time, cost, and capability constraints
- variable data maturity limiting effective deployment of digital twins, predictive maintenance, and optimisation tools
- rapid technological change outpacing formal training provision

Addressing these challenges requires AI upskilling that strengthens modelling capability, validation skills, and system-level thinking within regulated energy environments.

Current context and AI use

AI adoption in clean energy is closely linked to optimisation and modelling. Use cases include digital twins for infrastructure optimisation, predictive maintenance, grid balancing, and environmental modelling.

AI is primarily used as decision support rather than autonomous decision-making. Human oversight, validation, and explainability remain central, particularly in regulated contexts. Adoption varies across organisations, with larger firms more likely to embed advanced analytics into workflows, while SMEs demonstrate more limited structured capability.

Training needs priorities linked to clean energy workflows

AI training in clean energy must reflect infrastructure, engineering, and regulatory realities.

Training should prioritise:

- task-based learning linked to grid operations, predictive maintenance, digital twins, and environmental modelling
- validation, assurance, and explainability capability in safety-critical and planning contexts
- interpretation skills and strong human-in-the-loop oversight
- differentiated pathways aligned to engineering, regulatory, and operational roles
- flexible and modular delivery models suited to SME and time-constrained environments

Effective AI upskilling in clean energy must balance agility with assurance, enabling confident AI use without compromising safety, compliance, or professional judgement.

4.10 Financial Services

Key challenges AI upskilling can help address in financial services

The financial services sector is integrating AI into advisory, operational, and workflow processes within highly regulated environments. AI upskilling can help address several structural and workforce challenges, provided training strengthens governance, judgement, and practical capability alongside tool adoption. Key challenges include:

- training provision lagging behind rapid shifts toward generative and agentic AI tools
- inconsistent assurance and accountability capability in regulated advisory contexts
- uneven AI capability across workforce levels, with structured pathways concentrated in technical roles
- heavy reliance on voluntary CPD beyond mandatory risk training, limiting consistent capability development
- risk of widening capability gaps between large institutions and smaller firms or sole practitioners

Addressing these challenges requires AI upskilling that builds practical tool fluency, strengthens responsible use, and embeds structured progression routes across regulated financial environments.

Current context and AI use

AI use in financial services includes productivity copilots, agentic workflow experimentation, AI-assisted advice preparation, and automation of routine operational tasks. Analytics and automation platforms are increasingly used within financial workflows.

AI is primarily positioned as decision support rather than autonomous decision-making. Responsible use, compliance awareness, and human-in-the-loop oversight remain central, particularly in advisory and insurance contexts.

Adoption patterns vary. Larger institutions demonstrate more structured internal capability and experimentation, while structured progression routes are less consistently embedded across all workforce segments.

Training needs priorities linked to financial services workflows

AI training in financial services must reflect regulated advisory environments, client accountability, and evolving workflow integration.

Training should prioritise:

- mandatory baseline literacy focused on responsible and compliant AI use
- practical prompting and applied tool capability linked to everyday financial workflows
- critical evaluation and validation of AI outputs before client delivery
- clearer progression routes from foundational awareness to advanced applied capability
- differentiated pathways across technical, advisory, and operational roles

Effective AI upskilling in financial services must balance innovation with governance, enabling confident adoption while maintaining professional accountability, auditability, and client trust.

4.11 Summary

The demand for AI training is rising across all sectors, but training needs vary by context. Generative AI is already used in everyday tasks such as writing, communication, and reporting, particularly in health and social care, financial services, and professional services. Use remains more limited and uneven in sectors such as construction and social care. More advanced AI is emerging, but training has not kept pace.

Across sectors, AI use often outpaces structured training. Many workers build skills informally through trial and error, peer learning, or supplier tools. This is common in

construction, the creative industries, and SMEs. As a result, there is limited shared understanding of what safe and effective AI use looks like in practice.

Training needs are shaped by how work is organised. In fragmented sectors such as construction, social care, and the creative industries, training must be simple, flexible, and task based. Many workers sit outside formal training systems, including freelancers and subcontractors. In contrast, sectors such as health, life sciences, and defence require structured training. This must be embedded in existing systems and aligned with regulation, governance, and oversight.

In operational sectors such as manufacturing and clean energy, training must support real-world use. This includes interpreting AI outputs, maintaining quality, and ensuring safety. In digital and technology, and professional services, training must respond to changing roles. There is a growing need for skills in oversight, verification, and working alongside AI systems. Across several sectors, there is also a lack of clear progression pathways. There is uncertainty about what good AI training looks like.

Despite these differences, there are shared requirements across all sectors. Training must be practical and linked to real tasks. It must build confidence and judgement, not just technical skills. It must support responsible use and be accessible in format and delivery. This includes taking account of time constraints, shift patterns, and different levels of digital confidence.

Across sectors, this is illustrated clearly in multiple case studies in this report, including examples such as 100 School, LinkedIn Learning, KPMG, and NHS primary care. In these cases, organisations that moved from informal experimentation to structured capability-building achieved more consistent adoption. They also reported improvements in productivity, confidence, and quality of use.

These patterns are also reflected in the case studies included in this report (Annex 1), where organisations such as Airbus, KPMG, NHS primary care, and 100 School demonstrate how AI capability develops from informal experimentation to structured, embedded learning.

These shared training requirements form the basis of the PRIMES framework in the next section. The framework brings together six principles for designing AI training that is practical, reachable, integrated, modular, expandable, and sustainable.

Overall, the evidence shows that effective AI training must be tailored to sector context but built on shared principles. It must support immediate use in real work and build long-term capability across roles, organisations, and levels of digital maturity.

5.0 Derivation of the PRIMES framework

The PRIMES framework was developed using a mixed-methods approach combining qualitative and quantitative evidence (as outlined in Section 2: Methodology).

The framework is based primarily on qualitative evidence from 23 multi-stakeholder workshops involving around 150 organisations across the UK. These explored practical experiences of AI skills development, training delivery, and organisational readiness across sectors. The data were analysed using a structured thematic approach, allowing patterns to emerge across sectors, workforce groups, and organisational contexts.

The analysis focused on identifying recurring challenges, effective practices, and key features of successful AI training. Common themes included the need for practical, task-based learning, barriers to access and participation, weak alignment with organisational systems, and the importance of ongoing learning and governance.

Findings were tested and refined through ongoing engagement with UK training providers, providing insight into delivery constraints, learner needs and implementation challenges.

These themes were then grouped into broader categories based on their consistency across workshops and their relevance to training design and delivery. This process identified six core dimensions of effective AI training.

The case studies included in this report were selected from organisations identified during the workshop programme (except Cast Consultancy) as demonstrating effective or promising AI upskilling approaches. They were used to validate and illustrate the emerging themes, ensuring the framework reflects real-world practice across sectors.

Survey findings (n=536) were used to further support the results, confirming the importance of key areas such as flexibility, practical application, accessibility, and progression pathways.

The six PRIMES principles bring these findings together into a clear and practical framework. Each principle captures a key aspect of effective AI training:

1. Practical: grounded in real tasks and decision-making
2. Reachable: accessible and inclusive across workforce groups
3. Integrated: aligned with organisational systems and sector standards
4. Modular: flexible in format and pace
5. Expandable: scalable across roles and organisations
6. Sustainable: designed for ongoing adaptation and responsible use

Together, these principles provide a structured and practical guide for designing and delivering AI training across sectors.

6.0 PRIMES: The six principles of effective AI training

PRIMES sets out six evidence-based principles for effective AI training. They reflect consistent findings from 23 workshops, ten case studies and survey data, highlighting the importance of flexibility, practical application and clear progression.

Together, the principles form the PRIMES approach:

1. **P**ractical
2. **R**eachable
3. **I**ntegrated
4. **M**odular
5. **E**xpandable
6. **S**ustainable

The principles translate the sector-specific evidence presented in Section 4 into practical guidance for designing and delivering AI training across different sectors and workforce contexts. Evidence highlights the need for practical, role-based training, stronger governance and assurance, leadership support, and more flexible delivery models.

PRIMES (Table 2) is designed to be a flexible guide. It can support approved provider schemes, endorsement processes, or quality standards as AI tools and skills continue to change.

Table 2 Criteria for meeting PRIMES principles of effective AI training

PRIMES principle	Accreditation criteria
Practical	☐ Training links clearly to real tasks and decisions in the learner's role.
	☐ Learners practise using AI tools in work-relevant scenarios.
	☐ Training makes clear when AI should and should not be used.
	☐ Training recognises and builds on existing informal or self-taught AI use within roles.
Reachable	☐ Training is accessible in time (duration and flexible timing), format and language.
	☐ Learners are given paid time or protected time to take part.
	☐ Materials are suitable for people with different levels of digital experience.
	☐ Personalised support is available for learners who need it.
	☐ Training design explicitly considers intersecting barriers (e.g. income, age, disability, gender) rather than treating learners as single categories.
	☐ Training is designed to build confidence alongside skills, particularly for learners with prior exclusion from digital or technical education.
Integrated	☐ Training fits within existing systems so that workers find practical value and can immediately apply learning to their roles.
	☐ Content aligns with relevant professional standards, qualification or skills frameworks.
	☐ Training reflects sector-specific values and responsibilities, such as safety, accountability, or person-centred practice.
	☐ Provision supports benchmarking, quality assurance, and clear recognition of learning outcomes.
	☐ Employers and learners can identify training that is reliable, relevant to their work, and appropriate for their level of AI use.
	☐ Training aligns with organisational data infrastructure and digital systems to ensure practical and safe application.
	☐ Baseline AI training is mandatory before staff use workplace AI tools, particularly where AI use involves organisational data, confidential information, regulated activity, safety, or professional judgement.
	☐ Training helps learners understand relevant next steps, including further learning, safer AI use, or AI-related responsibilities where appropriate.
Modular	☐ Training is broken into short, manageable units.
	☐ Learners can complete training in different formats and at different speeds.
	☐ Content allows learners to enter at different levels of training according to their AI skills and return when needed.
Expandable	☐ Training develops transferable AI skills that can be applied across different tools, systems, roles and organisations where possible.
	☐ Core content remains consistent while allowing local or role-specific adaptation.
	☐ Provision can support rapid growth in demand as AI use spreads.
Sustainable	☐ Training can be updated as AI tools and uses change.
	☐ There are plans to review and refresh learning after delivery.
	☐ Providers monitor outcomes, including whether training improves confidence, quality of use, and decision-making.
	☐ Responsible use of AI is embedded as a core and enduring capability that remains essential as AI tools evolve. This includes confidentiality, data protection, transparency, and human oversight.
	☐ Learners are given opportunities to reflect on how AI is used in practice and identify further learning needs and progress towards more effective AI use.

6.1 Practical

Effective AI training is practical and supports day-to-day work. It helps people apply AI to real tasks and decisions and not just learn about tools. This is illustrated in case studies in this report, where NHS primary care settings used AI in real tasks such as documentation, and 100 School delivered challenge-based training requiring participants to create tangible work outputs, enabling learning to be applied directly in practice.

Training should show how AI fits into a person's role, when it is useful and when it is not. It should build on informal or self-taught AI use within roles, rather than assuming learners are starting from scratch.

Strong training aligns with the three AI skills categories set out in the *AI Skills for the UK Workforce* report:

- Technical AI skills
- Non-technical AI skills
- Responsible and ethical AI skills

These skills should be taught together through practical activities. Learners use AI tools, interpret outputs, and apply judgement as part of the same task.

Practical AI upskilling training programmes prioritise hands-on learning that links directly to real tasks. This includes:

- scenario-based activities such as drafting AI-supported care plans
- small applied projects with feedback
- use-case libraries that show safe and practical uses
- time for reflection and repeat practice

Training that mirrors everyday work helps people understand what AI can do, where its limits lie, and how to use it safely and responsibly.

6.2 Reachable

AI training programmes should be reachable for all workforce groups. This means removing practical barriers and supporting people with different levels of confidence, digital skill and experience.

One case study in this report shows how this can work in practice. The Good Things Foundation delivers accessible, bite-sized AI learning for digitally excluded groups. Its approach builds confidence alongside skills, making AI training achievable for people who might otherwise be excluded.

Reachable training provides:

- protected and paid time to take part

- well-designed course materials including plain language materials and closed captions (subtitles to support learners with hearing impairments or those accessing content without audio)
- technologically accessible training including mobile-friendly delivery and low-tech alternatives.

Support during training is important. Good AI training recognises that confidence is a barrier, not just access. Coaching and mentoring from local champions help learners who lack confidence or digital experience.

In-built reflection also helps. Simple tools can help workers identify how they would use AI and identify their future learning needs.

Inclusive AI training includes:

- early support for people with low digital or data skills
- entry modules that build confidence and explain how AI works in practice
- safe spaces to ask questions and test ideas

Designing training to be inclusive from the start prevents uneven take-up. Without this, only the most confident digital users benefit, which can widen skill gaps within teams and organisations. Training should reflect intersecting barriers such as income, age, disability, and gender, rather than treating learners as single categories.

6.3 Integrated

Effective AI training should be built into existing systems, roles, and ways of working. It should fit the tools, processes, and standards people already use rather than sit alongside them.

Training should align with organisational data, digital infrastructure and governance. This supports safe, effective use in practice and enables clear progression into AI-related roles and responsibilities.

This approach is shown in multiple case studies in this report. Organisations such as KPMG and Airbus embed AI training within existing systems, workflows, and governance structures, allowing staff to apply learning directly to their day-to-day work.

Across sectors, stakeholders emphasised that training should connect directly to the digital tools and processes staff work with every day. When training matches real systems, such as care records, building models, data platforms, or creative tools, people can use what they learn straight away.

Training must integrate sector values, responsibilities and regulation. In areas like health, social care, and construction, staff must focus on safety, accountability, and person-centred practice. When AI training supports these values, people are more likely to trust the tools and use them responsibly.

Integration with established training frameworks is essential. Adding AI content into apprenticeships, professional standards, and mandatory training will normalise AI use. It will help move AI use from informal experimentation to consistent and governed practice.

This integration will allow benchmarking, recognition, and shared standards on AI skills. This may include micro-credentials linked to qualifications, CPD credits or digital badges. This will support progression within roles and professions. It will also help organisations compare training provision.

Clear approval and quality checks are also important. Using approved provider lists, sector endorsements, or trusted brokers helps employers and learners find reliable training that meets agreed standards.

6.4 Modular

Effective AI training must be flexible in both format and pace. It should fit around different roles, workloads, and workplaces, rather than require fixed schedules. This is demonstrated in one case study in this report. LinkedIn Learning offers structured, modular learning pathways that allow learners to progress at different speeds and levels.

Good programmes offer a mix of delivery options. These include in-person sessions, online learning, hybrid models, workplace-based training, and self-paced study. This allows organisations to choose what works best for their staff and business.

Modular design is critical. Short, focused units make training easier to access and complete. In settings, such as SMEs and frontline services, very short (30 to 90 minutes), stackable modules are often more practical than longer sessions.

Microlearning formats allow skills to be built step by step and revisited when needed. Modular design also allows learners to enter at different points and return to content as their skills needs change. This approach works well for SMEs, freelancers, and frontline staff who have limited time.

Flexible training also supports different learning speeds. Learners can pause, repeat content, or move ahead as they feel confident. Follow-up check-ins and short refresh sessions help reinforce learning.

By offering modular and flexible pathways, AI training can reach more people, reduce drop-out rates, and support consistent learning across sectors.

6.5 Expandable

AI skills training needs to scale because AI tools spread quickly across functions and levels of responsibility. They rarely stay limited to one team or role.

Training programmes should be designed so they can be used across different work settings, from small community providers and SMEs, to large national employers. Training should work for varied roles, levels of digital experience, and sector needs.

This is illustrated in one of the case studies in this report. Airbus developed scalable training models applied across functions and geographies.

Scalable training relies on a clear core. Shared foundations help ensure consistency while allowing local adaptation. Role-based modules and use-case libraries can allow the same training to be used across teams, with changes only where needed.

As AI tools become more widely used, training demand will increase. Programmes that cannot scale risk leaving parts of the workforce unsupported. This can lead to uneven skills across the workforce, poor practice, and increased risk.

Expandable training helps organisations respond to growth in AI use without repeated redesign. It supports coordinated rollout across teams and supports shared standards as AI applications become more widely used.

6.6 Sustainable

AI training needs to last longer than a single session. AI tools are changing quickly, and training must be easy to update rather than be fixed. AI training needs to be sustainable in two ways: the training itself must be designed to evolve over time, and it must also equip individuals with skills that remain relevant and adaptable as AI continues to develop.

This is illustrated in one of the case studies in this report. Roche implemented ongoing training, reinforcement, and governance to sustain AI capability over time.

Many organisations started with generative AI tools that support tasks such as writing, summarising, or drafting content. AI is now moving towards more agentic forms, where tools can influence decisions, suggest actions, link tasks, and work with less direct input. As this happens, the skills people need will continue to change.

Training should be designed to be easily updated as AI evolves. Core content should be reviewed regularly to reflect new ways AI is being used. Revisiting training after 3 and 6 months helps people reflect on how they are using AI and adjust how they work.

Sustainable training also depends on checking whether it is making a difference. Simple review methods can help organisations understand whether training is improving confidence, quality of use, and decision-making, and where more support is needed.

Responsible use must be built in from the start. This includes confidentiality, consent, data protection, transparency, and human oversight. These elements should be part of everyday practice, not optional or advanced topics.

By combining regular updates, follow-up review, and clear expectations for safe use, AI training can remain relevant and trusted as tools and ways of working continue to change.