



AI Across Business Functions

(AIStatus 1)

Where and How AI Is Being Applied Across Organisations

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Edition: Version 1.0

Publication Date: September 2026

Preface

Artificial intelligence is now being used across a wide range of organisational activities.

Some applications have become familiar parts of everyday work. Others are being integrated more deeply into established systems and processes. Some remain pilots, experiments or recently introduced capabilities. In other areas, technological capability has developed more quickly than organisational adoption.

These differences can make the current position difficult to see clearly.

Announcements of new capabilities can be mistaken for evidence of widespread use. Individual experimentation can be interpreted as organisational adoption. A successful pilot can appear to represent routine deployment. Survey findings can describe very different forms of “AI use”. Developments visible in one country, industry or organisation may not represent the wider position.

AIStatus has been developed to provide a structured view of what is happening at a defined point in time.

This publication examines artificial intelligence through the **Business Functions** lens. It considers where and how AI is currently being applied across twelve important functions and activities of organisations, from Finance & Accounting and Human Resources to Leadership & Governance and Research & Knowledge Management.

The purpose is not to predict what these functions will become, recommend how organisations should adopt AI, or determine whether particular applications are desirable.

It is to establish, as coherently as the available evidence permits, **what is currently happening**.

The Status presented in this publication is assessed **as at 30 August 2026**.

Purpose of This AIStatus

AIStatus — Business Functions is designed to help readers **DISCOVER where and how artificial intelligence is currently being applied across the functions and activities of organisations**.

The publication examines twelve Business Functions:

- Finance & Accounting
- Human Resources & Recruitment
- Marketing & Communications
- Sales & Customer Experience
- Operations & Supply Chain

- Strategy, Innovation & Transformation
- Project & Programme Management
- Technology & Information
- Legal & Compliance
- Risk & Assurance
- Leadership & Governance
- Research & Knowledge Management

Each function is examined independently but through a common set of questions. This allows readers to explore a particular function on its own while also comparing developments across the wider organisational landscape.

The publication concentrates on the **current state**.

It distinguishes, where the evidence permits, between what AI systems can demonstrably do, what organisations are actually deploying, how established adoption appears to be, and what remains experimental, limited or uncertain.

This is not a forecast of the future of work or organisations. It is not a technology-selection guide, implementation manual, consultancy report or set of recommendations.

It is a point-in-time examination of the position as it can reasonably be understood from available evidence.

Global Perspective & Neutrality Statement

Artificial intelligence is developed, deployed and used across different countries, economies, industries, institutions and organisational environments.

Patterns of adoption are not uniform.

Technological infrastructure, access to AI systems, organisational resources, regulatory environments, labour markets, language, professional practices, data availability and institutional capabilities can all affect how AI is used.

This publication therefore does not assume that developments in any single country or region represent the global position.

International evidence and examples are included where they materially improve understanding of the Status. The absence of equivalent evidence from every region should not be interpreted as evidence of equivalent adoption, nor has geographical symmetry been manufactured where reliable evidence is unavailable.

AISF does not endorse or rank particular AI systems, providers, organisations, technologies or approaches.

References to particular organisations, systems or applications are included where they provide useful evidence of capability, deployment, adoption or development.

Their inclusion does not constitute endorsement.

Editorial Standard

AISF AIStatus publications are designed to provide structured, evidence-informed, globally aware, neutral and non-prescriptive examinations of the current AI landscape.

A central editorial discipline of this publication is the distinction between:

**demonstrated capability;
actual organisational deployment;
extent of adoption; and
announced, previewed, pilot or experimental development.**

These conditions are not treated as interchangeable.

The existence of a technological capability does not establish that organisations are widely using it.

The availability of a product or service does not establish adoption.

A pilot does not establish routine deployment.

An organisational announcement does not necessarily demonstrate operational use.

A survey reporting that respondents “use AI” does not necessarily indicate that AI has been integrated into core organisational workflows.

Evidence is therefore interpreted according to what it can reasonably establish.

Different surveys may measure different populations, definitions of AI, forms of use, industries, countries or time periods. Results that are not sufficiently comparable are not combined to create an artificial measure of adoption.

Provider evidence can be useful in establishing that a capability or deployment exists, but provider availability or reported customer examples are not treated by themselves as evidence of widespread adoption.

Where evidence is incomplete, uneven or uncertain, that uncertainty is preserved.

How to Use This AIStatus

This publication can be read in two ways.

Readers seeking an overall picture of AI across organisational functions may read the twelve Business Functions sequentially.

Readers interested in a particular area may go directly to the relevant function. Each Business Function has been designed to stand independently and provide sufficient context to be understood without requiring the reader to consult the other functions.

To provide consistency and comparability, every Business Function is examined through the same seven questions:

1. What is AI currently being used for?

Identifies important current applications and use cases.

2. What activities are changing?

Examines which activities, tasks or workflows appear to be materially affected and the nature of that change.

3. What can AI currently do?

Describes demonstrated current capabilities in accessible terms.

4. How established is its use?

Considers the present state of adoption, distinguishing where useful between established deployment, growing adoption, emerging use and experimentation.

5. What appears to be driving adoption?

Examines significant evidenced factors contributing to organisational adoption, testing or development.

6. What are the present limitations?

Identifies material technological, organisational, data, reliability, integration, skills, governance, economic or other limitations evident at the Status date.

7. What you should be aware of

Provides important context and qualifications needed to interpret the current Status, including where relevant uncertainty, human involvement, accountability, evidential limitations and differences between publicity and actual deployment.

Each Business Function concludes with **Evidence Notes** identifying principal sources supporting the Status assessment.

The same questions provide a common structure, but they do not imply that AI is developing at the same rate or in the same way across every function.

Differences are part of the Status.

Version & Governance

AIStatus 1 — AI Across Business Functions

Where and How AI Is Being Applied Across Organisations

Edition: Version 1.0 / 2026 Edition

Status Reference Date: 30 August 2026

Publication Date: September 2026

Series: AISF AIStatus

Published by: AI Sourced Facts (AISF) Pte. Ltd.

AIStatus publications provide point-in-time examinations of a changing artificial intelligence landscape.

The Status contained in this edition has been assessed using information available up to and including **30 August 2026**. Developments occurring after that date do not form part of the Status assessment for this edition.

Future editions may reassess the subject at a later reference date. Such editions may reflect changes in technologies, applications, organisational deployment, adoption, evidence and the structure required to describe the position adequately.

An earlier edition remains a record of the Status assessed at its stated reference date.

Editorial oversight of the AISF AIStatus series is maintained by AI Sourced Facts (AISF).

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Introduction

AIStatus — Business Functions examines where and how artificial intelligence is currently being applied across the functions and activities of organisations. It is designed as a point-in-time Status: a structured view of what can be evidenced as at 30 August 2026, rather than a forecast of the distant future or a guide to what organisations should do.

The publication covers twelve Business Functions: Finance & Accounting; Human Resources & Recruitment; Marketing & Communications; Sales & Customer Experience; Operations & Supply Chain; Strategy, Innovation & Transformation; Project & Programme Management; Technology & Information; Legal & Compliance; Risk & Assurance; Leadership & Governance; and Research & Knowledge Management.

Organisational functions do not operate as sealed compartments. Customer personalisation can sit across marketing, sales and service; strategic analysis can overlap leadership; cybersecurity can be viewed through technology, risk or governance; and enterprise search can be both technology infrastructure and knowledge management. The same AI capability may therefore appear legitimately in more than one chapter. Each chapter treats it from the perspective of the function being examined so that the chapter remains intelligible in its own right.

Every chapter uses the same seven questions:

1. What is AI currently being used for?

Purpose: applications — where and for what AI is presently being used.

2. What activities are changing?

Purpose: workflow/activity change — what is changing because of AI use.

3. What can AI currently do?

Purpose: capability — what the technology is presently capable of doing within the function.

4. How established is its use?

Purpose: adoption and establishment — how far actual use has progressed.

5. What appears to be driving adoption?

Purpose: drivers — why organisations are adopting, testing or developing these applications.

6. What are the present limitations?

Purpose: limitations — what presently constrains capability, deployment, usefulness or scale.

7. What you should be aware of

Purpose: awareness — important context and qualifications needed to form an informed judgement. This final question is interpretive rather than prescriptive: it does not tell organisations what they should do.

A short Status overview precedes the seven questions in each chapter. Evidence Notes follow Question 7. The Evidence Notes identify important sources and, where useful, explain the evidential role of a source, its geography, sample or methodology, and material qualifications. Provider material can be valuable evidence that a capability existed by the reference date; it does not by itself show how widely organisations had adopted that capability.

A central discipline throughout the publication is to distinguish four different propositions: demonstrated AI capability; actual organisational deployment; the extent of adoption; and announced, preview, pilot or experimental development. These are related but not interchangeable. A provider offering a feature does not establish widespread customer adoption. A pilot or preview is not routine deployment. Survey-reported “use” may describe anything from occasional individual assistance to deeply embedded workflow integration. Individual employee use is not necessarily institutional adoption, and AI assistance does not mean that consequential responsibility has been delegated to AI.

Adoption figures therefore require careful reading. Different surveys can examine different populations, countries, industries, organisation sizes, technologies and definitions of “use”. One survey may count experimentation; another may ask about formal implementation; another may measure weekly use by individual professionals. Their percentages should not automatically be combined or treated as measurements of one global adoption rate.

The publication takes a global perspective. International evidence is actively considered, and the chapters include material from multiple regions where the accepted evidence supports it. At the same time, public evidence is not geographically uniform. Some markets, sectors and large organisations are more extensively documented than others. A global perspective therefore means seeking and recognising relevant international evidence without manufacturing geographical symmetry where comparable evidence is unavailable.

AIStatus is neutral, educational and non-prescriptive. It seeks to help readers understand the current position: what AI is being used for, what is changing, what present systems can do, how established their use appears to be, what is driving adoption, what limitations remain and what qualifications matter when interpreting the evidence. The chapters do not rank vendors, recommend products or prescribe organisational action.

1. Finance & Accounting

Status as at 30 August 2026

Artificial intelligence is now visibly present across Finance & Accounting, but its use is highly uneven. In some organisations AI has become embedded in routine finance systems and everyday professional work. In others, deployment remains confined to individual productivity tools, pilots or selected processes.

The most established applications tend to involve activities that are repetitive, data-intensive or capable of being checked against defined rules: transaction processing, document extraction, matching, reconciliation, anomaly identification, forecasting support and routine analysis. Generative AI has widened the scope by allowing finance professionals to interrogate information using natural language, draft explanations and reports, summarise financial material and investigate variances without relying entirely on conventional system interfaces.

A further development visible in 2026 is the emergence of **AI agents** within finance software. These systems are intended not simply to answer questions, but to undertake portions of workflows, retrieve information, assess circumstances and initiate or complete permitted actions. Some such capabilities are operational; others remain in preview, early deployment or controlled implementation.

Consequently, the Finance & Accounting picture as at 30 August 2026 is neither one of widespread autonomous finance nor one of continued experimentation alone. It is a mixed environment in which established automation, predictive AI, generative AI and emerging agentic systems increasingly coexist.

1. What is AI currently being used for?

Transaction processing and accounting operations

One of AI's clearest present applications is reducing the manual handling of high-volume financial transactions.

AI-enabled systems can extract information from invoices, receipts, bank records and other financial documents; classify transactions; identify likely accounting treatments; match payments and remittances; detect discrepancies; and route exceptions for review.

Accounts payable and accounts receivable are therefore prominent areas of application. Current enterprise finance platforms incorporate AI for activities including invoice processing, payment matching, collections and cash application. Oracle, for example,

identifies finance agents covering payables, payments, expenses, ledgers and cash processing, while Microsoft describes AI-supported accounts receivable, accounts payable and reconciliation functions.

Research published in 2026 provides evidence that these applications extend beyond demonstrations. A field study covering more than 200,000 transactions from 79 small and medium-sized enterprises found generative-AI-supported accounting associated with less routine data-entry work, faster month-end closing and more detailed accounting records. Human accountants tended to intervene particularly where the AI system reported lower confidence.

Financial close, reconciliation and reporting

AI is increasingly being incorporated into the processes surrounding month-end and financial close.

Applications include transaction matching, account reconciliation, identifying unusual entries, investigating reconciling items, helping prepare explanations and supporting financial reporting workflows. Microsoft's Account Reconciliation Agent, for example, is designed to match and clear ledger transactions, although it remained a preview capability at the reference date.

Generative AI can also produce first drafts of management commentary, summarise movements between periods and retrieve supporting information. These functions do not remove the need to establish whether the underlying numbers, accounting treatment or explanation are correct.

Financial planning, analysis, budgeting and forecasting

Planning and analysis are among the most visible areas of current finance AI use.

AI can analyse historical financial and operational data, identify relationships and unusual movements, support forecasting, compare actual results with plans and assist with scenario analysis. Generative interfaces increasingly allow a finance user to pose questions in ordinary language rather than construct every analysis manually.

Deloitte's second-quarter 2026 survey of large North American companies found 44% of participating CFOs reporting AI use for financial planning and budgeting and 41% for analysing financial data. Because this was a survey of large organisations in one region, the percentages should not be treated as representing finance organisations globally, but they demonstrate that these applications have moved beyond isolated experimentation in at least part of the market.

KPMG's 2026 study of 1,013 senior finance leaders across 20 countries similarly reports AI becoming embedded in financial planning, reporting and analysis, with respondents reporting

improvements in decision speed and forecast accuracy. The findings are survey evidence rather than independent measurement of every claimed benefit, but they reinforce the direction of current deployment.

Treasury and cash management

AI is being applied to cash-flow forecasting, liquidity analysis, payment processing and the identification of cash-management issues.

Modern finance platforms increasingly combine enterprise financial information with predictive techniques to assist cash forecasting. Emerging agentic applications extend this towards systems that can investigate items, perform matching and progress routine work within established permissions.

Tax

AI use in tax includes document and information retrieval, research assistance, classification, data extraction, drafting and analysis.

Generative systems can substantially reduce the effort required to locate and summarise relevant material. Tax nevertheless illustrates particularly clearly why AI capability and professional responsibility must be separated: tax outcomes depend on jurisdiction, current law, factual circumstances and interpretation, and plausible-looking AI output may still be incomplete or incorrect.

Procurement-related finance

Procure-to-pay processes increasingly combine AI with traditional workflow automation.

Applications include extracting invoice information, comparing documents, identifying exceptions, assisting supplier analysis and supporting purchasing and payment processes. A notable 2026 example is the work by PwC and OpenAI to develop AI agents across finance workflows, including a procurement agent being developed inside OpenAI's own finance organisation. The initiative is evidence of real organisational experimentation and implementation, but it should not be interpreted as evidence that autonomous procurement has become standard practice across organisations.

Everyday professional productivity

Some of the broadest finance adoption may actually consist of comparatively ordinary uses of general-purpose AI.

Finance professionals use AI to summarise documents, draft emails and reports, prepare meeting material, explain concepts, formulate spreadsheet approaches, investigate information and create initial versions of presentations or commentary.

Deloitte found that 51% of CFO respondents said their finance functions used AI for operational productivity activities such as transcripts, drafting and administrative work. Gartner's March 2026 survey similarly found finance AI investment weighted more heavily towards productivity than towards improving decision quality.

These uses matter because they may spread more rapidly than major finance-system transformations, even though their effect is less visible in formal process maps.

2. What activities are changing?

The most significant current change is not that individual finance activities are disappearing, but that the **division of work between systems and people is shifting**.

Routine data gathering, document interpretation, transaction classification, matching and first-stage investigation can increasingly be performed or assisted by AI. This moves human effort towards exceptions, review, communication, interpretation and judgement.

The 2026 accounting field evidence is particularly instructive. Rather than simply finding reduced labour, researchers observed a reallocation of accountant time away from routine data entry and towards quality assurance and business communication.

Financial analysis is changing in a different way. Previously, obtaining an answer could require locating data, exporting it, manipulating spreadsheets and constructing reports before interpretation began. AI-enabled interfaces can increasingly compress portions of that sequence by retrieving information, analysing it and producing an initial explanation in response to a natural-language request.

Financial close is similarly becoming more exception-oriented. Matching and reconciliation technologies can process large populations of transactions and direct attention to items that fail to reconcile or otherwise require examination.

Reporting workflows are beginning to combine numerical outputs with AI-generated narrative. This reduces the effort involved in producing a first draft but shifts emphasis towards verifying whether the explanation accurately represents the financial results.

A further change concerns the way finance professionals interact with enterprise systems. Instead of navigating menus, reports and database structures exclusively through conventional interfaces, users can increasingly ask systems questions or instruct AI assistants using ordinary language. Microsoft's 2026 finance developments, for example, include natural-language access to ERP data and limited actions within accounts payable and receivable workflows.

The next stage is beginning to appear through agentic systems. Oracle announced finance applications in April 2026 intended to progress work using enterprise data, policies, workflows, permissions and approval structures, while surfacing exceptions where human judgement is important. Microsoft likewise had finance-oriented agentic functionality in preview during 2026.

This represents an important distinction. Generative AI primarily assisting a person is already relatively familiar. AI being authorised to carry parts of a finance process forward is newer and considerably less uniformly established.

3. What can AI currently do?

As at 30 August 2026, demonstrated finance applications show that AI can perform several different kinds of work.

It can **read and extract**: obtaining structured information from invoices, receipts, remittance advice, financial documents and other records.

It can **classify and match**: suggesting transaction categories, matching payments to invoices or ledger items and identifying likely relationships between records.

It can **detect**: identifying anomalies, unusual transactions, exceptions and patterns warranting investigation.

It can **predict**: supporting forecasts involving revenue, expenditure, liquidity, cash flows and other financial measures where suitable historical or operational information exists.

It can **analyse**: examining financial data, comparing periods or scenarios and helping investigate variances.

It can **generate**: producing draft explanations, management commentary, summaries, correspondence and other finance-related text.

It can **retrieve and converse**: allowing users to query financial information through natural language and combine information that would previously have required several searches or reports.

Increasingly, it can also **act within defined systems**. Agentic applications can be given controlled access to enterprise information and permitted actions so that they can perform portions of workflows rather than merely recommend the next step. Oracle's finance agents and Microsoft's emerging ERP agents illustrate this movement.

What AI cannot currently be assumed to do is exercise reliable, context-complete professional judgement across unrestricted financial circumstances.

The accounting field study found that AI assistance increased classification accuracy on average, but also that following non-consensus AI recommendations could increase error risk. The evidence therefore supports both capability and caution: AI can improve performance, but its output does not become correct merely because it is confidently expressed.

4. How established is its use?

The most accurate description is **established in some applications, growing rapidly in others, and still experimental in the most autonomous forms.**

Traditional AI and machine-learning techniques used for forecasting, matching, fraud or anomaly detection and document processing are relatively mature.

Generative AI for individual finance productivity, analysis, drafting and information retrieval is now widespread enough to be regarded as a meaningful part of the current environment, particularly within larger organisations.

KPMG's 2026 global survey reports active AI use somewhere across the finance function increasing from 30% in its 2024 study to 75% in 2026. Gartner reported 59% of surveyed finance functions using AI in its 2025 study. These figures are not contradictory: surveys use different populations, questions and definitions of “use”. They demonstrate why adoption statistics should be interpreted as indicators rather than precise measures of a universal finance adoption rate.

The contrast becomes clearer when different organisational populations are examined. A 2026 survey focused on accounting workflows found 63% of participating teams exploring AI but only 16% reporting implementation in day-to-day accounting workflows. Another 2026 study covering 437 accounting professionals, predominantly smaller firms, found 45% had not progressed their main AI assistant beyond relatively limited experimentation.

Regional evidence reinforces the unevenness. Research covering 270 senior finance leaders in Australia and New Zealand found 87% either scaling or piloting AI, while a South-East European CFO survey highlighted continued problems involving data, systems, spreadsheets and workforce training despite increasing AI adoption.

Consequently, “finance uses AI” is now a reasonable general statement. “Finance has transformed around AI” is not.

Agentic finance is even earlier. Products existed commercially by the reference date and some organisations were implementing them, but several major capabilities remained in preview or limited deployment. They therefore belong in the Status picture as a meaningful

developing category rather than an established universal operating model.

5. What appears to be driving adoption?

Productivity and capacity are major drivers. Finance functions contain substantial volumes of repetitive information handling, reconciliation, reporting and analysis. Reducing the time spent on those tasks can allow existing teams to process more work or redirect effort towards exceptions and higher-value analysis.

Gartner's March 2026 research illustrates the importance of this motive: 45% of participating finance leaders said their AI investments leaned towards productivity, compared with 20% leaning towards decision quality.

Speed is another driver. Faster extraction, matching, analysis, forecasting and reporting can shorten finance processes and make information available earlier.

Improved analytical capability is becoming increasingly important. Organisations are interested not only in processing finance information more efficiently but also in obtaining better explanations, forecasts and decision support. KPMG's global respondents reported improvements in decision speed, decision quality and forecast accuracy, although such reported benefits remain partly self-assessed.

Labour and skills pressures also matter. Finance teams face demands to undertake more analytical and strategic work while continuing to operate core accounting processes. AICPA & CIMA's international research describes significant skills gaps around AI, data analytics and related capabilities, demonstrating that workforce availability is simultaneously a driver of adoption and a constraint upon it.

Integration into mainstream finance software is lowering the barrier to adoption. Organisations increasingly encounter AI not as a separate experimental technology but as functionality incorporated into ERP, financial planning, accounting, tax and productivity platforms they already use. Oracle, Microsoft and Workday developments during 2026 illustrate this embedding of AI within established enterprise applications.

Competitive pressure and executive expectations are additional factors. As organisations observe peers experimenting with AI, finance leaders may feel pressure to demonstrate progress. This can accelerate adoption, although it can also encourage projects whose measurable value remains uncertain.

6. What are the present limitations?

Data remains fundamental

AI cannot compensate reliably for poor underlying financial information. Fragmented systems, inconsistent records, weak master data and inadequate data governance restrict what finance AI can achieve.

KPMG's 2026 global study found data quality identified by 36% of respondents as both a leading barrier and an important opportunity. The South-East European CFO survey similarly found organisations introducing AI while continuing to contend with spreadsheet reconciliation and distrust of underlying data and systems.

Reliability is not guaranteed

Generative AI can produce incorrect, incomplete or misleading output. Financial work is particularly sensitive because apparently minor errors can affect reporting, payments, tax, controls or decisions.

This limitation becomes more significant as AI moves from drafting or analysis towards taking actions.

Integration remains difficult

Finance information often sits across ERP systems, spreadsheets, banking platforms, procurement applications, planning systems and specialist software.

The practical value of AI therefore depends partly on whether it can access the correct information securely and in context. The continuing emphasis vendors place on ERP connectivity itself indicates that integration is a material implementation problem rather than a solved background issue.

Skills and organisational readiness vary considerably

Using a general-purpose AI assistant requires relatively little technical infrastructure. Redesigning a controlled finance process around AI requires much more: accounting knowledge, technology understanding, data capabilities, process expertise, change management and governance.

Only 8% of respondents in AICPA & CIMA's technology, productivity and skills research described themselves as very well prepared to adopt AI, despite 88% regarding AI as potentially transformative.

Governance and control are becoming more important

Finance systems operate inside environments involving authorisations, segregation of duties, audit trails, confidentiality and regulatory obligations.

As AI systems gain the ability to initiate actions rather than merely provide information, questions concerning permissions, monitoring, escalation and accountability become more significant.

Deloitte's 2026 CFO survey found that 59% of respondents regarded balancing pressure for rapid AI deployment against associated risks as their leading AI-governance challenge.

Demonstrating value remains difficult

High levels of AI activity do not necessarily mean high impact.

Gartner reported in June 2026 that although 84% of surveyed finance organisations had implemented or planned AI, only 7% reported high or very high impact. Its July research similarly highlighted a gap between productivity-oriented AI projects and the types of strategic outcomes boards may expect.

This distinction between **adoption and realised value** is central to understanding the present Status.

7. What you should be aware of

The Finance & Accounting environment as at 30 August 2026 contains substantial genuine AI activity, but publicity is running ahead of uniform organisational transformation.

The word **AI** encompasses different technologies and maturity levels. Predictive algorithms, document-processing systems, generative assistants and autonomous or semi-autonomous agents should not be treated as equivalent.

Similarly, a company described as “using AI in finance” might mean anything from employees using an AI assistant to an organisation redesigning its financial processes around integrated agents. Adoption statistics therefore require careful interpretation.

Much current evidence also comes from technology providers, professional firms and surveys of finance executives. These sources are useful and often contain substantial real-world information, but product capability does not establish widespread customer deployment, and executives reporting benefits does not independently prove the magnitude of those benefits.

Human involvement remains significant. Current evidence suggests that AI is often most effective where machines perform repetitive or information-intensive work while people investigate exceptions, assess ambiguous circumstances, apply professional judgement and remain accountable for important outcomes.

Finance also differs from many less controlled organisational activities because its outputs can enter statutory accounts, tax filings, payments, management decisions and formal control environments. Consequently, an AI-generated result that is plausible but wrong may matter considerably more than an imperfect draft in a lower-risk activity.

Agentic AI deserves particular attention because it changes the nature of the issue. An assistant that proposes an answer and an agent authorised to alter records, process transactions or progress workflows present different operational and control considerations. As at the reference date, the latter is clearly developing but should not yet be mistaken for the normal state of finance operations.

The clearest Status conclusion is therefore not that AI has “taken over finance”, nor that it remains principally experimental.

AI has become a material and expanding component of Finance & Accounting. Its strongest present foothold is in productivity, transaction processing, information handling, analysis and decision support. More integrated and agentic forms are beginning to move from demonstration into operational finance, but adoption, reliability, organisational readiness and measurable impact remain uneven.

Evidence Notes

1. **KPMG International — Global AI in Finance 2026 / The Decision Advantage, 11 May 2026.** Survey of 1,013 senior finance leaders across 20 countries and 13 sectors. Important source for cross-country adoption, reported benefits, data-quality constraints and governance maturity. [KPMG Global AI in Finance 2026](#)
2. **Gartner — Finance AI Investment Outcomes, 20 July 2026.** Survey of 204 finance leaders conducted in March 2026. Useful evidence distinguishing productivity-oriented AI investment from decision-quality outcomes. [Gartner CFO AI investment survey](#)
3. **Gartner — Finance AI Roadmaps, 8 June 2026.** Provides evidence of the distinction between AI implementation/plans and organisations reporting high impact. [Gartner finance AI roadmaps](#)
4. **Deloitte — Q2 2026 CFO Signals, 23 July 2026.** Survey of 200 CFOs in large North American organisations. Provides evidence on finance use cases and AI governance concerns. Geographically limited and therefore used as evidence of practice rather than as a global adoption measure. [Deloitte Q2 2026 CFO Signals](#)
5. **Choi & Xie — Human + AI in Accounting: Early Evidence from the Field, Journal of Accounting Research / Stanford GSB, 16 April 2026.** Particularly valuable independent evidence because it includes transaction-level field data covering more than 200,000 transactions and 79 SMEs, rather than relying exclusively on executive survey responses. [Stanford — Human + AI in Accounting](#)
6. **AICPA & CIMA — Future-Ready Finance: Technology, Productivity and Skills, 2026.** More than 1,400 finance leaders surveyed; useful evidence concerning skills and organisational readiness. [AICPA & CIMA Future-Ready Finance](#)

7. **AICPA & CIMA — Future of Finance 2.0 Emerging Themes, 29 March 2026.** Draws on more than 600 finance professionals internationally and provides broader professional context for changing finance roles and technology adoption. [AICPA & CIMA Future of Finance 2.0](#)
 8. **Wolters Kluwer — Future Ready CFO 2026.** Survey of 1,672 senior finance leaders across 20 markets, providing another international perspective on finance technology and AI. [Wolters Kluwer Future Ready CFO 2026](#)
 9. **PwC — South-East Europe CFO Compass Survey, March 2026.** More than 230 finance leaders. Useful counterbalance to major-market material, particularly regarding continuing data, systems, spreadsheet, training and trust problems. [PwC SEE CFO Compass 2026](#)
 10. **Weel / YouGov — 2026 CFO Report: Finance After the Pilot.** Survey of 270 CFOs and senior finance leaders in Australia and New Zealand conducted January–February 2026. Used as regional evidence concerning piloting, scaling and measurement of AI outcomes. [2026 CFO Report — Australia and New Zealand](#)
 11. **Oracle — Fusion Agentic Applications for Finance and Supply Chain, 9 April 2026; Oracle Financials 26B documentation.** Primary provider evidence establishing commercially available finance-agent capabilities. Used to establish what technology existed, not as independent evidence of industry-wide adoption. [Oracle Fusion Agentic Applications announcement](#)
 12. **Microsoft — Dynamics 365 Finance and 2026 Release Wave documentation.** Primary evidence on natural-language ERP interaction, reconciliation, finance agents and the distinction between released and preview functionality. [Microsoft Dynamics 365 Finance](#)
 13. **PwC/OpenAI — AI-Native Finance Function collaboration, 5 May 2026.** Organisation-level example involving actual development of agentic finance workflows including procurement, planning, forecasting, reporting, payments, treasury, tax and close. Used as evidence of developing organisational practice rather than general adoption. [PwC/OpenAI finance collaboration](#)
 14. **Accounting Seed — State of AI in Accounting 2026.** Survey of 128 finance and accounting respondents. Useful mainly in demonstrating the difference between exploring AI and embedding it in daily accounting workflows; smaller and vendor-associated, so treated cautiously. [State of AI in Accounting 2026](#)
 15. **AI Lab for Accountants — State of AI in Accounting Firms 2026.** Survey of 437 accounting professionals conducted May–July 2026, predominantly involving smaller accounting firms. Used cautiously as supplementary evidence of uneven adoption outside large enterprises. [State of AI in Accounting Firms 2026](#)
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2. Human Resources & Recruitment

Status as at 30 August 2026

Artificial intelligence is now materially present across Human Resources & Recruitment, but its use is uneven both between organisations and between different HR activities.

Recruitment is the most visible area. AI is being used to draft job advertisements, search for candidates, screen applications, identify skills, communicate with applicants, schedule interviews and support assessments. Elsewhere in HR, AI assists employee enquiries, learning, skills analysis, internal mobility, workforce planning, performance processes, people analytics and routine administration. Generative AI has also become an everyday productivity tool for many HR professionals, helping them draft communications, summarise information and retrieve organisational knowledge.

A newer development is the incorporation of AI agents into major human-capital-management platforms. These are intended to do more than generate text or make recommendations: within defined permissions, they can progress portions of HR workflows, answer employee questions and coordinate tasks across recruiting, administration, learning and talent processes. Some capabilities were commercially operational by August 2026; others remained newly released, in controlled deployment or part of vendors' developing autonomous-HR propositions.

HR differs importantly from many other business functions because some AI outputs can directly influence people's employment opportunities, careers, pay, performance assessment or continued employment. That makes the distinction between **AI assisting HR staff** and **AI materially influencing decisions about individuals** central to understanding the current Status.

1. What is AI currently being used for?

Recruitment and candidate sourcing

Recruitment is presently the strongest concentration of HR-specific AI activity.

Generative AI can draft or refine job descriptions, recruitment advertising, candidate correspondence, interview questions and related material. Search and matching systems identify potential candidates from applicant databases or professional networks by considering skills, employment history and other characteristics rather than relying exclusively on exact keyword matches.

AI also assists recruiters with large applicant populations. Systems can parse CVs, compare candidate information with requirements, highlight potentially suitable applicants and, in

some circumstances, rank, score or filter applications. LinkedIn's 2026 hiring developments, for example, included AI-supported identification of applicants meeting stated criteria, candidate sourcing, applicant evaluation and candidate messaging.

Conversational AI is being used earlier and more extensively in some high-volume recruitment. Candidates can interact with automated assistants to obtain information, complete preliminary steps, answer questions and arrange interviews. A documented example is Chipotle's recruitment transformation using Workday together with Paradox conversational AI. PwC reported that the redesigned process supported approximately 20,000 hires in around two months and substantially reduced time required to fill restaurant positions. This is evidence of significant organisational deployment, although it concerns a particular high-volume recruitment environment rather than recruitment generally.

Recruitment technology can extend further into candidate assessment. Automated tests and other systems may produce scores or recommendations used in deciding who progresses. The UK's Information Commissioner's Office found examples of automation being used throughout recruitment when it examined practices among more than 30 employers during 2025–26. In some processes, algorithmic outputs could materially influence whether an applicant proceeded to the next stage.

Onboarding and employee services

AI assistants increasingly answer routine employee questions concerning policies, benefits, leave, payroll and HR procedures, retrieving relevant information from organisational systems or knowledge bases.

They can also guide employees through tasks rather than simply supplying an answer. Major enterprise platforms are developing this model as a conversational interface to HR: an employee asks what they need to do and the system retrieves information, identifies an appropriate process and, where authorised, helps initiate or complete it.

Onboarding can similarly combine automated communications, information gathering, document handling, question answering and workflow coordination. SAP's 2026 SuccessFactors release, for example, linked AI-enabled recruiting more closely with core HR and onboarding processes.

Skills, learning and development

AI is increasingly being used to infer or organise workforce skills, identify possible gaps, recommend learning and match employees with development opportunities.

Learning systems can recommend courses according to an employee's role, existing capabilities or career interests. Generative AI can answer questions using organisational learning material and create or adapt training content. SAP introduced context-aware

question answering against organisational learning content in its first-half 2026 SuccessFactors release.

This area connects directly with another increasingly important use: **internal mobility**. AI matching can compare employee experience, skills and interests with internal vacancies, short-term projects or development opportunities. Workday's Talent Marketplace and Talent Mobility capabilities, for example, use machine learning and skills information to identify possible matches. A reported customer deployment at a large professional-services real-estate organisation was associated with a 30% increase in internal applications and increased internal movement, although these figures originate from vendor case-study evidence and should be interpreted accordingly.

Performance, talent and workforce management

AI is also entering performance and talent processes. Applications include summarising feedback, assisting goal setting, identifying skills or development needs, analysing workforce information and helping managers prepare performance discussions.

Algorithmic management extends further. Software can allocate tasks, monitor work, evaluate performance or support managerial decisions. OECD employer research covering France, Germany, Italy, Japan, Spain and the United States found algorithmic-management tools already widely used in most of the countries examined, although the types of tools differed considerably and evaluation tools were particularly prevalent in the United States.

This category is broader than generative AI and reminds readers that AI-enabled workforce management did not begin with large language models.

Workforce planning and people analytics

HR teams use analytical and predictive tools to examine turnover, workforce composition, skills, absence, recruitment demand and other employment information.

AI can help identify patterns across large workforce datasets, construct workforce scenarios and allow HR users to interrogate people information through natural-language interfaces. Developing systems increasingly seek to connect workforce information with business and financial planning rather than analysing HR data in isolation. SAP's 2026 developments, for example, included workforce-planning capabilities intended to link people, agents and business requirements.

Everyday HR productivity

Some of the broadest actual use is less specialised.

HR professionals can use general-purpose generative AI to draft policies and communications, summarise meetings or documents, prepare presentations, formulate

interview questions, restructure text, analyse survey comments and obtain first-stage research assistance.

Such use may occur independently of a formal HR-system transformation. Consequently, an organisation whose HR employees regularly use AI assistants and one whose recruitment or talent systems are algorithmically integrated are both legitimately “using AI in HR”, but at very different levels of operational embedding.

2. What activities are changing?

Recruitment workflows are becoming more machine-assisted from beginning to end.

Producing recruitment material can take less time because a first version of a job description, advertisement, sourcing message or interview guide can be generated quickly. Candidate discovery is moving from manually constructing searches towards systems able to interpret requirements and suggest prospects. Large applicant populations can be parsed and prioritised before a recruiter has examined every application individually.

The resulting shift is not simply one of faster work. It changes **where human attention enters the process**. Recruiters can spend less time on administrative searching, scheduling, initial communications and routine document review, while directing more attention towards candidate engagement, difficult evaluations and hiring-manager interaction.

High-volume recruitment demonstrates the potential scale. The Chipotle case indicates that conversational automation can remove substantial administrative work from individual restaurant managers while allowing candidates to progress through routine portions of the process quickly.

AI is simultaneously changing the behaviour of applicants. Candidates themselves use generative AI to research employers, improve CVs, draft applications and prepare for interviews. This can increase application volume and make written applications more polished but also more homogeneous. The International Labour Organization noted in May 2026 that online applications and generative AI had contributed to growing application volumes, in turn increasing employers' incentive to automate screening—a reinforcing cycle in which automation on one side produces greater automation on the other.

Skills management is changing from periodic inventories towards more continuous matching. Rather than waiting for an employee to search manually for an internal vacancy or course, systems can recommend jobs, projects or learning based on inferred skills and interests.

Employee service is also beginning to resemble self-service conversation rather than navigation through HR portals. Employees can increasingly ask a question in ordinary language and receive information or be directed into an appropriate workflow.

For HR professionals themselves, information gathering and first-draft work are being compressed. An HR practitioner who previously searched several policies, assembled workforce information and drafted an explanation manually can increasingly ask an AI system to retrieve and synthesise relevant material.

The newest change is agentic. Major HR technology providers are moving from AI that **recommends** towards AI that can **progress authorised work**. SAP's 2026 releases described connected agents spanning recruitment, administration, payroll, learning and talent, while Workday was commercially marketing agents across HR and talent acquisition. These developments were real by the reference date, but they should not be interpreted as evidence that autonomous HR administration had become normal organisational practice.

3. What can AI currently do?

As at 30 August 2026, demonstrated HR applications show that AI can perform several distinct types of work.

It can **generate**: producing first drafts of job advertisements, candidate communications, policies, learning material, interview questions, performance commentary and employee communications.

It can **extract and organise**: reading CVs, identifying qualifications and experience, structuring applicant information and categorising workforce data.

It can **search and match**: identifying candidates, matching workers with vacancies or internal opportunities and linking skills with jobs, learning or projects.

It can **rank or score**: applying specified criteria or learned relationships to assessments and applicant information to support—or in some configurations materially influence—selection decisions.

It can **converse**: answering candidate and employee questions, gathering information and guiding users through recruitment or HR-service processes.

It can **analyse and predict**: identifying patterns in workforce information relating to skills, recruitment, retention, performance or workforce requirements, subject to the quality and appropriateness of the underlying data.

It can **personalise**: recommending jobs, learning, career opportunities or HR information according to an individual's circumstances.

And increasingly it can **act within defined workflows**: undertaking permitted portions of recruiting or employee-service processes, retrieving information and initiating follow-on steps through agentic systems.

What current AI cannot be assumed to do is determine reliably who is the “best” employee or candidate across unrestricted real-world circumstances.

Employment decisions frequently involve qualities that are difficult to represent accurately in historical data or simple performance proxies. The ILO's 2025 examination of AI in HR highlights a fundamental problem: an algorithm's usefulness depends not simply on its technical sophistication but on whether the objective it has been given, the data used and the way the system operationalises those inputs actually correspond with good employment decisions. Poorly specified objectives or historically biased information can result in apparently precise but misleading outputs.

Current capability therefore varies greatly by task. Drafting a routine candidate email is technologically easier and lower consequence than determining whether a particular person should receive a job, promotion or adverse performance outcome.

4. How established is its use?

The current picture is substantial but uneven adoption.

Recruitment appears to be the most established HR-specific use area. SHRM's 2026 survey of 1,908 HR professionals found 39% reporting that their HR functions had adopted AI, with another 7% intending to launch it during the year. Recruiting was the most frequently reported HR practice area, but only 27% of the overall sample reported AI use there. The same study found learning and development at 17% and employee experience at 14%.

These results illustrate why statements that “HR has adopted AI” require qualification. An organisation can use AI somewhere in HR without embedding it across HR, and an HR function can use generative AI for drafting without using algorithmic systems to make employment decisions.

Other studies produce considerably different numbers because their populations and definitions differ. Australian HR Institute research published in April 2026 found only 16% of surveyed organisations using AI-assisted application review and about 12% using AI-assisted CV screening.

By contrast, Deloitte India's August 2026 campus-workforce study reported very high levels of AI involvement among the organisations it surveyed: 72% reported AI use for résumé screening, 48% AI-based assessments, 37% candidate engagement and 33% predictive hiring tools. That evidence points to significant adoption within the particular Indian campus-recruitment population studied, not a universal Indian or global recruitment rate.

The contrast is substantively important rather than something to average away.

Similarly, OECD evidence shows algorithmic-management systems established across several developed economies while finding meaningful national differences in what is used.

There is also evidence that enterprise AI products have moved beyond announcements. Workday reported in August 2026 that more than 5,500 customers were using at least one of its AI agents and that more than half its new customers during the quarter adopted at least one AI solution. These figures demonstrate genuine commercial uptake, although use of one Workday AI capability does not establish transformation of an organisation's entire HR function.

Overall, generative assistance, recruitment automation, matching and analytical applications are already meaningful components of the HR landscape. Integrated agentic HR is considerably newer. Fully autonomous employment decision-making is neither necessary to establish that AI adoption is real nor representative of normal HR operations.

5. What appears to be driving adoption?

Productivity and administrative capacity are major drivers. HR and recruitment involve substantial quantities of document preparation, searching, correspondence, scheduling, information retrieval and repetitive administration. Generative AI and automation can reduce the effort required for these activities.

Recruitment has an additional volume problem. Digital applications already made it easier to apply for jobs; generative AI has made it easier still to prepare applications. Larger candidate populations increase the attraction of automated screening, matching and communication.

Speed matters particularly in competitive or high-volume hiring. Faster communication, scheduling and screening can reduce delays between application and hiring.

Skills shortages and changing skill requirements provide another driver. Organisations increasingly need to understand what capabilities their employees possess, where gaps exist and whether people can be moved or developed internally rather than recruited externally. AI-based skills inference, talent marketplaces and learning recommendations are therefore being incorporated into mainstream HR platforms.

Labour-market evidence shows the skill environment itself changing. LinkedIn reported strong growth in jobs requiring AI literacy during 2026, while Indian employment data showed AI-related hiring increasing even when overall IT recruitment was declining.

Employee expectations of digital self-service also matter. Workers increasingly encounter conversational interfaces elsewhere in organisational life and may expect HR information to be accessible without navigating complex systems.

Embedding in existing software lowers the adoption barrier. Organisations do not necessarily make a separate decision to purchase an “AI HR system”; AI capabilities increasingly arrive within established recruiting, HRIS, HCM, learning and productivity platforms.

Finally, **competitive and executive pressure** is accelerating experimentation. AI has become a prominent organisational priority, making HR simultaneously a user of AI and a function expected to help the wider organisation manage workforce consequences arising from it.

6. What are the present limitations?

Employment is difficult to reduce to data

The central limitation is not merely whether an algorithm operates correctly. It is whether what the system measures is genuinely a suitable basis for the employment decision being made.

Historical recruitment and performance information can reflect past organisational choices and inequalities. Apparently objective correlations do not necessarily establish that a characteristic predicts future performance or should influence an employment decision.

The ILO's review identifies problems involving objectives, data quality, bias and opacity across recruitment, compensation, scheduling and performance management.

Reliability and generative-AI errors remain material

Generative systems can produce inaccurate or unsupported statements. That affects HR when AI drafts policy explanations, employment communications or summaries of rules and benefits.

Errors become more consequential where an AI output contributes to a decision about a candidate or employee rather than merely creating an editable first draft.

Skills information is incomplete

Skills-based systems require accurate information about workers, roles and organisational requirements. Employee profiles can be incomplete, inferred skills can be wrong and apparently similar skills may have different practical value.

Consequently, sophisticated matching does not eliminate the underlying problem of establishing what a job genuinely requires and what a person can actually do.

Integration and organisational readiness remain uneven

AI is most useful when it can obtain relevant contextual information from recruiting systems, employee records, learning platforms, policies and workforce data. Those systems are frequently fragmented.

HR teams also require sufficient knowledge to understand where AI is being used, what data underpins it and when its output should not be relied upon. Adoption of a tool does not establish organisational capability to govern it effectively.

Measuring value remains difficult

Much evidence for HR AI benefits comes from vendors, customer case studies and self-reported surveys. These sources can demonstrate deployment and provide useful operational evidence, but they do not independently establish that comparable benefits will occur generally.

SHRM's 2026 research found that 56% of participating HR professionals did not formally measure the success of their AI investments.

Bias, transparency and accountability become more significant as systems influence people

Automated recruitment illustrates the problem clearly.

The UK Information Commissioner's Office found enough concern around automated recruitment to examine more than 30 employers and subsequently communicate with organisations about improvements involving transparency, fairness, data protection and safeguards. The ICO recognises potential efficiency benefits while also identifying risks from unfair or biased outcomes and inadequate explanation.

The OECD likewise found managers raising concerns about unclear accountability, difficulty following algorithmic logic and worker protection even while reporting perceived benefits from algorithmic-management tools.

These limitations do not mean AI cannot assist employment decisions. They mean the evidential and organisational requirements increase substantially as AI moves from administrative assistance towards influencing consequential decisions.

7. What you should be aware of

AI in HR should not be treated as a single phenomenon.

An employee using a general-purpose assistant to draft an internal announcement, an applicant-tracking system highlighting relevant CVs, a chatbot scheduling interviews, an algorithm ranking candidates and an AI agent authorised to progress HR transactions all

involve AI, but they raise very different questions about capability, maturity and consequence.

Recruitment deserves particular attention because technology can affect a person who may never know an algorithm influenced the decision. Screening efficiency for the employer and procedural fairness for the applicant are therefore different dimensions of the same system.

Regulation increasingly reflects this distinction. The European Union AI Act identifies specified AI systems used for employment, worker management, recruitment and selection among its high-risk categories where the relevant statutory conditions are met. Its rationale explicitly recognises the potential effect of such systems on careers, livelihoods and workers' rights.

Legal and regulatory treatment nevertheless varies between jurisdictions and continues to develop. The UK's 2026 work on automated recruitment, for example, reflects its own data-protection framework and should not be read as a global rule.

Human involvement also needs careful interpretation. A nominal human decision-maker does not automatically provide meaningful oversight if that person routinely accepts algorithmic recommendations without understanding or challenging them. Conversely, the existence of AI assistance does not mean that an employment decision has been automated.

Geographical differences are significant. Evidence from Australia, India, Europe and multi-country OECD research demonstrates different adoption patterns, institutional environments and uses. There is no defensible single global HR-AI adoption percentage.

There is also an increasingly important interaction between AI used **by employers** and AI used **by candidates and employees**. Employers automate screening partly to cope with application volume, while applicants use AI to generate and refine applications. AI-generated CVs and application material can in turn make assessment more difficult. Recruitment is therefore becoming an environment in which both sides increasingly employ AI rather than a process in which only the employer possesses advanced technology.

Finally, highly visible announcements about autonomous HR should not obscure the more ordinary applications responsible for much present adoption. Drafting, searching, matching, candidate communication, employee self-service, learning recommendations and administrative assistance are already materially changing HR work. More autonomous agents capable of progressing processes are now entering commercial use, but they occupy an earlier and less uniformly established stage.

The clearest Status conclusion as at 30 August 2026 is therefore that **AI has become a material but uneven component of Human Resources & Recruitment. Its strongest current foothold is in recruitment, administrative productivity, information retrieval, employee service, skills matching, learning and analytical support. AI is increasingly capable of progressing defined HR workflows, but the more directly it influences**

consequential employment decisions, the more important unresolved questions of data quality, fairness, transparency, reliability, human involvement and accountability become.

Evidence Notes

1. **SHRM — *The State of AI in HR 2026*** — 2026. Survey of 1,908 HR professionals undertaken December 2025. Important adoption evidence: 39% reported AI adopted in HR functions; use concentrated particularly in recruiting, HR technology, learning and development and employee experience; substantial numbers remained non-adopters; measurement of investment outcomes was limited. [SHRM — State of AI in HR 2026](#)
2. **International Labour Organization — Berg & Johnston, *AI in human resource management: The limits of empiricism*** — November 2025. Institutional working paper examining recruitment, compensation, scheduling and performance management; particularly useful for limitations concerning objectives, data, bias and opacity. [ILO working paper](#)
3. **International Labour Organization — *The messy business of managing people at work: Is AI the solution?*** — 15 May 2026. Current discussion of recruitment automation, rising application volumes and the interaction between generative AI used by applicants and automated employer screening. [ILO — AI and managing people at work](#)
4. **OECD — *How widespread is algorithmic management in workplaces?*** — 19 December 2025. Employer evidence spanning France, Germany, Italy, Japan, Spain and the United States; useful for establishing that algorithmic management is already materially deployed but differs between countries and applications. [OECD algorithmic-management evidence](#)
5. **UK Information Commissioner's Office — *Recruitment rewired*** — findings based on evidence from more than 30 employers gathered March 2025–January 2026. Primary regulatory evidence concerning automated recruitment, meaningful human involvement, transparency, safeguards, fairness, bias, lawful basis and data-protection impact assessment. [ICO — Recruitment rewired](#)
6. **UK Information Commissioner's Office — *automated recruitment materials*** — 31 March 2026. Explains practical automated recruitment including CV review, scoring, ranking and filtering and sets out regulatory concerns regarding fairness and transparency. [ICO — automated recruitment decisions](#)
7. **European Union — Regulation (EU) 2024/1689, Artificial Intelligence Act**. Primary legal source. Employment, worker-management and recruitment/selection AI systems within specified circumstances are classified within the Act's high-risk architecture, subject to the Regulation's detailed provisions and exceptions. [EUR-Lex — EU Artificial Intelligence Act](#)
8. **Australian HR Institute — *Managing the 5Rs in a rapidly changing environment*** — April 2026. Australian evidence finding relatively limited use of advanced recruitment tools among its respondents, including approximately 16% using AI-assisted application review and 12% AI-assisted CV screening. Useful counterweight to higher adoption estimates from other populations. [AHRI — Managing the 5Rs](#)
9. **Deloitte India — *Campus Workforce Trends 2026*** — 27 August 2026. Recent Indian evidence concerning campus recruitment; reported substantial use of résumé screening, AI assessments, candidate engagement and predictive tools among participating organisations. Survey evidence is specific to its organisational and campus-hiring population and has therefore not been generalised to India as a whole. [Deloitte India — Campus Workforce Trends 2026](#)
10. **SAP — SuccessFactors 1H 2026 release** — 13 April 2026. Provider evidence establishing available and newly released HR capabilities involving recruiting, workforce administration, payroll, learning,

performance, talent development, skills governance and agentic AI. Used as capability evidence rather than evidence of general customer adoption. [SAP SuccessFactors 1H 2026 release](#)

11. **SAP — autonomous HCM developments** — 14 May 2026. Provider evidence concerning developing assistant/agent architecture and workforce-planning capabilities. The vendor's “autonomous HCM” terminology has deliberately not been treated as evidence that autonomous HR is established practice. [SAP — Autonomous HCM developments](#)
 12. **Workday — AI agents and Talent Mobility**. Provider materials establishing commercially available capabilities involving employee self-service, talent acquisition, candidate experience, job matching, skills and internal mobility. Used principally to demonstrate capability.
 13. **Workday customer evidence — AI talent mobility**. Customer case-study material reports a 30% increase in internal application rates, increased internal movement and improved retention at a Fortune 500 real-estate/professional-services organisation. Results are identified as vendor case-study evidence rather than independent universal performance estimates.
 14. **PwC — Chipotle hiring transformation** — 23 January 2026. Deployment case involving Workday and Paradox conversational AI. Reports approximately 20,000 hires in around two months and substantial reduction in time-to-fill for restaurant roles. Useful evidence that conversational recruitment automation has progressed beyond demonstration in some high-volume settings. [PwC — Chipotle hiring transformation](#)
 15. **Workday Q2 FY2027 results / reporting — August 2026**. Commercial-adoption evidence. Workday reported more than 5,500 customers using at least one AI agent, while Reuters reported that more than half of new customers in the quarter adopted at least one AI solution. This establishes meaningful commercial uptake of the provider's AI offerings but not uniform adoption across customers' HR processes.
 16. **LinkedIn — Hiring Product Update** — 13 May 2026. Provider evidence for applicant highlighting, intent-based search, sourcing, evaluation, candidate messaging and ATS integration. Used as capability evidence rather than proof of general organisational adoption.
 17. **LinkedIn Economic Graph — 2026 labour-market research**. Evidence concerning changing skill requirements and the growth of AI-literacy requirements; useful principally to establish workforce and skills pressures affecting HR rather than HR-system adoption itself.
 18. **Reuters / Naukri — India AI hiring** — 3 July 2026. Labour-market evidence showing AI-related recruitment increasing within India's IT sector despite weaker overall IT hiring, illustrating changing skills demand.
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3. Marketing & Communications

Status as at 30 August 2026

Artificial intelligence is now a material part of Marketing & Communications, but the depth of its use varies considerably.

The most visible change has been the rapid spread of generative AI into everyday work. Marketing and communications professionals use AI to develop ideas, draft and edit text, produce and modify images and video, summarise research, adapt material for different audiences and languages, and accelerate routine production. In advertising, AI is also embedded much more deeply: machine-learning systems have long supported targeting, bidding, recommendation and campaign optimisation, while newer generative systems increasingly create or adapt the advertising itself.

A second development is becoming increasingly important. AI is moving beyond helping people produce individual pieces of content towards connecting activities across marketing workflows. Current platforms can analyse customer information, identify or construct audience segments, generate variations of content, select creative material, personalise messages, optimise campaign delivery and report on performance. Agentic systems intended to undertake several of these activities in sequence were commercially available or being deployed by the reference date, but their establishment remained substantially behind ordinary generative-AI use.

AI is also changing the environment in which marketing operates. Consumers increasingly obtain information through AI-generated answers and conversational interfaces rather than solely through conventional search results, websites and social feeds. This is beginning to alter search marketing, brand discovery and the way organisations think about whether their information will be found and represented by AI systems.

The resulting Status is therefore broader than “AI-generated marketing content”. As at 30 August 2026, AI is established across parts of digital advertising and widely used for individual productivity and content work; increasingly integrated into personalisation, analytics and campaign workflows; and beginning, but not yet uniformly, to assume more autonomous marketing tasks.

1. What is AI currently being used for?

Research, audiences and insight

AI is used to analyse large volumes of customer, market and behavioural information, identify patterns and trends, classify feedback, develop audience segments and assist marketers in understanding customer interests and responses.

Natural-language generative systems have widened access to these capabilities. A marketer can ask questions about research, summarise customer comments, compare competitors, develop initial audience profiles or interrogate marketing information without constructing every analysis manually.

AI also supports social listening, media monitoring and sentiment analysis. Communications teams can process large volumes of news, social-media discussion and other public information to identify mentions, emerging subjects, reputational issues and changes in sentiment. These applications are useful for directing human attention, although interpretation of tone, irony, cultural meaning and causation remains less dependable.

Content and creative production

Content creation is among the most widespread current applications.

AI can generate or assist with advertising copy, emails, social posts, articles, scripts, headlines, product descriptions, presentations, press materials and other written communication. It can create and edit images, generate video and audio, develop storyboards and concepts, translate or localise material and produce multiple versions of an asset for different audiences or channels.

This is increasingly built directly into mainstream marketing and advertising platforms rather than requiring a separate general-purpose AI tool. Meta reported in July 2026 that more than eight million advertisers were using at least one of its generative-AI advertising creative tools. Amazon had expanded AI image generation for advertisers into additional European and Asia-Pacific markets by July, while TikTok was incorporating generative video and automated creative selection into its advertising products.

The significance is not merely that AI can make one advertisement. It can make many variants rapidly, allowing different formats, languages, products, audience groups and channels to be served without reproducing the entire conventional production process for each variation.

Advertising, media and campaign optimisation

AI has a more established history in digital advertising than the recent generative-AI discussion sometimes suggests.

Advertising platforms use machine learning to determine which advertisements to show, predict responses, optimise bids and budgets, identify relevant audiences, select placements and measure performance. Increasingly, these optimisation systems are being combined with generative AI.

Google's AI Max, Meta's Advantage+ environment, Amazon's Brand+ and Performance+ and TikTok's Smart+ illustrate a broader movement towards AI-supported campaign operation in which targeting, creative selection and optimisation are increasingly automated.

The scale is meaningful. IAB's 2026 US advertising research found extensive use of generative AI in advertising creative and growing interest in agentic systems for media buying and campaign execution. This evidence is geographically specific and should not be treated as a global adoption rate, but it demonstrates that AI-supported advertising has progressed well beyond isolated experimentation.

Personalisation and customer engagement

AI is used to determine which message, recommendation, offer or content variation may be most relevant to a particular customer or audience.

The underlying concept predates generative AI, but generative systems make personalisation more practical because organisations can produce far more content variations. Instead of selecting only from a small collection of pre-produced material, systems can increasingly adapt wording, imagery, offers and combinations of assets.

Adobe's 2026 global research found personalisation among organisations' major AI investment objectives, while also showing that many organisations lacked sufficiently unified customer data to deliver their ambitions at scale.

Conversational marketing is developing alongside this. AI-powered chat and conversational interfaces can answer questions, recommend products, assist discovery and move a customer towards a transaction. These capabilities increasingly blur boundaries between marketing, sales and customer service.

Public relations and corporate communications

Generative AI has become commonplace in parts of PR and communications.

Applications include brainstorming, drafting and editing releases and pitches, summarising information, developing social content, researching media contacts, monitoring coverage, analysing sentiment and producing reports.

Muck Rack's 2026 survey found 76% of participating PR professionals using generative AI, with editing, content creation and writing prominent applications. Cision's separate research of nearly 600 US and UK communications professionals found 91% reporting generative-AI use somewhere in their workflow, including idea generation, writing, media monitoring and reporting. Different samples and methodologies explain why these figures should be read as evidence of substantial use rather than combined into a universal PR adoption percentage.

Search and brand discovery

AI is changing not only how organisations create marketing but also how audiences discover information.

AI-generated search summaries, conversational search and standalone AI assistants can answer a user's question without requiring the traditional sequence of search result, click and website visit. Adobe's global consumer research reported that 25% of surveyed customers regarded AI platforms such as ChatGPT as their top research tool.

This has produced growing attention to terms such as answer-engine optimisation and generative-engine optimisation: attempts to make accurate brand and product information discoverable and intelligible to AI-generated answers. The practices remain less mature than conventional search-engine optimisation, and the mechanisms by which AI systems select, synthesise and cite information can change quickly.

2. What activities are changing?

The clearest change is in the economics and speed of content production.

A conventional campaign may require separate stages for ideation, copywriting, design, resizing, localisation, production and revision. AI can compress parts of this sequence. Initial concepts can be generated rapidly; text and imagery can be produced together; an existing asset can be adapted into multiple formats; and localisation can be undertaken without recreating every asset manually.

The result is not simply faster production. It permits substantially more experimentation. Marketing teams can create and test variations that previously would have been uneconomic to produce.

Creative work is consequently becoming more iterative. Human effort can move from producing every first draft towards setting direction, selecting, refining, checking and combining AI-generated possibilities. This does not eliminate creative work: it changes the distribution of work within the creative process.

Campaign management is changing differently. Digital advertising already relied heavily on algorithms, but marketers increasingly specify objectives, budgets, source material and constraints while platforms undertake more decisions concerning targeting, bidding, placement and creative selection.

Measurement is also becoming more closely connected with execution. AI systems can identify performance patterns, summarise campaign results and recommend or make

adjustments. Adobe's 2026 marketing research found measurement and performance insights the most valued AI capability among surveyed organisations evaluating marketing platforms.

Communications monitoring is similarly moving from collection towards interpretation. Systems can monitor large information flows continuously, cluster coverage, classify themes and surface anomalies or emerging issues. This increases the amount that can be observed but does not establish that an automated interpretation of public opinion or reputational significance is correct.

Search marketing is undergoing a more structural change. Organisations historically sought visibility principally through conventional search results, advertising, websites and social platforms. AI-generated answers can mediate the interaction between the organisation and the audience. Marketing therefore increasingly includes consideration of what AI systems know or infer about a brand, whether they surface its information and how accurately they represent it.

The emerging agentic model could extend these changes further. Salesforce, for example, introduced marketing agents in 2026 intended to collaborate across campaign development, content, audience and optimisation activities. Such products establish that multi-step marketing automation was technically and commercially available by the reference date. They do not establish that autonomous marketing departments had become normal organisational practice.

3. What can AI currently do?

As at 30 August 2026, demonstrated Marketing & Communications applications show that AI can perform several materially useful types of work.

It can **generate and transform content**: producing text, images, audio and video; rewriting and summarising material; changing tone or format; translating content; and adapting existing assets into new variations.

It can **analyse information**: processing customer data, research, campaign results, social discussion, media coverage and other large information collections to identify patterns, themes and anomalies.

It can **classify and segment**: grouping customers, content, feedback or media coverage according to characteristics or predicted relevance.

It can **predict and optimise**: estimating the probability of engagement or conversion and using performance signals to influence advertising delivery, bidding, audience selection, recommendations and budget allocation.

It can **personalise**: selecting or generating different messages, creative assets, offers and experiences for different audiences or individuals where appropriate data is available.

It can **retrieve and converse**: allowing marketers to interrogate information in natural language and allowing customers to interact conversationally with brands, products and services.

Increasingly, it can **coordinate and act**. Agentic systems can undertake sequences such as analysing a brief, researching an audience, generating campaign material, preparing activation and responding to performance information within configured systems and permissions.

These capabilities nevertheless have different maturity levels. Generating ten headline variants is considerably easier than independently deciding what an organisation should communicate during a reputational crisis. Optimising an advertising bid against a defined conversion objective is different from determining the long-term meaning of a brand.

Current AI is particularly strong where the objective can be specified, large amounts of relevant data exist, outputs can be compared or tested, and mistakes can be detected before they cause significant harm. Its reliability is less assured where communication depends on factual precision, cultural nuance, originality, ambiguous social context, organisational judgement or reputational sensitivity.

4. How established is its use?

AI use in Marketing & Communications is now substantial, but “adoption” covers very different realities.

Algorithmic advertising optimisation and recommendation are established parts of the digital marketing environment. Many organisations have used machine learning in targeting, bidding, segmentation, recommendations and analytics for years, often without users describing each activity as an AI project.

Generative AI for individual productivity and content creation has also moved into mainstream professional use. Australian Data & Marketing Association research covering 1,092 marketing professionals found 77% using AI at least weekly. Muck Rack reported 76% generative-AI use among its surveyed PR professionals. ISBA's 2026 UK advertiser survey found 99% of participating advertisers engaging with generative AI at some level, although only 14% reported a significant effect on business results.

Other evidence illustrates why broad adoption claims require qualification. Gartner's 2026 survey of 401 predominantly large-company marketing leaders in North America and Europe

found CMOs allocating an average 15.3% of marketing budgets to AI initiatives, while only 30% described their organisations as having mature or fully developed readiness to scale AI.

Geographic evidence also shows meaningful use outside North America. Salesforce reported 81% AI adoption among marketers in its 2026 India research. Australian research found frequent individual use but limited formal training. Japanese research from Yano Research Institute found a more mixed digital-advertising market: 25.8% of surveyed advertisers used general-purpose AI tools, 14.3% advanced external AI tools and 12.8% internally developed AI, while 38.3% reported no AI implementation.

These figures use different definitions, samples and questions and should not be reconciled into one global percentage. Collectively, however, they support a clear conclusion: routine AI-assisted marketing is established across significant parts of the market, while organisational depth varies considerably.

More integrated personalisation, content supply chains and AI-supported campaign orchestration are growing but less uniform. Agentic marketing is earlier still. Products existed and organisations were piloting or deploying them by the reference date, but evidence of routine, large-scale autonomous marketing remained substantially more limited than evidence of ordinary generative-AI use.

5. What appears to be driving adoption?

Speed and productivity are immediate drivers. Marketing and communications organisations continuously produce written, visual and multimedia material. Generating first drafts, variations, summaries, translations and routine analysis more quickly can materially increase output.

Production economics are also significant. Generative AI lowers the marginal effort involved in producing additional creative variations. IAB's January 2026 US study found cost efficiency had become the most frequently cited benefit of AI advertising among participating advertising executives.

Personalisation provides another incentive. The practical constraint on personalisation has historically included not only data but the cost of producing enough relevant content. AI makes large-scale variation more feasible.

Performance optimisation remains fundamental. Advertising platforms have strong incentives to use AI where better predictions concerning audiences, placements, bids or creative selection can improve measurable campaign results. This is one reason AI has become deeply embedded in digital advertising infrastructure.

Content demand and channel proliferation matter as well. Organisations communicate across websites, search, email, social platforms, video, marketplaces, mobile applications and numerous local markets. The volume and variety of material required has grown faster than traditional production processes were designed to accommodate.

Changing consumer discovery behaviour is creating a newer driver. As consumers increasingly use AI assistants and AI-mediated search for research and product discovery, organisations are beginning to adapt content and search practices to remain visible in those environments.

Finally, **integration into mainstream platforms** lowers the practical barrier to adoption. Marketers increasingly encounter AI inside the advertising, CRM, creative, analytics and communications systems they already use. Adoption can therefore occur incrementally without an organisation undertaking a separate large-scale AI transformation.

6. What are the present limitations?

Data and integration

Deeply personalised or agentic marketing depends on access to accurate, relevant and connected customer and organisational information.

That foundation is frequently incomplete. Adobe's 2026 global research found data fragmentation and integration among the principal constraints on agentic deployment, with only 39% of surveyed organisations reporting a shared customer-data platform capable of supporting large-scale agentic-AI rollout.

An AI system can generate polished marketing from poor data; polish does not correct the underlying information.

Reliability and factual accuracy

Generative systems can fabricate facts, misinterpret sources or produce plausible but incorrect claims. This is particularly consequential in corporate communications, public relations and regulated advertising, where inaccurate statements can become public immediately.

The problem is amplified by production scale. AI makes it possible to produce far more content, but organisations may not have proportionately expanded their capacity to verify it.

Brand, cultural and contextual understanding

AI can imitate tone and follow brand instructions, but consistency is not guaranteed. Outputs can be generic, inappropriate, culturally insensitive or inconsistent with an organisation's established identity.

Communications involving crises, contested issues, humour, social sensitivities or stakeholder relationships often depend on context that is difficult to encode completely.

Consumer acceptance and authenticity

The ability to generate convincing content does not mean audiences welcome it.

IAB's 2026 US research found a substantial gap between advertiser expectations and younger consumers' attitudes towards AI-generated advertising. Japanese industry research similarly found conditional rather than unconditional acceptance: 52% of respondents considered generative-AI advertising acceptable if appropriate conditions were met, while concerns included unnaturalness, accuracy and copyright. Australian research found 72% concerned about AI-generated advertising, particularly its capacity to mislead.

Consumer attitudes therefore form part of the current limitation, not merely a future ethical question.

Rights, privacy and governance

Marketing AI can involve personal data, intellectual property, likenesses, voices, copyrighted creative material and inferred customer characteristics.

Legal and regulatory treatment varies between jurisdictions. In the European Union, AI Act transparency obligations applying from 2 August 2026 include requirements relating to AI-generated or manipulated content and deepfakes. Existing advertising, privacy, consumer-protection and intellectual-property requirements continue to apply alongside AI-specific regulation.

Skills and organisational readiness

Easy access to generative AI can disguise the difference between using a tool and integrating it responsibly into a marketing process.

ADMA's Australian research found 77% of surveyed marketers using AI at least weekly but only 13% having received formal training. Gartner likewise found a large gap between CMO ambitions and reported organisational readiness.

Measurement and value

High AI use does not automatically establish improved marketing outcomes.

Productivity improvements such as faster drafting are comparatively easy to observe. Establishing whether additional AI-generated content improves brand equity, customer relationships, campaign effectiveness or revenue is harder.

The ISBA UK survey illustrates this distinction: virtually all participating advertisers were engaging with generative AI, but only a minority reported significant business impact. Adoption, output and realised value therefore remain separate measures.

7. What you should be aware of

Marketing & Communications is one of the organisational functions in which AI can appear more established than it actually is because AI-generated output is highly visible.

The visibility is genuine: AI-written copy, generated images, automated advertising and conversational interfaces are already part of the current environment. But visible content generation should not be confused with comprehensive transformation of the marketing function.

There is also an important distinction between **AI used by a marketer** and **AI operating marketing processes**. An employee using a general-purpose assistant to draft a social post represents a materially different level of organisational integration from a system combining customer data, generating content, selecting an audience, allocating advertising expenditure and changing a campaign in response to performance.

Human involvement consequently remains significant. IAB's 2026 digital-video research found buyers expressing strong interest in agentic AI while also seeking human involvement, audit trails and limits on agent authority. In communications, Muck Rack reported that 98% of surveyed PR users always or often edited AI-generated text. Current practice is therefore more accurately characterised by varying forms of human-AI collaboration than by widespread autonomous communication.

The information environment itself is changing. AI systems increasingly mediate what audiences discover about organisations, but organisations do not fully control how an AI answer selects, summarises or represents their information. Search visibility in an AI-mediated environment is therefore both commercially important and technically unsettled.

Trust is another central qualification. AI enables highly realistic synthetic images, voices and video at the same time that organisations, journalists and audiences are concerned about misinformation and authenticity. Cision's global 2026 journalist research found 53% opposed

to AI-generated PR pitches, while attitudes differed materially by region. The European Union's new transparency requirements and emerging industry disclosure frameworks reflect the growing significance of this issue.

Finally, much of the available adoption evidence comes from technology providers, advertising platforms, agencies, professional bodies and surveys of marketing practitioners. These are useful sources for establishing that technologies exist and that substantial professional use is occurring, but they have limitations. Vendor-reported performance does not independently establish comparable results for every organisation; survey respondents may define “using AI” differently; and highly visible examples of AI-generated campaigns can exaggerate the apparent maturity of the wider market.

The clearest Status conclusion as at 30 August 2026 is therefore that **AI has become a significant and expanding component of Marketing & Communications. Its strongest current footholds are in digital advertising optimisation, content and creative production, professional productivity, analytics and audience-related work. Personalisation and integrated campaign orchestration are advancing, while agentic marketing is beginning to move into operational use but remains substantially less established. At the same time, AI is changing how audiences discover organisations, creating a second transformation in the external marketing environment. Data readiness, reliability, brand and cultural judgement, consumer trust, rights, governance and measurable business impact continue to limit how far these capabilities can be treated as mature or autonomous.**

Evidence Notes

1. **Adobe — AI and Digital Trends 2026, February–June 2026.** Global research undertaken with Oxford Economics covering 3,000 executives and practitioners and 4,000 customers across North America, Latin America, Europe, Asia-Pacific and the Middle East. Supports propositions concerning content production, personalisation, customer behaviour, fragmented data, organisational readiness and agentic-AI deployment. Adobe reports 76% of organisations seeing moderate or significant improvement in content ideation/production from generative AI and identifies continuing gaps between AI ambition and enterprise-wide readiness.
[Adobe 2026 AI and Digital Trends](#)
2. **Adobe — State of Marketing in an AI-Driven World, 2026.** Supports the assessment that AI is increasingly producing content variations at scale while human oversight remains the dominant operating model, and that marketing organisations increasingly value performance measurement and insight rather than content volume alone.
[Adobe marketing research](#)
3. **Gartner — 2026 CMO Spend Survey, 11 May 2026.** Survey of 401 CMOs and marketing leaders in North America, the UK and Europe, predominantly in organisations with annual revenues above US\$1 billion. Gartner reports an average 15.3% of marketing budgets allocated to AI initiatives, while only 30% of respondents considered their organisations mature or fully developed in AI readiness. Useful evidence of

the gap between investment and capacity to scale.

[Gartner 2026 CMO Spend Survey](#)

4. **Interactive Advertising Bureau — The AI Ad Gap Widens, 15 January 2026.** US survey of 104 advertising executives and 505 Gen Z/Millennial consumers. Reports 83% of participating ad executives saying their companies had deployed AI in the creative process and identifies a substantial difference between advertiser assumptions and consumer attitudes towards AI-generated advertising. Geographic and sample limitations have been retained in the substantive assessment.
[IAB — The AI Ad Gap Widens](#)
5. **Interactive Advertising Bureau — 2026 Digital Video Ad Spend research, May–July 2026.** Provides evidence of widespread generative-AI use in US digital-video creative and of agentic-AI experimentation and deployment. Importantly, the research also records demand for human involvement, audit trails and limits on agent authority, supporting the distinction between interest in autonomy and unrestricted autonomous operation.
[IAB 2026 Digital Video research](#)
6. **Interactive Advertising Bureau — 2026 Outlook Study, January 2026.** Research based on more than 200 US brands and agency buyers. Supports evidence of AI moving into campaign planning, activation and optimisation and growing attention to content intended for AI-generated answers. As US advertising-industry evidence, it has not been generalised into a global adoption rate.
[IAB 2026 Outlook Study](#)
7. **Google — AI Max and AI-era Search advertising developments, April–June 2026.** Establishes commercially available AI-supported search advertising capabilities involving search-term matching, creative customisation and landing-page selection. Google's June update postponed automatic Dynamic Search Ads migration until February 2027, illustrating why announced transitions should not be treated as completed deployment at the reference date.
[Google AI Max for Search](#)
8. **Google — A New Era for AI Search, 19 May 2026.** Primary evidence of continued integration of generative and agentic functionality into Search. Google reported AI Mode exceeding one billion monthly users, relevant to the changing discovery environment facing marketing organisations. This is provider-reported usage rather than independent audience measurement.
[Google AI Search developments](#)
9. **Meta — advertising AI developments, January–July 2026.** Primary provider evidence for AI-supported ad ranking, creative generation and campaign tools. Meta reported in July that more than eight million advertisers used at least one of its generative-AI creative tools. This establishes substantial platform use while remaining a provider-reported figure rather than evidence of depth of use within each advertiser.
[Meta advertising AI developments](#)
10. **Amazon Ads — Creative and campaign AI, July 2026.** Primary evidence of generative image, video and audio production, conversational creative development and AI-supported advertising optimisation. Amazon expanded its AI image-generation advertising tools into India, Japan, Australia and additional European countries in July 2026, providing evidence of international availability.
[Amazon Ads AI creative solutions](#)
11. **TikTok — TikTok World 2026, 13 May 2026.** Primary provider evidence of generative-video capabilities, automated creative selection, AI-supported campaign optimisation and performance summaries within advertising workflows. Establishes available capability rather than universal advertiser adoption.
[TikTok World 2026 advertising developments](#)

- 12. Salesforce — marketing AI and agentic marketing, February–July 2026.** Provider research and product evidence covering AI-supported campaign creation, personalisation and agentic workflows. Salesforce's India research reported 81% AI adoption among participating marketers and identified fragmented customer data as a significant constraint. Australia/New Zealand findings similarly showed widespread AI adoption alongside continuing generic campaigns and data problems. These are attributed survey findings, not universal regional adoption measures.
[Salesforce India State of Marketing findings](#)
- 13. Australian Data & Marketing Association — State of AI in Marketing, March 2026.** Survey of 1,092 Australian marketing professionals. Reports 77% using AI at least weekly but only 13% having received formal training, supporting the distinction between widespread tool use and organisational capability/governance.
[ADMA State of AI in Marketing](#)
- 14. Yano Research Institute — Japanese digital advertising AI research, February/May 2026.** Japanese advertiser research reports 25.8% using general-purpose AI tools, 14.3% advanced external AI tools and 12.8% internally developed AI, while 38.3% had not introduced AI. Provides useful counterweight to high adoption figures from some Western marketing surveys and illustrates differing definitions and stages of implementation.
[Yano Research — AI in Japanese digital advertising](#)
- 15. Japan Interactive Advertising Association — 2026 Internet Advertising User Survey, 6 August 2026.** Japanese consumer evidence concerning generative-AI advertising. Reports 52% considering such advertising acceptable where appropriate conditions are met, alongside concerns regarding authenticity, accuracy, copyright and transparency.
[JIAA 2026 consumer advertising survey](#)
- 16. Roy Morgan / Ad Standards Australia — Community Sentiment Tracker, 6 May 2026.** Australian national research reports 72% concerned about AI-generated content in advertising, particularly its potential to mislead through unrealistic or fake material. Supports the conclusion that technological adoption and consumer acceptance should not be treated as equivalent.
[Roy Morgan / Ad Standards AI advertising research](#)
- 17. ISBA — 2026 Gen AI Survey, 22 July 2026.** UK survey of 200 advertisers. Reports 99% engaging with generative AI but only 14% reporting significant impact on business results. Particularly useful evidence for distinguishing participation or experimentation from realised organisational impact.
[ISBA 2026 Gen AI Survey](#)
- 18. Muck Rack — State of AI in PR 2026, January/February 2026.** Survey of more than 500 PR professionals. Reports generative-AI adoption at 76%, extensive use for editing and content creation, and 98% of AI users always or often editing generated text. Agentic use was materially less developed.
[Muck Rack State of AI in PR 2026](#)
- 19. Cision — Inside PR 2026 and State of the Media 2026.** Inside PR research covering nearly 600 US and UK PR professionals reports 91% using generative AI in workflows, including ideation, writing, media monitoring and reporting. Separate State of the Media research covering more than 1,800 journalists internationally found significant regional differences in journalists' own AI use and 53% opposition to AI-generated PR pitches.
[Cision 2026 State of the Media](#)
- 20. Global Alliance for Public Relations and Communication Management — Reimagining Tomorrow 2026, May 2026.** Survey of 536 communications professionals across six geographic regions. Reports 95.9% of represented organisations permitting AI use, 47% having a responsible-AI framework and

approximately one-third already using or piloting AI agents. Provides geographically broader communications evidence while also demonstrating that permission to use AI, governance maturity and agent deployment are different measures.

[Global Alliance Reimagining Tomorrow 2026](#)

21. Global Alliance — Global Perceptions and Insights about the Practice of Public Relations 2026.

Evidence drawn from professional associations representing more than 21,000 members in Australia, Bangladesh, Czech Republic, Ireland, Nigeria, Philippines, South Africa and the United Kingdom. Supports the global assessment that AI is simultaneously viewed as a major opportunity and threat within communications and that adoption patterns and toolsets differ geographically.

[Global Alliance 2026 global PR report](#)

22. European Commission — AI Act transparency obligations / Code of Practice, July–August 2026.

Primary regulatory evidence. Article 50 transparency obligations applying from 2 August 2026 address identification or marking of specified AI-generated or manipulated content and disclosure concerning deepfakes and certain AI-generated publications. Relevant to marketing and communications use of synthetic media within the EU.

[European Commission — AI-generated content transparency](#)

4. Sales & Customer Experience

Status as at 30 August 2026

Artificial intelligence is now materially present across both sales and customer experience, but its maturity varies considerably by activity and organisation.

In sales, some of the most established applications assist people rather than replace customer-facing work: prospect and account research, lead scoring, forecasting, preparation for meetings, drafting communications, analysing customer information and recommending next actions. Generative AI has made these capabilities easier to access because sellers can increasingly ask questions, prepare material and interrogate customer or CRM information through natural language.

Customer service has progressed further in direct AI-to-customer interaction. Chatbots and virtual assistants have existed for years, but generative AI has substantially widened what they can understand and discuss. Current systems can answer questions using organisational knowledge, interpret less structured requests, converse across multiple turns and languages, and increasingly complete permitted actions rather than simply supply information. AI is also being used behind the customer interaction to summarise conversations, retrieve knowledge, draft responses, route cases, analyse sentiment and assist human service representatives.

Operational evidence shows that these are not merely demonstrations. AI-assisted service is deployed in banks, telecommunications companies, insurers, retailers, technology businesses and other organisations across multiple regions. Some organisations now allow AI agents to resolve substantial portions of incoming service demand or undertake parts of sales prospecting and qualification.

The important development during 2025–26 is therefore the movement from **AI that informs or drafts** towards **AI that participates in customer workflows and sometimes acts**. Sales agents can research prospects, initiate or continue outreach and qualify leads. Service agents can perform actions such as changing bookings, progressing requests or completing simple transactions within defined systems.

That does not mean autonomous selling or autonomous customer service has become the general organisational model. Adoption evidence remains highly dependent on how “AI use” is defined, and deployment ranges from employees using general-purpose assistants to deeply integrated customer-facing systems. Customer acceptance, data quality, integration, reliability, governance and demonstrable economic value continue to limit scale.

The present Status is consequently one of **substantial and expanding AI use, with customer service among the more visibly affected organisational functions, while more autonomous sales and customer-experience agents remain a rapidly developing but unevenly established layer**.

1. What is AI currently being used for?

Prospecting, lead identification and qualification

AI is increasingly used at the beginning of the sales process to identify potential customers, research organisations and individuals, enrich lead information and help determine which opportunities deserve attention.

Systems can combine CRM information with other permitted data sources, identify characteristics associated with likely opportunities and produce summaries before a salesperson becomes involved. Generative AI can then help create personalised initial communications.

More agentic systems extend this further. Microsoft's Sales Qualification Agent, for example, could by the reference date autonomously research assigned leads and assess their fit against defined customer profiles. In its more automated mode it could also engage leads, follow up and pass qualifying prospects to human sellers according to configured hand-off rules. This establishes current technical capability; it does not establish that autonomous qualification has become standard sales practice.

Seller preparation and productivity

A broader and probably more widespread form of use is assistance with the everyday work surrounding selling.

AI can summarise accounts, meetings and previous interactions; research customers and competitors; draft emails and follow-ups; prepare meeting briefs; generate proposal material; extract actions from conversations; and help sellers update or interrogate CRM information.

These uses are important because selling traditionally contains considerable non-selling work. Salesforce's 2026 global sales survey reported AI being used for prospecting, forecasting, lead scoring and email drafting, while Gartner's research found AI tools saving sellers an average of 4.8 hours per week. These are survey findings rather than universal measurements, but they demonstrate meaningful organisational use beyond isolated experimentation.

Sales analytics, forecasting and recommendations

Predictive AI was used in sales before the present generative-AI wave.

Current applications include analysing pipelines, estimating likelihood of conversion, identifying potentially at-risk opportunities, forecasting revenue, examining customer behaviour and recommending actions to sellers.

Generative interfaces increasingly make these analytical capabilities accessible conversationally. Instead of manually navigating multiple reports, a seller or manager can ask for a summary of an account, pipeline or opportunity and receive an initial analysis.

Gartner's 2026 research identified account and buyer intelligence, personalised messaging, signal monitoring and AI-enabled “next best actions” among areas already producing practical sales value.

Customer self-service and conversational support

Customer service is one of the clearest areas of direct customer interaction with AI.

AI assistants can answer questions about products, accounts and services; explain procedures; troubleshoot problems; locate information; help customers navigate processes; and operate through chat, messaging and increasingly voice.

Deployment is geographically broad. Singapore-based DBS reported in July 2026 that its generative-AI-enabled virtual assistants reached more than 10 million customers across Singapore, Hong Kong and Taiwan. Its DBS Joy assistant had also begun completing simple banking tasks conversationally for corporate and SME customers in Singapore.

Bank of America's Erica provides another example of scaled deployment: the bank reported nearly 700 million customer interactions with Erica during 2025 and more than 3.2 billion interactions since its 2018 introduction.

These systems should not all be equated with generative AI. The installed customer-service landscape combines earlier conversational and predictive systems with newer generative and agentic capabilities.

AI assisting human customer-service employees

A substantial part of customer-service AI remains invisible to customers because it assists the human representative.

Applications include retrieving relevant knowledge during conversations, summarising previous interactions, transcribing calls, generating case summaries, suggesting replies, translating communications, recommending actions and preparing post-call notes.

Bank of America reported in July 2026 that more than 18,000 customer-service employees were using its EricaAssist system, which provides real-time guidance during client conversations. The bank said the system reduced average call times by nearly one minute.

AIA had similarly deployed generative-AI assistance in contact centres in Singapore and Thailand, including automated case and conversation summaries and assistance with email drafting. This illustrates an important part of the current Status: AI can materially affect customer experience even where a person remains the visible point of contact.

Resolution and action

The boundary between answering and acting is increasingly significant.

Customer-service agents can now be connected to operational systems so that, within configured permissions, they can undertake activities such as rescheduling appointments,

processing certain refunds or cancellations, updating information, managing subscriptions or progressing service requests.

DBS's move from conversational assistance towards agentic transaction completion is one example. The UK Competition and Markets Authority's March 2026 guidance similarly recognised practical business uses of agents for engaging customers and processing refunds.

The capability therefore exists for AI to participate directly in customer workflows. Its establishment varies substantially by organisation, transaction and risk level.

2. What activities are changing?

The clearest change is that portions of both sales and service workflows can increasingly occur before a person becomes involved.

In sales, prospect research that previously required manually gathering information from CRM systems, websites, company information and previous correspondence can increasingly be assembled automatically. AI can summarise that material, identify relevant signals and prepare a suggested approach.

Lead handling is also beginning to change. Traditionally, sales-development teams reviewed, contacted and repeatedly followed up leads. AI agents can now perform portions of that sequence continuously and transfer promising opportunities to people. Salesforce reported that its own sales agents contacted 130,000 previously untouched leads and generated 3,200 opportunities over four months. This is evidence of one company's deployment, not evidence that such a model is typical across sales organisations.

Sales conversations themselves remain substantially human, particularly in complex B2B selling. Gartner's 2026 buyer research found human sales representatives were still rated substantially more highly than generative AI for understanding customer needs, creating confidence and helping buyers progress decisions. AI is therefore changing the work surrounding important sales conversations more rapidly than it is eliminating those conversations.

Customer service is undergoing a somewhat deeper workflow change.

Traditional chatbots generally handled narrowly defined questions or directed customers through predefined pathways. Generative systems can interpret much less structured language and maintain conversational context. When connected to enterprise systems, they can increasingly progress a request rather than merely explain how a customer could progress it.

At the same time, human service work is becoming more exception-oriented. Routine information retrieval, summarisation, transcription and initial responses can increasingly be performed by AI. Human representatives can therefore spend a greater proportion of their time on unusual, sensitive, disputed or complex situations.

AI is also changing what happens during a human conversation. A service representative can receive relevant information and recommended actions in real time rather than searching manually through multiple systems. After the interaction, AI can create the summary and update supporting records.

The emerging operating pattern is consequently not simply **customer versus chatbot**. It increasingly includes AI self-service, AI-supported human service and hand-offs between them.

3. What can AI currently do?

As at 30 August 2026, demonstrated systems show several distinct capabilities.

AI can **research and synthesise**: gathering permitted information about prospects, accounts or customers and converting it into concise summaries.

It can **classify and prioritise**: scoring leads, categorising customer requests, routing cases and identifying opportunities or situations requiring attention.

It can **predict and recommend**: supporting forecasts, identifying sales signals and suggesting likely next actions.

It can **generate**: drafting sales emails, follow-ups, proposals, service replies, summaries and other customer communications.

It can **listen, transcribe and summarise**: converting customer conversations into records, identifying important points and reducing manual after-call work.

It can **retrieve and converse**: answering questions in natural language using product information, knowledge bases and connected organisational information. Current systems can sustain multi-turn interactions and operate across multiple languages and communication channels.

It can increasingly **act**: where authorised and integrated with operational systems, agents can progress portions of sales or service processes rather than merely recommend what should happen.

There is also evidence of considerable scale in particular organisations. Cars24 reported in July 2026 that its AI agents were handling more than one million monthly conversation minutes and had helped recover previously lost seller leads. DBS reported customer-facing generative assistants reaching more than ten million users.

But these capabilities depend heavily on context. AI does not possess complete knowledge of a customer merely because it can converse fluently. Its answer can be wrong because underlying data are incomplete, instructions are ambiguous, organisational knowledge is outdated or the model generates an unsupported response.

Nor does conversational ability imply reliable negotiation, empathy or judgement in every customer circumstance. Current evidence continues to show important value for people where situations are complex, emotionally sensitive, disputed or commercially consequential.

4. How established is its use?

AI use across Sales & Customer Experience is now sufficiently extensive that it cannot reasonably be characterised as principally experimental. What remains difficult is determining exactly how deeply it is embedded.

Salesforce's 2026 survey of 4,050 sales professionals across 22 countries reported that 87% of participating sales organisations were using some form of AI and 54% said they had used AI agents. HubSpot's 2026 research of more than 1,000 sales and revenue professionals similarly reported very high overall AI use.

These figures demonstrate breadth, but “using AI” may include relatively modest activities such as drafting emails alongside much more integrated CRM or agentic deployment. They should not be interpreted as meaning that most sales processes are autonomous.

Customer service shows particularly strong momentum. Salesforce's 2026 international survey of 3,075 service professionals reported growing use of AI agents, while Gartner found service and support leaders allocating a median 12% of their 2025 budgets to AI in one cross-functional study.

Operational examples confirm substantial real deployment. DBS, Bank of America and other organisations have customer-facing AI operating at considerable scale. AI assistance to human service employees is also established in organisations such as AIA.

Regional evidence demonstrates that this is not solely a US development. Salesforce's 2026 service research included respondents across North America, Latin America, Asia-Pacific and Europe. Its Australia/New Zealand findings reported active customer-facing and agentic-AI investment, while deployments can be identified across Asian banking and insurance, European telecommunications and financial services, and organisations in Latin America.

Nevertheless, adoption is uneven.

Gartner found that although customer-service organisations were investing heavily, only 24% of service and support leaders in one 2026 study demonstrated positive financial returns across their AI use cases. In sales, Gartner found strikingly divergent outcomes: 25% of surveyed organisations reported returns of 50% or more on AI investment, while 20% reported negative returns of 50% or more.

The current picture is therefore one of **established AI assistance and predictive applications; rapidly growing generative AI; meaningful direct customer-facing deployment; and emerging but increasingly real agentic action.**

5. What appears to be driving adoption?

Capacity and productivity **are major drivers**.

Salespeople spend substantial time researching prospects, preparing communications, recording activity and administering CRM systems. Customer-service operations handle large volumes of repetitive enquiries, searches and documentation. AI offers the possibility of reducing these demands without requiring every interaction to be handled manually.

Speed and availability are particularly important in customer-facing work. Customers can seek support outside normal working hours, while sales opportunities may deteriorate if leads are not contacted promptly. AI systems can provide continuous availability and immediate initial responses.

Customer expectations are also changing. Gartner's 2026 customer research found people increasingly using general-purpose generative AI during service journeys, including to complete tasks rather than simply obtain answers. This means organisations are responding not only to available technology but also to customers becoming accustomed to conversational AI elsewhere.

Personalisation and information access provide another motivation. AI can combine customer history, current circumstances and organisational knowledge to give a seller or service representative a more complete starting point for an interaction.

Integration into mainstream CRM and contact-centre platforms is lowering the barrier to adoption. AI capabilities increasingly arrive inside software already used for sales, service and customer management rather than requiring organisations to build standalone AI systems.

Executive and competitive pressure is also substantial. Gartner reported in February 2026 that 91% of surveyed customer-service leaders felt executive pressure to implement AI. Its August research found AI spending among service and support leaders rising 38% while their overall functional budgets increased only 2%.

Finally, there is a potential economic incentive to shift some high-volume interactions from human handling towards automated resolution. That incentive is real, but realised savings depend on resolution quality, implementation cost, customer behaviour and whether supposedly automated cases later require human intervention.

6. What are the present limitations?

Customer and organisational data

Useful sales and service AI depends on accurate information about customers, products, transactions, policies and previous interactions.

Disconnected CRM systems, incomplete customer records and poorly maintained knowledge bases limit the quality of AI output. Salesforce's Australia and New Zealand sales research, for example, found substantial numbers of respondents identifying disconnected systems as obstacles to AI initiatives.

AI can retrieve information quickly; it cannot make inaccurate organisational information correct.

Reliability and context

Generative systems can misunderstand requests or generate plausible but incorrect responses.

The consequences vary considerably. An imperfect draft sales email may be easily corrected. Incorrect advice concerning a financial transaction, insurance claim, contractual commitment or customer complaint may have much greater consequences.

This becomes more important as AI moves from providing information towards executing actions.

Integration

Agentic capability depends on access to operational systems.

An AI assistant that knows a customer wants a refund is different from an agent authorised to check eligibility, initiate the refund and update records. The latter requires system integration, permissions, identity controls, business rules, monitoring and exception handling.

The continuing emphasis placed by major technology providers on connecting agents to CRM, contact-centre and enterprise data demonstrates that this remains an implementation challenge rather than a solved background issue.

Customer acceptance and human access

Customers do not necessarily prefer AI merely because an AI interaction is available.

Gartner's survey of 3,566 B2B and B2C customers in early 2026 found that 87% considered access to a human agent essential when companies use generative AI for customer service. It also found customers approximately three times more likely to use third-party generative-AI tools during service interactions than company-provided chatbots.

This creates an unusual current situation: customer adoption of generative AI is increasing, but this does not automatically translate into preference for every organisation's automated service channel.

Skills and workflow design

Providing employees with an AI tool does not ensure that the organisation captures value from it.

Gartner found AI saving sellers an average of 4.8 hours per week, but 72% of surveyed sales organisations reported low reinvestment of that saved time into higher-value sales activities. This illustrates the difference between task efficiency and functional transformation.

Economics and measurable value

High adoption or expenditure does not necessarily establish economic return.

Both sales and service research in 2026 showed considerable variation in realised value. Implementation costs, data preparation, integration, licences or consumption charges, monitoring and continuing human support can affect the economics.

Governance, consumer protection and transparency

Direct customer interaction introduces legal and governance considerations beyond ordinary internal productivity use.

In the European Union, AI Act transparency obligations applying from 2 August 2026 include requirements concerning disclosure when people interact with certain AI systems.

The UK's Competition and Markets Authority likewise made clear in March 2026 that businesses remain responsible where AI agents acting for them breach consumer law.

As systems become capable of transacting, modifying customer information or making commitments, questions of authority, disclosure, auditability and accountability become increasingly significant.

7. What you should be aware of

Sales & Customer Experience contains several different AI developments that can easily be confused.

An employee using generative AI to draft a follow-up email, a predictive model scoring sales opportunities, an AI assistant recommending information to a call-centre representative and an autonomous service agent completing a customer transaction are not equivalent forms of AI use.

This matters when interpreting adoption statistics. An organisation described as “using AI in sales” may have AI embedded throughout its sales process or may simply have sellers using general-purpose assistants. Similarly, reported use of AI agents can encompass substantially different levels of autonomy.

Customer service deserves particular attention because AI is already interacting directly with large numbers of people. Yet direct interaction does not necessarily mean complete autonomous resolution. Systems frequently rely on organisational knowledge, deterministic business rules, conventional automation and human escalation alongside generative models.

The human role also remains important in sales. Buyers increasingly use AI themselves to research suppliers and products, but Gartner's 2026 evidence indicates that human sellers continue to provide particular value in validating information, understanding needs, establishing confidence and helping buyers progress complex decisions.

Customer expectations are similarly nuanced. People may appreciate immediate AI assistance while still expecting access to a person when an issue becomes difficult, sensitive or disputed.

Evidence quality requires qualification. Much adoption evidence comes from technology providers, professional research organisations, vendor-sponsored surveys and organisations publicising successful implementations. These sources provide substantial evidence that the capabilities and deployments exist, but vendor customer stories should not be treated as representative of all organisations, and survey responses reporting value are not equivalent to independently measured financial results.

Agentic AI introduces a further distinction. An AI system that recommends a response leaves the decision with a person. An agent that communicates directly, qualifies a prospect, modifies an account, initiates a refund or completes another transaction has entered the operational process itself. The reliability, authority and accountability questions are therefore materially different.

The clearest Status conclusion as at 30 August 2026 is that **AI has become an important operational component of Sales & Customer Experience rather than merely an experimental technology. Its strongest current footholds are in research, productivity, analytics, customer-service assistance and conversational self-service. Direct AI-to-customer interaction is already deployed at significant scale in some organisations. More agentic systems are extending AI from answering and recommending towards qualifying, resolving and acting, but their adoption and economic impact remain considerably less uniform than the speed of product development and publicity might suggest.**

Evidence Notes

1. **Gartner — Customer-service customer behaviour, July–August 2026.** Survey of 3,566 B2B and B2C customers conducted February–March 2026. Gartner reported customers approximately three times more likely to use third-party GenAI than company-provided chatbots in service interactions, while 87% regarded access to a human agent as essential when GenAI is used. Gartner also reported that 58% of customers using GenAI had used it to complete a task, rising to 74% in B2B settings.
[Gartner — customer use of GenAI in service interactions](#)
2. **Gartner — Customer-service investment, 26 August 2026.** Survey of 199 service and support leaders conducted April–May 2026. Reported AI spending increased 38% while overall function budgets increased 2%. This is useful evidence of investment intensity, not evidence that all investments have produced successful deployment.
[Gartner — AI spending by customer-service leaders](#)

3. **Gartner — Customer-service implementation pressure, February 2026.** Survey of 321 service and support leaders conducted October 2025. Ninety-one per cent reported executive pressure to implement AI. [Gartner — customer-service leaders and AI implementation pressure](#)
4. **Gartner — Sales productivity, May 2026.** Survey of 210 CSOs and senior sales leaders conducted January–February 2026 found average reported AI time savings of 4.8 hours per seller per week, but 72% of organisations reported low reinvestment of those savings into higher-value activity. Gartner also reported highly divergent AI investment returns. [Gartner — AI and seller productivity](#)
5. **Gartner — Sales workflow and buyer evidence, May 2026.** Research covering 227 CSOs and 645 B2B buyers found associations between AI-enabled next-best actions and commercial performance while also finding that human sellers were rated more highly than GenAI for understanding needs, creating confidence and advancing purchases. The buyer survey also found 45% had used GenAI during a recent purchase and 69% preferred to validate AI-generated insights with sales representatives. [Gartner — AI-enabled sales workflows](#)
6. **Gartner — Sales ROI, May 2026.** Survey of 227 CSOs found 31% identifying difficulty proving ROI from AI-driven tools as a leading challenge to 2026 sales objectives. [Gartner — proving ROI from sales AI](#)
7. **Salesforce — State of Sales, February 2026.** Double-anonymous survey of 4,050 sales professionals across 22 countries, conducted August–September 2025. Reported 87% of participating sales organisations using some form of AI and 54% having used agents. Salesforce also reported its own sales agents contacted 130,000 previously untouched leads and generated 3,200 opportunities in four months. These are useful adoption and organisational-use indicators but remain vendor-produced survey and company evidence. [Salesforce — State of Sales 2026 findings](#)
8. **Salesforce — Australia and New Zealand State of Sales evidence, February 2026.** The underlying global survey included 250 respondents in Australia and 100 in New Zealand and reported high AI use alongside continuing problems with disconnected systems and data hygiene. Useful for regional balance, while subject to the same vendor-survey qualification. [Salesforce — Australia and New Zealand sales findings](#)
9. **Salesforce — State of Service: AI Agents Edition, May–June 2026.** Survey of 3,075 service professionals across North America, Latin America, Asia-Pacific and Europe. Reported substantial growth in AI-agent use. Australian and New Zealand results also provide evidence of customer-facing AI investment and regional adoption. Because respondents are service professionals and the study is vendor-produced, the percentages are best treated as adoption indicators rather than a definitive global rate.
10. **Microsoft — Dynamics 365 Sales Qualification Agent, updated April–June 2026.** Product documentation establishes available capability to research leads, evaluate fit, draft outreach and, in research-and-engage mode, communicate and follow up autonomously under configured rules. This supports capability, not market-wide adoption. [Microsoft — Sales Qualification Agent documentation](#)
11. **Bank of America — Erica and EricaAssist, March and July 2026.** The bank reported nearly 700 million Erica interactions during 2025 and more than 3.2 billion since launch. In July it reported more than 18,000 employees using EricaAssist and an average call-time reduction of nearly one minute. These are organisation-reported operational figures and provide strong evidence of scaled deployment, although the claimed benefits are not independently measured here. [Bank of America — EricaAssist deployment](#)
12. **DBS — virtual assistants, 28 July 2026.** DBS reported generative-AI-enabled virtual assistants reaching more than 10 million users across Singapore, Hong Kong and Taiwan and DBS Joy becoming agentic for corporate and SME customers in Singapore. This provides particularly useful Asia-based evidence of customer-facing deployment and the transition from answering towards transactional action. [DBS — generative and agentic virtual assistants](#)

13. [AIA / Microsoft](#) — **customer-service Copilot deployment, January 2025**. AIA deployed Copilot in contact centres in Singapore and Thailand following assessment of fairness, bias, security and other issues. Reported applications include case and conversation summarisation, knowledge retrieval and email drafting; AIA Thailand reported almost 50% reduction in conversation wrap-up time.
[AIA customer-service deployment case study](#)
 14. [Cars24 / OpenAI](#) — **operational AI deployment, July 2026**. Cars24 reported AI agents handling more than one million monthly conversation minutes, higher support-resolution rates and recovery of previously lost seller leads. This provides evidence from an India-centred automotive platform of AI spanning customer support and sales re-engagement; performance figures are organisation/provider reported.
[Cars24 operational AI case study](#)
 15. **European Commission — AI Act transparency obligations, July–August 2026**. Commission guidance confirms that Article 50 transparency obligations applied from 2 August 2026, including requirements relevant to people interacting with AI systems. This is directly relevant to customer-facing AI in the European Union.
[European Commission — AI transparency obligations](#)
 16. **UK Competition and Markets Authority — Agentic AI and consumers, 9 March 2026**. CMA guidance explicitly discusses businesses using AI agents to engage customers and process refunds and states that businesses remain responsible where agents acting for them breach consumer law.
[UK CMA — complying with consumer law when using AI agents](#)
 17. [HubSpot](#) — **State of Sales 2026**. Research involving more than 1,000 sales leaders and revenue professionals reported widespread AI use but varying depth across teams and use cases. This provides corroborative adoption evidence rather than a universal sales-AI adoption rate.
[HubSpot — State of Sales 2026](#)
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5. Operations & Supply Chain

Status as at 30 August 2026

Artificial intelligence is already materially present across Operations & Supply Chain, but the extent and depth of deployment vary substantially.

The strongest established applications are generally focused on bounded operational problems for which organisations possess substantial data and measurable outcomes: demand forecasting, inventory and production planning, scheduling, predictive maintenance, quality inspection, process optimisation, logistics and warehouse optimisation, and supplier or procurement analysis. Computer vision and machine learning have been used in industrial environments for years; generative AI is now adding conversational access to operational information, document generation, troubleshooting assistance and engineering support.

A further development visible in 2026 is the movement from individual AI applications towards connected operational intelligence. Some advanced manufacturers are combining AI with sensors, digital twins, planning systems, enterprise software, automation and physical machinery so that information from one part of an operation can influence decisions elsewhere. The World Economic Forum's 2026 Global Lighthouse evidence provides examples across China, India, Saudi Arabia, Singapore and other countries where AI has become part of scaled manufacturing and supply-chain systems rather than remaining an isolated experiment.

At the same time, these leading sites are not representative of every organisation. Gartner's 2026 research found that only 17% of surveyed supply-chain organisations were pursuing immediate transformational process redesign, while 83% were applying AI incrementally or gradually scaling it into integrated processes. Integration, data readiness, workforce capability and uncertain returns continue to constrain adoption.

Consequently, Operations & Supply Chain as at 30 August 2026 is best understood as a mixed landscape: mature AI in selected analytical and automation applications; substantial and expanding deployment in advanced industrial operations; rapid growth in generative AI assistance; and much earlier development of genuinely autonomous, agentic or self-orchestrating operations.

1. What is AI currently being used for?

Planning, forecasting and inventory

Demand and supply planning are among AI's most established operational applications.

Machine-learning systems analyse historical demand, orders, promotions, seasonal patterns, inventory, lead times and other variables to produce forecasts and identify changing demand. These outputs can feed production plans, purchasing decisions, replenishment and inventory allocation.

AI is also being incorporated into integrated business planning and scenario analysis. Ericsson, for example, describes using AI-driven forecasting, demand sensing and multi-echelon inventory optimisation within its global supply-chain planning transformation. The significance of such systems is not that human planners disappear, but that they can evaluate larger amounts of information and refresh forecasts more frequently than traditional manually intensive planning allows.

Production, process control and scheduling

Manufacturers are using AI to improve production sequencing, resource allocation, process settings, throughput and energy consumption.

AI can analyse information from production systems and equipment, identify relationships between operating conditions and outcomes, and recommend or automatically implement adjustments where systems have been designed to permit this.

Evidence from advanced manufacturing sites demonstrates that this is already operational in some environments. The World Economic Forum's 2026 Lighthouse cohorts include China's EVE Energy using AI for real-time quality diagnosis, process self-optimisation and predictive maintenance; India's DCM Shriram using AI-enabled process control; and CIMC Reefer Containers in China using AI-enabled applications for production and resource optimisation.

Maintenance, reliability and asset management

Predictive maintenance is another significant established application.

Rather than relying only on fixed maintenance intervals or waiting for equipment to fail, AI can analyse sensor readings, operating history, vibration, temperature, pressure and other equipment information to detect abnormal behaviour or estimate failure risk.

Generative AI is extending this by helping technicians and engineers interrogate maintenance records, retrieve technical information, interpret alarms and generate troubleshooting guidance. A 2026 manufacturing case study published in *Production Planning & Control*, for example, examined a generative-AI-enabled predictive-maintenance system for tyre-manufacturing curing presses, illustrating the movement from conventional predictive models towards systems that combine operational data with generative interfaces.

Quality, inspection and operational assurance

Computer vision is widely applicable to visual quality inspection because cameras and AI models can inspect products repeatedly at production speed.

Systems can identify surface defects, dimensional or assembly problems, missing components and other abnormalities. AI can also analyse process and quality information to identify causes of defects rather than merely detect the finished defect.

At Faurecia's Yancheng automotive site in China, machine learning, deep learning and generative AI were incorporated into multimodal quality control. Rockwell Automation's

Singapore facility uses AI-enabled quality control alongside intelligent maintenance. These examples demonstrate scaled capability, although they come from advanced manufacturing sites rather than representing manufacturing generally.

Procurement and sourcing

AI is increasingly used to analyse spending, classify purchases, retrieve supplier information, draft sourcing documents, compare bids and contracts, identify supplier risks and assist negotiation or purchasing workflows.

Generative AI is particularly suited to information-intensive procurement tasks: summarising supplier material, preparing requests for proposals, drafting statements of work and allowing users to interrogate procurement data conversationally.

More autonomous applications are emerging in which agents undertake portions of sourcing or procurement workflows. Their maturity should not be overstated. Gartner's 2026 procurement research found productivity gains from generative AI but also found only 36% of surveyed chief procurement officers very confident in their ability to redesign roles and processes around AI. European research based on 50 CPO interviews found 75% still experimenting with generative AI, including 35% running pilots.

Warehousing, logistics and fulfilment

AI is used for inventory positioning, picking and fulfilment decisions, warehouse optimisation, transportation planning, route selection, shipment visibility, estimated arrival times and disruption detection.

At RRS Qingdao Smart Logistics Park in China, an AI-enabled platform supports order fulfilment, warehouse operations, vehicle scheduling and carrier bidding. Unilever's Hefei distribution centre reported AI-supported daily demand forecasting, inventory decisions, intelligent picking and warehouse management.

AI also supports predictive logistics visibility by combining shipment and supply-chain information to identify potential delays and disruptions earlier. The practical objective is increasingly not merely to report what has happened, but to indicate what is likely to happen and what responses are available.

Operational engineering and technical work

Engineering activity connected with operating, maintaining and improving assets is also being affected.

Engineers can use AI to search technical documentation, summarise equipment history, interpret operating information, assist fault diagnosis, generate or explain code, analyse engineering data and support simulation and optimisation.

Industrial AI platforms increasingly combine equipment information, engineering knowledge and generative interfaces so that operational personnel can ask questions in ordinary language. This is important because a substantial amount of operational knowledge has

historically been dispersed across manuals, databases, maintenance records and the experience of individual employees.

2. What activities are changing?

A central change is the movement from **periodic analysis towards continuous analysis**.

Traditional planning often involved periodic forecast cycles, spreadsheet consolidation and scheduled planning meetings. AI allows demand, inventory, production and logistics information to be reassessed more frequently as conditions change. Planners can therefore spend less time assembling information and more time examining exceptions, scenarios and trade-offs.

Maintenance is moving in a similar direction. Fixed schedules and reactive repair increasingly coexist with condition monitoring and predictive techniques. Equipment can be monitored continuously, with abnormal behaviour identified before a technician would necessarily detect it manually.

Quality assurance is becoming more data-intensive. Visual inspection can be augmented by machine vision, while process data can be analysed to identify conditions associated with defects. Human quality personnel increasingly investigate unusual or ambiguous cases and analyse underlying causes rather than manually inspecting every item.

The relationship between employees and operational systems is also changing. Generative interfaces allow planners, procurement professionals, engineers and maintenance personnel to ask questions of complex systems in natural language, retrieve information and obtain initial explanations without navigating every underlying database or application separately.

A second significant change is **greater connection between activities**. Forecasting, inventory, production, procurement and logistics have traditionally been managed through different systems and organisational units. Advanced deployments increasingly combine these information flows. The World Economic Forum describes leading industrial sites moving from optimisation of individual processes towards more integrated operating systems.

Procurement illustrates another change: AI can compress the information-handling portions of sourcing. Supplier research, spend analysis, document preparation and comparison can increasingly be undertaken with AI assistance, leaving people to concentrate more heavily on commercial judgement, negotiation, relationships, exceptions and accountability.

The emerging development is AI progressing work rather than simply analysing it. In May 2026, SAP announced supply-chain assistants and agents spanning planning, manufacturing, logistics, engineering and asset management, with availability being phased through 2026. This establishes that enterprise software was moving towards agentic operational workflows by the reference date, but phased product availability is not evidence that autonomous supply-chain operation had become routine organisational practice.

Physical operations are changing more gradually. AI-enabled robots, autonomous vehicles and machinery can perform defined material-handling and production tasks, but highly visible demonstrations should be separated from reliable operation in real industrial environments. This is particularly relevant to humanoid robotics: as at August 2026, specialised automation remained substantially more established for most factory tasks than general-purpose humanoids.

3. What can AI currently do?

Current evidence demonstrates several distinct capabilities.

It can predict. AI can estimate demand, equipment failure, delivery times, inventory requirements and other future operational conditions where sufficient relevant data exists.

It can detect. Computer vision and analytical models can identify defects, abnormal equipment behaviour, unusual process conditions, inventory anomalies and other exceptions across volumes of data that would be difficult to examine manually.

It can optimise. AI can evaluate alternative production schedules, inventory positions, routes, process parameters or resource allocations against defined objectives and constraints.

It can interpret operational information. Generative AI can summarise maintenance histories, procurement documents, operating reports and technical material and answer questions across large bodies of information.

It can generate. Systems can produce draft procurement documents, maintenance instructions, reports, explanations, work summaries and other operational material.

It can assist diagnosis. By combining current conditions with historical information and technical knowledge, AI can help engineers and technicians identify possible causes of equipment or process problems.

It can perceive and control aspects of physical operations. When connected with cameras, sensors, industrial automation or robotics, AI can classify physical objects and conditions and influence machinery or operational processes within defined boundaries.

Increasingly, **it can act.** Agentic systems can be authorised to retrieve information, evaluate circumstances, initiate tasks and progress defined workflows. Gartner identified agentic AI and physical AI among its principal supply-chain technology trends for 2026.

These capabilities should not be interpreted as general operational intelligence. Performance depends heavily on the particular process, available data, permitted actions and operating environment. A model that forecasts demand successfully does not thereby understand the commercial consequences of every inventory decision; a maintenance model identifying an abnormal signal does not necessarily know the actual cause; and a generative assistant producing convincing engineering guidance may still be wrong.

Physical operations impose an additional constraint: mistakes can damage equipment, interrupt production or create safety consequences. The threshold for allowing AI to recommend an action can therefore be substantially lower than the threshold for allowing it to execute that action autonomously.

4. How established is its use?

There is no single meaningful adoption level for Operations & Supply Chain.

Machine learning for forecasting, optimisation, predictive maintenance and quality inspection is established in many large and technologically advanced organisations. Conventional industrial automation combined with AI is also commercially mature in particular structured applications.

Advanced manufacturing provides strong evidence of scaled deployment. The World Economic Forum's Global Lighthouse Network contained 238 leading industrial sites following its June 2026 additions, with examples across China, India, Saudi Arabia, Singapore, Switzerland and the United States. These sites demonstrate that integrated AI-enabled industrial operations are not merely hypothetical. They are deliberately selected advanced sites, however, and should not be treated as a representative sample of world manufacturing.

Broader supply-chain evidence suggests a considerably more incremental picture. Gartner's survey of 140 senior supply-chain leaders found 83% pursuing specific use cases or gradual scaling rather than immediate transformational redesign. Another Gartner analysis found 56% identifying integration with legacy systems and processes as a major challenge and 50% reporting limited internal AI expertise or talent.

Procurement appears similarly mixed. Generative AI is already producing individual productivity gains, but redesign of procurement workflows around AI remains much less established. Another 2026 procurement study reported 65% of participating organisations piloting AI while only 11% considered themselves ready to use AI and machine learning across procurement operations. Survey populations and methodologies differ, so these figures should be treated as indicators of uneven maturity rather than combined into a supposed global adoption rate.

Generative AI assistance is spreading quickly because it can be introduced without redesigning an entire factory or supply chain. More deeply integrated AI requires reliable enterprise and operational data, system connectivity and process redesign and therefore progresses more slowly.

Agentic operations are earlier still. Commercial capabilities existed by August 2026, and leading organisations were moving AI from pilot to production, but autonomous end-to-end supply chains were not the normal operating model.

5. What appears to be driving adoption?

Productivity and cost pressure are major drivers. Manufacturing, logistics and supply-chain operations contain large volumes of planning, monitoring, scheduling, inspection, movement and information-processing activity. Even relatively small improvements can have substantial economic consequences at industrial scale.

Operational reliability is another important motive. Equipment downtime, production disruption and quality failures can be expensive. Predictive maintenance, anomaly detection and process monitoring offer the possibility of identifying problems earlier.

Supply-chain volatility and resilience have become increasingly important. Geopolitical disruption, transport constraints, demand volatility and changing trade patterns increase the value of faster visibility, scenario analysis and replanning. Gartner's 2026 research explicitly linked geopolitical volatility with growing interest in AI-enabled supply-chain orchestration.

Complexity and speed matter as well. Supply chains may contain thousands of products, suppliers and transactions distributed across multiple countries and systems. Human planners can manage this complexity, but AI can continually evaluate more combinations of information and potential responses.

Workforce and skills pressures are significant in some industries and countries. AI can capture aspects of technical knowledge, support less experienced personnel and reduce repetitive information work. Rockwell Automation's Singapore Lighthouse, for example, reported substantially shorter time-to-competency as part of its broader digital and AI transformation.

Quality and consistency are strong manufacturing drivers. AI inspection and process analysis can operate repeatedly and at production speed, while accumulated quality data can be used to identify causes that are difficult to recognise through individual observations.

Energy, materials and sustainability pressures are also encouraging operational optimisation. The DCM Shriram and Saudi Aramco Lighthouse examples show AI being deployed in operating environments where energy use, process efficiency, reliability and emissions are closely connected.

Finally, AI is increasingly incorporated into mainstream enterprise, planning, procurement and industrial software. This lowers the practical barrier to experimentation because organisations may encounter AI as an extension of systems they already operate rather than as an entirely separate technology programme.

6. What are the present limitations?

Operational data are difficult

Industrial data can be fragmented across ERP systems, manufacturing execution systems, warehouse applications, planning platforms, maintenance systems, sensors, spreadsheets and older equipment.

Records may be incomplete, inconsistent or collected for purposes other than AI. Physical sensors introduce another problem: an apparently precise data stream may itself be inaccurate because of calibration, deterioration or operating conditions.

AI performance therefore depends not simply on possessing data, but on possessing sufficiently reliable, contextualised and accessible data.

Integration with existing operations remains difficult

Supply chains and factories commonly contain legacy systems and equipment installed over many years. AI applications that work in isolation may be much easier to demonstrate than systems that must exchange information reliably with production, procurement, inventory, engineering and logistics platforms.

The fact that 56% of respondents in Gartner's supply-chain study identified integration with legacy systems and processes as a major challenge indicates that this remains a material barrier to scaling.

Reliability requirements can be demanding

Operational recommendations can have physical and economic consequences. An incorrect production schedule can disrupt customer deliveries; an erroneous maintenance recommendation can contribute to equipment failure; an incorrect procurement action can affect contractual commitments; and an unreliable control instruction can create safety consequences.

Generative AI introduces an additional difficulty because plausible language can disguise uncertainty or factual error.

Industrial environments are context-specific

A successful model in one factory, production line or distribution network cannot automatically be transferred elsewhere. Equipment, products, process conditions, supplier structures and operating practices differ.

This makes scaling more difficult than deploying a general-purpose office assistant.

Skills and organisational readiness are uneven

Effective operational AI requires combinations of process knowledge, engineering, supply-chain expertise, data science, information technology, operational technology and change management.

The ILO's 2026 examination of AI in manufacturing emphasised both productivity opportunities and significant implications for skills, work organisation and the workforce. Gartner's supply-chain research likewise found talent and expertise among major barriers to scaling.

Economics are not always clear

AI activity does not automatically establish economic value.

In August 2026 Gartner reported that 55% of surveyed chief supply-chain officers were unclear about the return on their AI investments even though AI accounted for a large share of reported supply-chain digital investment. The finding is important because it distinguishes expenditure and deployment activity from demonstrated return.

Autonomy raises additional governance questions

As AI moves from forecasting and recommendation towards initiating procurement, changing schedules, dispatching maintenance or controlling physical processes, permissions and accountability become more important.

Operational systems may require limits on what an AI can alter, defined approval points, monitoring, auditability and mechanisms for human intervention. The governance problem therefore changes as the technology moves from **advising** to **acting**.

7. What you should be aware of

Operations & Supply Chain contains some of the clearest examples of AI producing measurable real-world operational outcomes, but it also contains unusually large differences in maturity.

A computer-vision system inspecting products, a forecasting algorithm recommending inventory, a generative assistant helping an engineer and an autonomous agent progressing a supply-chain workflow are all described as AI, yet they represent very different capabilities, risks and levels of establishment.

Leading industrial examples can also distort perceptions of average adoption. Global Lighthouse sites demonstrate what advanced organisations are actually achieving, which is important evidence of capability and scaled deployment. Their purpose, however, is to identify leading operations. They do not demonstrate that equivalent capability exists throughout manufacturing or supply chains globally.

Similarly, technology-provider announcements establish that particular functions are commercially available, not that customers have deployed them extensively.

Human involvement remains central. Current operational AI often changes where people contribute rather than eliminating their involvement: systems forecast, monitor, inspect, retrieve or optimise, while people investigate exceptions, balance competing objectives, manage suppliers, interpret unusual circumstances, exercise engineering judgement and remain responsible for consequential decisions.

There are also important geographical and industrial differences. Advanced AI-enabled manufacturing is clearly visible across China and other parts of Asia as well as North America and Europe; the 2026 Lighthouse evidence includes significant examples from

China, India, Singapore and Saudi Arabia. But adoption depends on industrial structure, capital availability, digital infrastructure, workforce capabilities and the existing sophistication of operational systems.

Physical AI requires particular caution when interpreting publicity. Industrial robots, automated guided vehicles, machine vision and specialised autonomous systems already perform substantial operational work. More general-purpose humanoid robots attracted intense attention in 2026, but highly visible demonstrations should not be confused with reliable, economically scalable factory deployment.

The clearest Status conclusion is therefore neither that AI has autonomously transformed Operations & Supply Chain nor that it remains primarily experimental.

AI has become a material operational technology. Its strongest current position is in forecasting, planning, optimisation, quality, maintenance, process improvement and operational decision support. Leading organisations are demonstrating more deeply connected AI-enabled operations at industrial scale, while generative AI is widening access to operational and engineering knowledge. More autonomous and agentic operating models are beginning to appear, but across the wider organisational landscape integration, data, skills, reliability, governance and demonstrable economic return remain significant constraints.

Evidence Notes

1. **World Economic Forum — Intelligent Industrial Operations Outlook 2026 — April 2026.** Broad international assessment of the movement from conventional automation towards intelligent connected operations, including AI and physical AI.
[Intelligent Industrial Operations Outlook 2026](#)
2. **World Economic Forum — Global Lighthouse Network, January 2026.** Evidence from more than 220 leading industrial sites across more than 30 countries; useful for scaled operational deployment and examples including EVE Energy, Faurecia, Midea and Unilever in China. The population represents advanced sites and is not a general adoption survey.
[Global Lighthouse Network — January 2026 cohort](#)
3. **World Economic Forum — New Global Lighthouse Sites — June 2026.** Sixteen additional awards, bringing the network to 238 sites. Provides international deployment examples from China, India, Saudi Arabia, Singapore, Switzerland and the United States, including AI-enabled planning, process control, quality, maintenance, logistics and asset management.
[New Global Lighthouse Sites — June 2026](#)
4. **Gartner — AI and supply-chain operating-model transformation — May 2026.** Survey of 140 senior supply-chain leaders. Found 17% pursuing immediate transformational redesign while 83% were applying AI incrementally or gradually scaling integrated processes.
[Gartner supply-chain operating-model survey](#)
5. **Gartner — Integration and talent barriers — April 2026.** Same broad survey population; 56% identified integration with legacy systems and processes as a major challenge and 50% limited internal AI expertise or talent.
[Gartner AI scaling barriers research](#)

6. **Gartner — AI investment returns — August 2026.** Reported 55% of surveyed CSCOs unclear about ROI from AI investments and provides evidence of the gap between investment activity and established value.
[Gartner CSCO AI investment returns survey](#)
 7. **Gartner — Procurement role and process redesign — May 2026.** Survey of 101 CPOs conducted January–February 2026. Found only 36% very confident in their ability to redesign procurement roles and processes around AI and noted that individual GenAI productivity gains were not necessarily becoming broader organisational gains.
[Gartner procurement AI research](#)
 8. **Gartner — Supply-chain technology trends — June 2026.** Identified agentic AI and physical AI among significant 2026 supply-chain technology developments, useful principally as evidence of the direction of available and emerging capability rather than widespread adoption.
[Gartner 2026 supply-chain technology trends](#)
 9. **International Labour Organization — AI in manufacturing — March 2026.** International institutional assessment covering AI, productivity, employment, skills, work organisation and decent-work considerations in manufacturing.
[ILO — AI in manufacturing](#)
 10. **SAP — Autonomous Supply Chain Management — May 2026.** Provider evidence of assistants and agents being incorporated across planning, manufacturing, logistics, engineering, asset and service activities, with general availability phased through 2026. Useful as evidence of available/developing capability, not general adoption.
[SAP autonomous supply-chain announcement](#)
 11. **SAP / Ericsson — Supply-chain planning transformation — 2026.** Organisational case material describing AI-driven forecasting, demand sensing, multi-echelon inventory optimisation and scenario-based planning within Ericsson's global supply chain. Outcomes are organisation/provider-reported.
[Ericsson supply-chain transformation case](#)
 12. **EFESO — CPO Annual Pulse Report — 2026.** Interviews with 50 CPOs in European mid-cap and large organisations; reported 75% still experimenting with GenAI, including 40% in early exploration and 35% running pilots. Useful as procurement-specific European evidence, not a global adoption measure.
[2026 CPO Annual Pulse Report](#)
 13. **GEP / ProcureCon — 2026 CPO Study.** Procurement survey evidence reporting substantial AI piloting alongside much lower readiness for AI/ML across procurement operations. Useful as evidence of the ambition-readiness gap; methodology and population should be interpreted separately from other procurement surveys.
[2026 ProcureCon CPO Study](#)
 14. **Production Planning & Control — Generative AI for predictive maintenance — May 2026.** Academic case study examining implementation of GenAI-enabled predictive maintenance for curing presses in tyre manufacturing; useful evidence that generative AI is moving into operational maintenance applications while empirical evidence remains comparatively limited.
[Predictive-maintenance case study](#)
 15. **Maersk — AI in lead logistics — July 2026.** Provider/operator perspective describing AI applications in predictive logistics visibility, disruption anticipation and actionable supply-chain decision support. Useful for capability and logistics practice, while claims should be understood as provider evidence.
[Maersk — AI in lead logistics](#)
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6. Strategy, Innovation & Transformation

Status as at 30 August 2026

Artificial intelligence is becoming a meaningful part of Strategy, Innovation & Transformation, but its position is more advanced in the analytical and exploratory parts of these activities than in the making of consequential strategic decisions.

AI is already being used to gather and synthesise market intelligence, analyse competitors, search large bodies of internal and external information, generate and compare ideas, assist scenario development, prepare strategic materials, support innovation work and help organisations examine possible changes to processes and operating models. Generative AI has widened access to these capabilities because managers can interrogate information, develop alternatives and challenge assumptions through ordinary language rather than relying entirely on specialist analytical teams.

There is nevertheless an important difference between **AI supporting strategy** and **AI determining strategy**. Research published in 2026 indicates that AI is producing consistent benefits in information-intensive strategy activities such as research and market intelligence, while evidence is substantially weaker for high-stakes activities involving acquisitions, partnerships, portfolio choices and other decisions requiring extensive judgement. BCG estimates that more than 80% of activities commonly undertaken by strategy functions have high or medium exposure to AI augmentation or automation, but also finds that most strategy functions are not yet systematically exploiting that potential.

The position is similarly mixed in innovation and transformation. Controlled organisational research demonstrates that generative AI can improve aspects of innovation work, while organisations are increasingly using AI itself as both a transformation tool and a reason to reconsider how work, decisions and operating models are organised. Yet enterprise-wide transformation remains much less common than experimentation, individual productivity use and selected workflow deployment. The World Economic Forum's 2026 work on organisational transformation describes movement from isolated AI use cases towards connected workflows, but its evidence also reinforces how far most organisations remain from comprehensive redesign.

The current Status is therefore best understood as one of **rapidly expanding assistance rather than autonomous strategic management**. AI is reducing the cost and time involved in research, analysis, ideation and preparation; extending the range of alternatives organisations can examine; and beginning to influence how transformation itself is designed. Human judgement, organisational knowledge, negotiation, accountability and decisions about objectives and trade-offs remain central.

1. What is AI currently being used for?

Strategic research, environmental scanning and competitive intelligence

One of the clearest current applications is gathering and interpreting information about the external environment.

AI can search, classify and summarise large volumes of material concerning competitors, markets, technologies, regulation, customers and wider economic or geopolitical developments. It can compare organisations, extract themes from reports and announcements, identify changes and produce initial competitor or market profiles.

This is particularly suited to strategy because the function traditionally spends substantial effort finding, processing and synthesising information. BCG's 2026 assessment found market intelligence and research to be the area in which strategy leaders were already reporting the most consistent positive impact from AI tools and agents. More specialised systems are emerging that continuously monitor very large numbers of external sources rather than waiting for a strategist to initiate each search.

Actual organisational examples also exist. Spirent, for example, implemented a generative-AI-supported process that summarised competitive and industry information and fed it into Salesforce, replacing a manual scanning and summarisation activity that had consumed several hours each week. This is vendor-reported evidence, but it illustrates how AI-supported intelligence can move from occasional research into a continuing organisational workflow.

Strategic analysis and decision support

AI is increasingly being used to organise evidence, develop analyses, compare alternatives and prepare material for executive decision-making.

A 2026 Capgemini Research Institute study covering 500 executives in 16 countries found that more than half were using AI selectively or actively to support or inform strategic decisions, although only about one in six reported active incorporation throughout the strategic decision journey. Present use remained concentrated particularly in research, analysis and summarisation rather than autonomous decision-making.

AI can also act as a form of analytical challenger: generating alternative explanations, identifying assumptions, suggesting questions, comparing strategic options or exposing information that may have been overlooked. Chief strategy officers in Capgemini's research reported particularly strong perceived improvements in foresight, although these findings represent executive assessments rather than independent measurement of strategic outcomes.

Scenario analysis and planning

AI is being applied to scenario development and strategic planning where organisations need to examine multiple interacting possibilities.

Generative systems can rapidly create alternative scenarios from specified assumptions, identify variables that may alter an outcome, explore consequences and assist with sensitivity or “what-if” analysis. Decision-intelligence products are also beginning to combine generative interfaces with modelling and simulation. Gartner's 2026 assessment of AI use cases for strategy and strategic planning specifically identified applications intended to improve the speed, quality and accessibility of planning and support more adaptive approaches.

These capabilities should not be confused with prediction of an unknowable future. Their current value is principally in helping people explore alternatives, interrogate assumptions and organise uncertainty.

Innovation and idea development

Generative AI has made idea generation one of the most accessible AI applications within innovation.

Organisations can use AI to brainstorm products and services, generate alternative concepts, combine knowledge from different fields, develop preliminary propositions and challenge an existing concept from multiple perspectives. AI can also assist later stages through research, design support, simulation, prototyping, technical development and preparation of innovation material.

Evidence increasingly extends beyond demonstrations. A field experiment involving professionals at Procter & Gamble working on real product-innovation problems found that individuals using AI achieved performance comparable with conventional two-person teams without AI. AI also helped reduce differences between commercially oriented and technically oriented specialists, producing more balanced proposals across those knowledge domains. Importantly, however, human judgement retained value in evaluating and selecting ideas.

A 2026 multiple-case study involving 13 organisations likewise found several different patterns of generative-AI adoption within innovation management, indicating genuine organisational use while also showing substantial differences in technological readiness and the role assigned to people.

Transformation analysis and organisational redesign

AI has a dual role in transformation. Organisations are transforming **because of AI**, while also using AI **to help conduct transformation**.

AI can assist teams in mapping processes, documenting existing activities, analysing organisational information, identifying duplication or bottlenecks, generating alternative workflow designs, comparing operating-model choices and preparing transformation plans.

More significantly, some organisations are beginning to redesign workflows around combinations of employees, conventional automation and AI agents rather than simply adding an AI assistant to the existing process. The World Economic Forum's 2026 study, drawing on discussions with more than 450 executives, identifies movement from isolated use cases towards connected systems and continuous processes across operations, R&D, strategic planning, customer experience and workforce activities.

This deeper redesign remains considerably less established than using AI to assist individual transformation tasks

2. What activities are changing?

The clearest change is in the **information cycle preceding strategic judgement**.

Research that previously required people to locate reports, read documents, construct comparisons and prepare summaries can increasingly begin with AI searching or interrogating a much larger information base. This can shorten the distance between a question being asked and an initial body of evidence being available.

The strategist's analytical workflow is consequently changing. AI can produce an initial competitor assessment, organise evidence into a framework, generate hypotheses, construct preliminary models and draft a strategic narrative. Human effort can move towards questioning the evidence, determining which assumptions matter, resolving contradictions and deciding what the organisation should actually do.

Planning may also become less episodic. Conventional strategic processes often operate around annual planning cycles and periodic reviews. AI-supported monitoring can continuously detect changes in markets, competitors or other external conditions and surface them for examination. This does not make strategy automatically “real time”, because organisational decisions, investments and negotiations still require human processes, but the intelligence feeding strategy can become more continuous.

Innovation work is changing in a related way. Generative AI dramatically lowers the effort required to produce a large initial set of ideas or alternative formulations. The scarce activity can therefore shift from **generating possibilities** towards **evaluating them**. Experimental evidence supports this distinction: AI can expand or improve creative output, but additional ideas do not automatically translate into better innovation, and the processes by which people analyse, integrate and select them continue to matter.

Transformation activity is beginning to change from introducing technology into individual tasks towards reconsidering complete workflows. McKinsey's 2025 global AI survey found that organisations reporting the strongest AI results were much more likely than others to have fundamentally redesigned workflows. Yet only about one-third of respondents overall said their organisations had begun scaling AI across the enterprise.

The change is therefore uneven. AI can compress research and preparation substantially faster than it can alter the social and institutional parts of strategy: obtaining commitment, resolving conflicting interests, negotiating priorities, exercising leadership and implementing difficult organisational change.

3. What can AI currently do?

As at 30 August 2026, demonstrated applications show that AI can perform several useful roles within Strategy, Innovation & Transformation.

It can **search and synthesise**: locating relevant information across large document collections or external sources and producing summaries, comparisons and thematic analyses.

It can **monitor and detect**: continually examining information streams for competitor moves, technological developments, policy changes, emerging risks or other signals.

It can **analyse and model**: manipulating structured information, supporting financial and strategic models, comparing alternatives and helping users explore relationships within data.

It can **generate alternatives**: producing strategic options, product concepts, business-model possibilities, scenarios, hypotheses, questions and alternative interpretations.

It can **simulate and pressure-test**: examining how assumptions or decisions might behave under different conditions where suitable models, rules and data are available.

It can **connect knowledge**: bringing together technical, commercial and other information that may previously have been separated by organisational or professional boundaries. The Procter & Gamble experiment provides particularly useful evidence of this capability in innovation work.

It can **draft and communicate**: producing initial strategy papers, presentations, workshop materials, business cases, transformation documentation and explanations.

Increasingly, AI can also **undertake multi-step analytical work** through agents that retrieve information, use tools, construct analyses and progress a task towards an objective. However, evidence of consistent value from such systems is substantially stronger for bounded research and analytical tasks than for high-stakes strategic choices.

What AI cannot currently be assumed to do is determine an organisation's strategy reliably and autonomously. Strategy involves incomplete information, competing objectives, organisational politics, stakeholder interests, ethical considerations and judgements about uncertain futures. An AI system can construct a persuasive analysis while relying on incomplete evidence or questionable assumptions.

Current evidence therefore supports AI as a potentially powerful **strategic analytical and creative capability**, not as a generally reliable substitute for accountable strategic leadership.

4. How established is its use?

Use is meaningful but highly uneven.

General-purpose generative AI for research, summarisation, drafting, brainstorming and preliminary analysis is already sufficiently accessible that it has entered everyday strategy and innovation work in many organisations. Deloitte's 2026 survey of 148 executives responsible for their organisations' strategic agendas found AI being incorporated into planning, insight generation and performance analysis. Yet only 28% of participating chief strategy officers co-led enterprise AI-related decision-making, and 39% described their organisations as remaining in pilot or early execution stages. Only 16% reported using AI to fundamentally reimagine lines of business or create new sources of competitive advantage.

Capgemini's broader multinational C-suite research points to a similar distinction. More than half of executives used AI selectively or actively in strategic decision-making, but only 17% actively incorporated it on a regular basis; substantial experimentation remained alongside that use.

At the wider enterprise level, high reported AI use should not be mistaken for transformation. McKinsey found 88% of respondents reporting regular AI use somewhere in at least one business function in late 2025, while nearly two-thirds said their organisations had not begun enterprise-wide scaling. PwC's 2026 Global CEO Survey similarly found only 15% of CEOs reporting AI deployed to a large or very large extent in organisational direction-setting.

Geographic evidence also cautions against assuming a single global maturity level. PwC's New Zealand findings, for example, showed high reported organisational and technology readiness but substantially more limited operational impact, while World Economic Forum evidence from Asia reported high adoption of advanced AI but fewer than one-third of organisations achieving sustained value. The measures are not directly comparable, but both illustrate the difference between access to AI and deep organisational transformation.

Innovation use has firmer evidence in particular activities. Organisational case research and controlled experiments demonstrate AI being used for genuine innovation work, while

conventional AI has long supported modelling, optimisation and R&D. Generative AI's role across complete innovation portfolios is newer and less uniform.

The overall picture is therefore one in which **AI-assisted strategy and innovation are increasingly established, AI-integrated strategic processes are growing, and autonomous strategic decision-making or comprehensive AI-driven organisational transformation remain emerging or experimental.**

5. What appears to be driving adoption?

Speed and analytical capacity are major drivers. Strategy teams operate in environments containing more information than people can practically read and analyse. AI can shorten research cycles and allow comparatively small teams to examine larger bodies of evidence.

Environmental complexity and volatility also matter. Strategy leaders are dealing simultaneously with technological change, geopolitical developments, shifting regulation, economic uncertainty and changing competitive conditions. At the World Economic Forum's 2026 Industry Strategy Meeting, involving more than 300 strategy leaders, participants described such forces as part of the continuing operating environment rather than isolated disruptions.

Pressure on strategy capacity reinforces this. Deloitte's 2026 global CSO survey found half of participating strategy leaders reporting too many priorities and insufficient time. AI offers a way of expanding research and analytical throughput without expanding strategy teams proportionately.

Innovation productivity is another driver. Generative AI makes experimentation inexpensive: organisations can create and compare many concepts, formulations or designs before committing resources to development. In product innovation, controlled field evidence now demonstrates that AI can improve the quality of work under some conditions rather than merely accelerate it.

Enterprise pressure to realise value from AI investment is increasingly important. AI has become a board and CEO issue rather than solely a technology programme. BCG's 2026 AI Radar, covering 2,360 executives in 16 markets, found nearly three-quarters of CEOs identifying themselves as their company's key AI decision-maker.

Finally, **AI itself is creating transformation pressure.** Organisations are not merely asking how AI can improve an existing process; some are reconsidering roles, workflows, decision rights and operating models because AI can perform work that previously shaped those structures. This helps explain why strategy and transformation functions increasingly sit close to enterprise AI programmes.

6. What are the present limitations?

Strategic information is not automatically reliable

AI can process large amounts of information rapidly, but the result depends on the quality, completeness, currency and accessibility of the underlying material. Internal knowledge may be fragmented across systems, while external information can be inaccurate, commercially motivated or contradictory.

Generative systems can also produce plausible but incorrect statements. In strategy, an error may propagate into a market assessment, investment case or scenario rather than remaining an isolated drafting mistake.

Strategic decisions contain judgement that data alone does not resolve

Many strategic choices concern objectives rather than facts: which risks are acceptable, which markets matter, what the organisation values and which stakeholder interests should prevail.

BCG's 2026 research is instructive here. AI impact was reported most consistently in market intelligence and research, while more judgement-intensive areas such as M&A, partnerships and portfolio management had not demonstrated comparable material improvement.

More ideas do not necessarily mean better innovation

Generative AI can produce alternatives rapidly, but volume can create its own evaluation burden. Research on team creativity suggests that AI can increase idea diversity, while the conversion of that diversity into genuine novelty depends on how people analyse and integrate the material.

Innovation therefore retains an important selection problem: recognising which idea is technically feasible, commercially useful, strategically appropriate and worth funding.

Organisational context is difficult to encode

A strategy may depend on tacit knowledge, relationships, culture, political constraints and implementation history that are poorly represented in formal data. AI may consequently produce a theoretically coherent proposal that does not fit the organisation that would have to execute it.

Transformation requires more than technology

Evidence across enterprise AI studies repeatedly shows a gap between deploying tools and redesigning organisations. The World Economic Forum describes operating-model redesign,

human accountability, talent, trust and disciplined experimentation as central to scaling AI, while Roland Berger's 2026 study of 472 executives similarly identifies unchanged operating models as an important reason AI investment fails to translate into enterprise performance.

Value remains difficult to establish

Strategic value is intrinsically difficult to measure because outcomes may emerge years after a decision and cannot easily be separated from market conditions or management execution.

The broader AI evidence reinforces this problem. PwC's 2026 global CEO research found 56% of CEOs reporting neither increased revenue nor reduced costs from AI during the previous year, despite widespread investment. This does not show that AI lacks value in strategy; it shows why activity, adoption and realised organisational value should not be treated as equivalent.

Governance and accountability constrain autonomy

Capgemini's executive research identified legal risk, explainability and data quality among major concerns surrounding AI-supported decisions. Most executives did not expect autonomous strategic decision-making in the near term.

These concerns become more significant as systems move from providing information towards recommending or initiating actions.

7. What you should be aware of

Strategy, Innovation & Transformation is particularly susceptible to exaggerated interpretations of AI because the language surrounding the technology—"reasoning", "agents", "decision intelligence" and "AI-first transformation"—can make emerging capabilities appear more organisationally established than they are.

There is substantial genuine activity. AI is already changing how research is undertaken, how information is synthesised, how ideas are generated and how initial strategic analysis is prepared. Controlled field experiments demonstrate meaningful effects in innovation work, and multinational surveys show executives already incorporating AI into portions of their decision processes.

But several distinctions remain important.

AI producing a strategy analysis is not the same as **AI making strategy**. **AI generating scenarios** is not the same as accurately predicting future conditions. **AI producing hundreds of ideas** is not evidence that an organisation has become more innovative. And an

organisation **launching an AI transformation programme** is not evidence that its operating model has actually been transformed.

The evidence base also requires care. Surveys measure different populations and definitions. Consulting and technology organisations contribute much of the available evidence and often study comparatively large enterprises. Smaller organisations, less digitised sectors and many parts of the world are less visible in published evidence. Reported improvements in foresight, creativity or decision quality are often assessments by participants rather than independently observed long-term strategic outcomes.

Human involvement remains particularly important because strategy determines direction, priorities and resource allocation. These decisions can affect employees, customers, investors, communities and other stakeholders. Accountability therefore does not disappear merely because an analysis has been generated by a sophisticated model.

Transformation deserves similar caution. AI can expose possibilities for reorganising work, and some organisations are moving towards workflows in which humans and AI systems operate together. But enterprise evidence continues to show far more experimentation and selective deployment than complete AI-centred organisational redesign. McKinsey's global research, for example, found widespread AI use but only about one-third of organisations beginning to scale it across the enterprise.

A further caution comes from implementation itself. Reuters reported in August 2026 that Meta's ambitious internal effort to redesign parts of its organisation around smaller AI-supported teams encountered employee resistance, reliability and security concerns and weaker-than-expected productivity results, leading the company to scale back elements of the initiative. One company's experience should not be generalised across organisations, but it provides useful evidence that even organisations with exceptional AI capabilities can encounter substantial difficulty translating technological ambition into organisational redesign.

The clearest Status conclusion is therefore that **AI has become a material tool within Strategy, Innovation & Transformation, especially for research, intelligence, analysis, ideation, scenario exploration and preparation. Its influence is beginning to extend into continuous planning, innovation workflows and organisational redesign. However, the more an activity depends on uncertain futures, competing objectives, tacit organisational knowledge, consequential trade-offs and human commitment, the less the evidence supports treating AI as an autonomous substitute for strategic judgement.**

Evidence Notes

1. **Boston Consulting Group / BCG Henderson Institute — “The Corporate Strategy Function in an AI-First World” — March 2026.** Analysis of AI exposure across strategy-function activities; reports more than 80% of common activities as having high or medium exposure and distinguishes stronger

demonstrated impact in market intelligence and research from weaker impact in judgement-intensive strategic activities.

[BCG — The Corporate Strategy Function in an AI-First World](#)

2. **Deloitte / Monitor Deloitte — 2026 Global Chief Strategy Officer Survey — 2026.** Survey of 148 executives owning organisational strategic agendas, fielded September–November 2025. Supports evidence concerning strategy capacity, AI involvement in planning and insight generation, CSO participation in AI decisions and the relatively limited proportion reporting transformational AI use.
[Deloitte — 2026 Global CSO Survey](#)
3. **Capgemini Research Institute — “Inside the C-suite: How AI is quietly reshaping executive decisions” — January 2026.** Survey of 500 C-suite executives, including 100 CEOs, across 16 countries and 13 industries, supplemented by executive interviews. Supports current use of AI in research, analysis, strategic decision support and foresight, together with evidence concerning governance, explainability, data quality and continuing human accountability.
[Capgemini — Inside the C-suite](#)
4. **World Economic Forum / Accenture — “Organizational Transformation in the Age of AI: How Organizations Maximize AI's Potential” — March 2026.** Draws on the Forum's AI Transformation of Industries community of more than 450 executives. Supports the distinction between isolated use cases and connected systems and evidence concerning operating-model redesign, continuous processes, human accountability and AI use in strategic planning, R&D and other enterprise activities.
[World Economic Forum — Organizational Transformation in the Age of AI](#)
5. **World Economic Forum — Industry Strategy Meeting 2026 — March 2026.** Evidence from more than 300 strategy leaders concerning the strategic environment, including geoeconomic fragmentation, AI disruption, energy volatility and workforce pressures.
[World Economic Forum — What global strategy leaders say they need in 2026](#)
6. **McKinsey & Company / QuantumBlack — “The state of AI in 2025: Agents, innovation, and transformation” — November 2025.** Global survey evidence showing widespread AI use but much more limited enterprise scaling; also provides evidence concerning workflow redesign, innovation objectives, agent experimentation and enterprise-level financial impact.
[McKinsey — The state of AI in 2025](#)
7. **PwC — 29th Global CEO Survey — 2026.** Supports evidence concerning limited extensive deployment in organisational direction-setting and the distinction between AI investment, deployment and measurable revenue or cost outcomes.
[PwC — 29th Global CEO Survey](#)
8. **PwC New Zealand — 29th Global CEO Survey, New Zealand findings — February 2026.** Illustrates regional unevenness between reported organisational readiness and realised AI impact and deployment.
[PwC New Zealand — CEO Survey 2026](#)
9. **World Economic Forum — “Why human roles still matter for Asia's AI transformation” — June 2026.** Regional evidence indicating high reported adoption of advanced AI across surveyed Asian organisations but substantially lower achievement of sustained value.
[World Economic Forum — Asia's AI transformation](#)
10. **Dell'Acqua et al. — “The Cybernetic Teammate: A Field Experiment on Generative AI and Teamwork” — Organization Science, June 2026.** Preregistered field experiment involving professionals at Procter & Gamble undertaking real product-innovation challenges. Provides unusually strong evidence concerning AI-supported innovation performance, cross-functional knowledge integration and the continuing importance of human evaluative judgement.
[Organization Science — The Cybernetic Teammate](#)
11. **Academy of Management Proceedings — “From Diversity to Novelty: How Information Elaboration Unlocks the Creative Power of AI in Teams” — 2025.** Five preregistered randomised field experiments involving 528 individuals across 176 teams. Supports the qualification that increased idea diversity from generative AI does not automatically produce greater novelty without effective human information

elaboration.

[Academy of Management — From Diversity to Novelty](#)

12. **European Journal of Innovation Management — “Genius innovation management – a typology of GenAI use in innovation management” — July 2026.** Multiple-case study involving 13 organisations across industries and sizes, providing direct evidence of differing forms and maturity of organisational generative-AI use within innovation management.
[European Journal of Innovation Management study](#)
 13. **Gartner — “AI Use-Case Assessment for Strategy and Strategic Planning” — April 2026.** Identifies AI use cases intended to improve the speed, quality and accessibility of strategic planning, including adaptive planning applications. Used principally as evidence of available/developing capability rather than proof of widespread deployment.
[Gartner — AI Use-Case Assessment for Strategy and Strategic Planning](#)
 14. **BCG — AI Radar 2026 — January 2026.** Global survey of 2,360 executives, including 640 CEOs across 16 markets. Supports the increasing strategic and executive-level importance attached to enterprise AI investment and decision-making.
[BCG — AI Radar 2026](#)
 15. **Roland Berger — “The AI-First Organization” — July 2026.** Global study based on 472 executives and senior leaders. Supports the distinction between technology deployment and operating-model transformation and the continuing difficulty organisations experience converting AI activity into measurable enterprise performance.
[Roland Berger — The AI-First Organization](#)
 16. **Spirent / SnapLogic case study — available by 2026.** Vendor-published organisational case evidence of a deployed generative-AI-supported competitive-intelligence workflow. Used as an illustrative deployment example rather than evidence of general adoption.
[Spirent competitive-intelligence case study](#)
 17. **Reuters — Meta organisational-transformation reporting — 26 August 2026.** Independent reporting on Meta's Project OT provides a useful counter-example to transformation publicity: an ambitious AI-supported organisational redesign encountered reliability, security, productivity and employee-trust problems and was subsequently scaled back. Used as a specific case, not as evidence that other organisations will experience the same outcome.
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7. Project & Programme Management

Status as at 30 August 2026

Artificial intelligence is becoming a visible part of project and programme work, but its depth of use varies substantially.

The most widespread applications are relatively assistive: drafting project documents, summarising meetings and reports, researching information, creating initial plans and work breakdowns, searching project records, preparing stakeholder communications and helping analyse risks, schedules or project data. These uses can occur through general-purpose AI assistants as well as through AI functions embedded in project-management and enterprise software.

A second category is more deeply connected to project delivery. AI is being used to analyse schedules, forecast delay and other risks, monitor construction progress, identify project exceptions, support resource allocation, interpret large bodies of project information and generate status reporting. Specialist systems in engineering, infrastructure and construction can combine machine learning, computer vision and historical project data with schedules, models or site information.

A further development evident during 2026 is the arrival of AI agents and workflow systems that can create or update project tasks, trigger actions, route information, monitor work and undertake portions of workflows rather than simply providing an answer. Commercial capabilities exist and some organisations are deploying AI-driven workflows, but autonomous project management is not the normal state of practice. Microsoft still described Copilot in Planner as a preview capability, while Atlassian, Asana, monday.com and other platforms were progressively introducing agents and AI workflow functionality during 2026.

Consequently, the Status as at 30 August 2026 is best understood as a combination of increasingly common AI-assisted project work, growing integration into project-management platforms and specialist project controls, and much earlier experimentation with systems capable of independently progressing portions of project workflows.

1. What is AI currently being used for?

Project planning and work definition

Generative AI is increasingly being used to produce the first version of a project plan.

Given a description of an objective, AI systems can propose activities, milestones, work packages, dependencies, goals and other elements of a project structure. Microsoft Copilot in Planner, for example, can generate tasks, goals and work groupings and create an initial plan

from a prompt. Jira's Rovo can generate proposed work items and descriptions from a stated objective for a user to review before creating them.

This is particularly suited to creating a starting point rather than establishing an authoritative project baseline. Requirements, dependencies, durations, constraints and organisational circumstances still need to be validated.

AI is also used for requirements support: summarising source material, turning notes into draft requirements, identifying ambiguities or missing information, breaking broad requirements into smaller tasks and generating acceptance criteria or other documentation.

Scheduling, forecasting and project controls

AI is increasingly being applied to schedules and historical project information to identify patterns that conventional monitoring may not reveal easily.

Applications include detecting potentially unrealistic schedule assumptions, identifying activities associated with greater delay risk, forecasting milestone outcomes, examining dependencies, assessing schedule quality and supporting scenario analysis.

Specialist construction platform nPlan, for example, states that its systems have been trained using approximately 750,000 historical schedules representing more than US\$2 trillion of construction activity. Customers cited by the company include Anglian Water, the Transpennine Route Upgrade, contractors and other major project organisations using AI to analyse schedules and project-delivery risk. This demonstrates operational use of specialised AI project controls, although the provider's performance claims should remain distinguished from independent evaluation.

AI is also being applied to resource and workload analysis. Project systems can identify overloaded resources, compare work against capacity or propose allocations. The Association for Project Management's March 2026 UK research found respondents reporting AI use for resource allocation, task scheduling, forecasting and decision support among other applications.

Reporting, documentation and project communications

Administrative and information-handling work is one of AI's clearest present footholds.

Project professionals can use AI to draft progress reports, summarise meetings, extract actions, produce executive summaries, prepare presentations, draft stakeholder communications, summarise technical material and transform detailed project data into more accessible narrative.

AI also changes retrieval. Instead of manually searching folders, task registers, correspondence and project systems, users can increasingly ask questions in ordinary language and receive summaries assembled from connected project information.

Atlassian, for example, provides AI functions for summarising work items, identifying blockers and next steps, searching project information using natural language and drafting release material.

These comparatively ordinary applications matter because project environments generate large quantities of changing information. Reducing the effort of locating, consolidating and rewriting that information can affect everyday work even where the underlying project-control process remains substantially unchanged.

Risk and issue management

AI is being used to help identify and prioritise risks, exceptions and potential problems.

This ranges from asking a generative assistant to analyse a risk register to specialist machine-learning systems examining project histories, schedules, design information or current project records.

Autodesk's Construction IQ, for example, applies machine learning to project information to identify and prioritise risks involving areas such as design issues and requests for information, including their potential implications for cost and schedule.

Such systems can widen the volume of information reviewed and direct human attention towards particular items. They do not establish that the identified risk will materialise, nor that an unflagged risk is insignificant.

Capital projects, engineering and construction

AI applications become particularly diverse in major physical projects because project management intersects with design, engineering, construction and site execution.

Computer vision can compare site images against plans or models to estimate construction progress and identify work that appears incomplete. AI can assist with design coordination, analyse project schedules, interpret drawings and documents, identify potential quality or safety concerns and support cost, risk and progress analysis.

Nordic contractor NCC initially piloted Buildots' AI-based progress tracking on an 8,000-square-metre Helsinki residential project and subsequently expanded its use to three additional projects, according to the supplier's case study. This provides an example of an application progressing beyond a single trial, although reported performance improvements are vendor-reported rather than independently measured.

Engineering-project platforms increasingly connect 3D models, project schedules and other project data, while emerging AI interfaces allow professionals to interrogate or act upon engineering information through natural language. These developments bring AI into design coordination and engineering delivery as well as conventional project administration.

Programme and portfolio support

At programme and portfolio level, AI can consolidate information across multiple projects, identify common risks, compare performance, summarise portfolio status and assist prioritisation.

The potential value is partly one of scale. A programme office may have hundreds or thousands of activities, risks, documents and status updates. AI can search and summarise those populations more rapidly than manual review alone and can identify relationships or anomalies for further investigation.

The decision to start, stop, fund or materially redirect a programme or project nevertheless remains substantially different from producing the analysis informing that decision.

2. What activities are changing?

The most visible current change is the compression of information-handling work.

Producing a project report traditionally involves collecting updates, reviewing meeting records, finding supporting information, reconciling differing accounts, drafting narrative and repeatedly reformatting material for different audiences. AI can now perform parts of that sequence: extracting relevant information, summarising it and generating a first draft.

Planning is changing similarly. A project manager no longer necessarily begins with a blank page when developing a work breakdown, risk list, stakeholder communication plan or set of project activities. AI can generate an initial structure that the professional then interrogates and adjusts.

This shifts effort from initial production towards validation.

Project monitoring is also becoming more exception-oriented. Machine-learning systems can analyse schedules, task data or site observations at larger scale and identify activities or conditions warranting attention. In construction, automated progress capture can reduce reliance on manually establishing the state of every installed component before project staff decide how to respond.

The interaction with project software is changing as well. Natural-language interfaces allow users to ask what is late, what has changed, which tasks are blocked or what occurred since the previous reporting period instead of manually constructing every filter or report.

A more consequential change is beginning as agents are inserted into workflows. Jira permits agents to be assigned to work items, while project and work-management platforms increasingly allow AI to classify work, update records, generate reports, route requests or trigger subsequent steps. Asana, for example, describes AI workflows that can validate incoming work, classify and route it, flag risks and produce reporting.

This changes the division of responsibility between system and professional. An AI assistant drafting a status report leaves the human running the process. An AI agent authorised to update project records or progress work through a defined workflow is participating in execution.

As at the reference date, the first arrangement is considerably more established than the second.

3. What can AI currently do?

Demonstrated applications show that AI can currently perform several useful classes of project work.

It can **read and summarise** large volumes of project documentation, meeting records, correspondence, requirements and technical material.

It can **generate** first drafts of project plans, tasks, work breakdowns, reports, risk descriptions, communications and other project documents.

It can **retrieve and connect information**, allowing a project professional to interrogate connected systems using ordinary language rather than manually searching each source.

It can **classify and organise**, including categorising project items, applying labels, routing work, extracting actions and structuring unorganised information.

It can **analyse and forecast**, using historical and current data to identify patterns associated with project risk, delay, resource pressure or other outcomes.

It can **observe aspects of physical progress** where computer vision has appropriate site imagery and a reliable reference model or plan.

It can **compare**, helping identify changes, inconsistencies, missing information and deviations between planned and observed conditions.

Increasingly, it can **act within project systems** by creating or updating tasks, triggering workflows and performing bounded activities under defined permissions.

These capabilities should not be confused with an ability to run an unrestricted project reliably.

Projects operate through incomplete information, changing objectives, contractual relationships, organisational politics, engineering judgement, negotiation, regulation and human behaviour. AI can help process information relating to these matters but cannot be assumed to understand all of their consequences or reliably determine the correct course of action.

The more ambiguous, novel or consequential the decision, the more significant contextual and human judgement generally remains. PMI's earlier work on generative AI similarly distinguished relatively suitable AI-supported tasks from complex work requiring substantially more human involvement.

4. How established is its use?

AI use in project work is clearly beyond isolated experimentation, but its establishment depends strongly on what is counted as "use".

In the United Kingdom, APM's September 2025 survey of 1,000 project professionals found 70% reporting that their organisation used AI, compared with 36% in its 2023 survey. Among respondents reporting benefits from implementation, task and schedule automation, resource allocation, risk analysis and forecasting, reporting and stakeholder communications were prominent areas.

Its March 2026 research, again involving 1,000 UK project professionals, provides a more demanding indicator: 27% said AI was **fully embedded** in their workflows. The figure was 28% among construction respondents and 25% among engineering respondents. These results show meaningful organisational integration while simultaneously demonstrating that reporting some AI use is not equivalent to having AI deeply embedded across project delivery.

International construction evidence tells a similarly mixed story. Mastt surveyed 108 construction project-management professionals internationally between March and June 2026. Some 72.2% reported using AI at least weekly and 48.1% daily or more frequently. Yet use was dominated by general-purpose systems: 66.7% reported ChatGPT and 50.9% Microsoft Copilot, whereas only 3.7% reported AI functions inside Procore, Autodesk or similar platforms and 0.9% reported specialist AI tools in the category measured. Only 9.3% said they were currently using AI agents.

These figures should not be treated as universal construction adoption rates: the sample is modest and supplier-sponsored. They nevertheless illustrate a highly important maturity distinction. Frequent use of general AI assistance can coexist with very limited penetration of specialist or autonomous AI into core project controls.

Other regional evidence reinforces the uneven picture. Capterra's 2025 study covered 2,545 project-management software decision-makers across Australia, Brazil, Canada, France, Germany, India, Italy, Mexico, Spain, the United Kingdom and United States. Indian respondents, for example, showed particularly strong interest in acquiring AI functionality, but the same international research also identified security, workforce and implementation considerations around project-management software.

In Saudi Arabia, a 2026 academic study of 216 private-sector construction professionals found positive relationships between reported AI integration, operational efficiency, managerial decision-making and project outcomes. Its authors nevertheless noted that Saudi adoption remained at an early stage and that the sample included professionals familiar with AI as well as actual users, making it evidence of developing adoption rather than proof of widespread embedded deployment.

The overall Status is therefore layered. General-purpose AI for project productivity is increasingly established. AI embedded in project-management systems, analytics and project controls is growing. Specialist applications in construction and engineering have demonstrable operational deployments but remain uneven. Agentic project execution is emerging.

5. What appears to be driving adoption?

The first major driver is **administrative capacity**.

Projects create substantial volumes of meetings, actions, status updates, documentation, correspondence and reporting. Generative AI can reduce the effort involved in converting this information into usable project material.

The second is **speed of analysis**. Projects may contain more activities, dependencies, risks and records than a project team can examine continuously. AI can process larger populations and direct attention towards exceptions.

The third is **predictability**. Cost overruns and schedule delays create strong incentives for organisations undertaking capital and complex projects to improve forecasting. Historical-data and machine-learning approaches are attractive because they offer another means of challenging optimistic assumptions or identifying patterns associated with poor delivery.

The fourth is **accessibility**. AI is increasingly appearing inside software already used by project teams. Atlassian AI is available across mainstream paid cloud plans, Microsoft is integrating AI into Planner and Copilot, and work-management platforms such as Asana and monday.com are embedding AI workflows and agents into existing interfaces. Organisations therefore do not always encounter AI as a separate technology implementation.

The fifth is **pressure for greater project throughput and productivity**. Organisations expect project teams to coordinate growing volumes of work without proportionately increasing administrative staffing. AI makes automation of knowledge work more accessible than previous rule-based systems alone.

Finally, **competitive and professional pressure** is visible. The appearance of AI standards, training programmes, new software functions and rapidly rising reported use creates pressure on project functions to understand and experiment with the technology. PMI's June 2026 publication of *The Standard for Artificial Intelligence in Portfolio, Program, and Project Management* reflects the extent to which AI has become a live professional-management concern.

6. What are the present limitations?

Project data are fragmented and variable

AI is most useful when it receives reliable and sufficiently current information. Project data frequently sit across schedules, spreadsheets, project-management systems, document repositories, engineering models, cost systems, email, contracts and contractor platforms.

These sources may disagree.

An AI system can summarise incorrect project information just as efficiently as correct information. Missing updates, inconsistent work-breakdown structures, outdated schedules and weak document control therefore remain significant constraints.

Evidence from Australia and New Zealand construction illustrates the readiness problem. An August 2026 survey of 34 general contractors reported strong belief in the strategic importance of AI but only 9% saying they had the data foundation described by the researchers as necessary to act on that belief. The sample is small and provider-sponsored, but it illustrates the difference between enthusiasm and implementation readiness.

Reliability and context remain imperfect

Generative AI can produce plausible but incorrect conclusions, invent details or overlook relevant circumstances.

In a project environment, an erroneous summary may affect a decision about scope, schedule, risk, contractual entitlement or technical work. The consequences can therefore exceed those of an inaccurate low-risk draft.

APM's 2025 survey found 41% of AI-using respondents identifying inaccuracy or untrustworthiness as a challenge.

Specialist predictive systems have another limitation: probabilities and detected patterns do not determine what will happen. Projects may be affected by circumstances absent from historical data, and relationships learned from previous projects may not transfer perfectly to a new one.

Integration is difficult

Project work is inherently cross-system and cross-organisational.

Contractors, consultants, owners and suppliers frequently use different software and maintain different information environments. AI capable of searching one platform may therefore see only part of the project.

Connecting AI to more systems increases usefulness but also expands questions of permissions, information security, confidentiality and data ownership.

Governance becomes harder as AI gains agency

The risk profile changes when AI moves from producing information to taking actions.

An assistant proposing a task is different from an agent creating it, assigning it, changing its priority and triggering downstream workflows.

Questions then arise concerning who authorised the action, what information the agent used, whether approvals were bypassed, how the action is audited and who remains accountable.

PMI's decision to publish a specific global AI standard for portfolio, programme and project work in June 2026 is itself evidence that issues involving governance, ethics, compliance and AI-specific risk have become material to current professional practice.

Skills and organisational readiness are uneven

Project professionals need enough understanding to determine when an AI output is useful and when it is misleading.

APM's 2025 survey found 49% of AI-using respondents citing technical knowledge and training as a challenge, 44% security or data privacy and 42% integration with organisational workflows.

This becomes more demanding in engineering and major projects, where validating AI output may require substantial technical, commercial or contractual knowledge.

Evidence of value remains uneven

Many current claims concerning project AI benefits come from vendors, users participating in surveys or organisations publicising successful projects.

These sources demonstrate real activity but not universal outcomes.

A vendor showing that AI can optimise a schedule does not establish that most organisations use it. A user survey reporting greater productivity does not independently measure the amount gained. A successful construction case study does not demonstrate that equivalent performance will occur on every project.

7. What you should be aware of

AI in Project & Programme Management should not be interpreted as a single maturity story.

There is already substantial use of AI around project work. Project professionals are drafting, summarising, researching, analysing and communicating with AI, and these activities are sufficiently widespread in some surveyed populations to constitute a meaningful part of contemporary project practice.

Deeper integration is much less uniform.

AI analysing formal project schedules, interpreting connected project data, monitoring construction progress or operating inside project-control workflows represents a more consequential form of adoption than an individual project manager using a general-purpose assistant. Both may legitimately be described as "AI use", but they should not be treated as equivalent.

Agentic AI requires an additional distinction. By August 2026, commercial platforms could assign work to agents, permit AI-driven workflow actions and allow agents to interact with project records. These are demonstrated capabilities. The evidence does not establish autonomous project management as a widespread organisational operating model. Construction survey evidence, for example, showed interest in agents substantially ahead of actual use.

Human involvement therefore remains central. Project work combines planning and information processing with negotiation, leadership, technical judgement, accountability and responses to circumstances that could not be completely specified in advance. AI can increasingly perform portions of the information-intensive work surrounding those activities,

while project professionals continue to determine whether outputs make sense and remain responsible for consequential decisions.

The evidence base itself also requires care. Professional-body surveys differ in geography, population and definition. Supplier studies contain useful operational evidence but commercial incentives. Academic studies may measure reported perceptions or statistical relationships rather than verified organisational outcomes. Product announcements establish capability, not adoption.

The clearest Status conclusion as at **30 August 2026** is therefore neither that project management has been automated nor that AI remains principally experimental.

AI has become a material and expanding component of project and programme work. Its strongest current foothold is in information handling, documentation, reporting, planning assistance, analysis and decision support. More specialised applications are already operating in scheduling, project controls and construction progress monitoring. AI systems capable of taking bounded actions within project workflows are now appearing, but their organisational adoption is substantially less mature than AI-assisted professional work. The scale of adoption, quality of project data, integration, reliability, governance and measurable impact remain uneven.

Evidence Notes

1. **Project Management Institute (PMI), June 2026 — *The Standard for Artificial Intelligence in Portfolio, Program, and Project Management*.** Evidence that AI governance in project work had become sufficiently established to generate a formal global professional standard; addresses AI business cases, risk, ethics and compliance. [PMI announcement](#)
2. **Association for Project Management (APM), March 2026 — survey of 1,000 UK project professionals.** Reported 27% saying AI was fully embedded in workflows and identified current applications including forecasting, decision support, administration, risk, reporting, resource allocation and scheduling. Sector results included construction and engineering. [APM 2026 research](#)
3. **Association for Project Management, September 2025 — Censuswide survey of 1,000 UK project professionals.** Reported 70% organisational AI use and identified benefits and implementation challenges including training, security/privacy, workflow integration and output reliability. Survey definitions mean this should not be equated with embedded use. [APM adoption survey](#)
4. **PMI, 2024–25 global generative-AI research.** PMI's research included project professionals in multiple countries and industries and demonstrated rapid expansion of GenAI use among an intentionally AI-using respondent population. Useful particularly for capability, productivity and the distinction between lower- and higher-adoption users; not a general-population adoption rate. [PMI Pushing the Limits report](#)
5. **Mastt, July 2026 — *State of AI in Construction Project Management 2026*.** Survey of 108 construction project-management professionals internationally during March–June 2026. Reported 72.2% using AI at least weekly and 48.1% daily or more, but strong dominance of general-purpose AI and only 9.3% current

agent use. Useful evidence of the difference between frequent AI assistance and specialist/agent adoption; modest sample and vendor-sponsored. [Mastt 2026 survey](#)

6. **Capterra, 2025 Project Management Software Trends Survey.** 2,545 respondents across Australia, Brazil, Canada, France, Germany, India, Italy, Mexico, Spain, the UK and US. Provides useful international evidence about AI functionality influencing project-management software decisions and differences between markets. [Capterra international PM research](#)
7. **Jamal & Khoja, King Abdulaziz University, *Buildings*, 19 August 2026.** Study of 216 professionals in Saudi Arabia's private construction sector examining reported AI integration, operational efficiency, managerial decision-making and project performance. Authors explicitly identify Saudi construction AI adoption as relatively early; sample included AI users and professionals familiar with AI. [Saudi construction study](#)
8. **Visibuild, August 2026 — Australian/New Zealand construction survey.** Survey of 34 general contractors working on projects ranging from approximately A\$20 million to A\$2 billion; reported a marked gap between expectations concerning AI and organisations reporting an adequate data foundation. Useful readiness evidence but small and vendor-sponsored. [Australia/New Zealand construction report](#)
9. **nPlan — project-controls capability and customer evidence, accessed August 2026.** Describes AI analysis of project schedules using a historical schedule dataset and identifies deployments involving organisations including Anglian Water and the Transpennine Route Upgrade. Useful evidence of specialised schedule-risk AI in operational project environments; effectiveness claims remain provider/customer claims. [nPlan project-controls evidence](#)
10. **Buildots/NCC case study — Nordic construction deployment.** NCC piloted AI-based progress tracking on a Helsinki project and subsequently expanded use across three additional projects. Provides evidence of an application progressing beyond a single pilot; quantified performance improvements are supplier-reported. [NCC deployment case study](#)
11. **Autodesk Construction IQ — current construction risk-analysis capability.** Demonstrates commercial machine-learning functionality for prioritising design and RFI risks affecting construction projects. Provider evidence establishes capability rather than prevalence of customer adoption. [Autodesk Construction IQ](#)
12. **Microsoft Planner/Copilot documentation, accessed August 2026.** Demonstrates generative planning, task and goal creation, workload interrogation and project status functionality. Microsoft continued to identify Copilot in Planner as preview functionality, which is material to maturity classification. [Microsoft Copilot in Planner](#)
13. **Atlassian Jira/Rovo documentation and 2026 release material.** Demonstrates natural-language project search, content generation, work-item creation and the ability to assign agents to project work or incorporate them in workflows. Some functionality was rolling out or beta, and therefore should not be interpreted as universal deployment across Jira customers. [Atlassian Rovo in Jira](#)
14. **Asana AI Studio, accessed August 2026.** Demonstrates commercially available AI workflow capabilities involving intake, classification, routing, risk flagging, reporting and triggering actions. Used to establish available capability rather than market-wide adoption. [Asana AI Studio](#)
15. **monday.com, March–May 2026.** Company announcements document infrastructure allowing AI agents to operate within its work platform and a broader move towards human-agent workflows. Evidence of available commercial capability and supplier direction, not evidence that agentic project management was widespread among customers. [monday.com agent announcement](#)
16. **Academic literature — 2025 systematic reviews of AI and project/construction management.** Reviews identify current research involving planning, prediction, optimisation, risk and decision support while also highlighting barriers, fragmented evidence and uneven implementation maturity. Used principally to cross-check the broader application and limitation categories rather than to infer adoption rates. [Project-management AI systematic review](#)

8. Technology & Information

Status as at 30 August 2026

Artificial intelligence has become a substantial part of the Technology & Information function, although its maturity differs considerably by activity.

The most visible change has occurred in software development. AI assistants now generate and explain code, create tests and documentation, assist debugging and review code. Increasingly, agentic systems can undertake multi-step development tasks rather than merely suggest the next line of code. Evidence from technology professionals indicates that AI-assisted development has moved well beyond isolated experimentation, although high usage does not mean that generated code is accepted without human review. Google's 2025 DORA research, based on nearly 5,000 technology professionals internationally, reported AI use by around 90% of respondents, while continuing to identify concerns about trust and software-delivery stability.

The wider Technology & Information picture is broader than coding. AI is being incorporated into IT service management, incident investigation, infrastructure and cloud operations, cybersecurity, data engineering, analytics, enterprise information retrieval and technical documentation. Natural-language interfaces are also changing how people interact with technical systems: users increasingly ask questions about code, data, infrastructure or organisational information without needing to know every underlying command, query language or system structure.

A further development visible by 2026 is the transition from **AI that assists technical professionals to AI that can perform bounded portions of technical workflows**. Commercially available systems can investigate incidents, build data pipelines, conduct code reviews, classify support incidents and carry out defined IT-service tasks. However, the maturity of these applications varies considerably. Some are generally available and being used operationally; others remain previews, controlled deployments or early agentic implementations.

The Technology & Information Status as at 30 August 2026 is therefore one of extensive AI-assisted work, increasing integration into mainstream technology platforms, and emerging automation of multi-step technical activity—but not autonomous operation of organisational technology as a whole.

1. What is AI currently being used for?

Software development

Software development is one of the clearest areas of current AI use.

Developers use AI to generate and complete code, explain unfamiliar code, translate between programming languages, produce tests, identify errors, suggest fixes, refactor software, draft documentation and answer questions about repositories and technical frameworks.

The capability is extending beyond conversational assistance. Coding agents can increasingly work from a higher-level instruction, inspect repositories, modify multiple files, run tests and undertake sequences of development activity. Code review is also becoming AI-assisted. By March 2026, GitHub reported that its Copilot code-review service had conducted more than 60 million reviews and accounted for more than one in five code reviews on GitHub; its review system could retrieve wider repository context rather than examining a code change in isolation.

These developments do not mean that software development has become autonomous. AI-generated changes still pass through testing, security, integration, review and deployment processes, and organisations differ substantially in how much authority they permit AI systems to exercise.

Testing, quality assurance and documentation

AI is being applied throughout activities surrounding code production.

Systems can generate unit tests, suggest test cases, identify possible defects, explain failures, examine code changes and produce technical documentation. AI-assisted security scanning can similarly become part of development pipelines.

Singapore provides a public-sector example outside the US market. GovTech reported in August 2026 that its SHIP-HATS software delivery pipeline incorporates AI-assisted code scanning and testing, automating portions of security review and quality assurance.

The significance is that AI is increasingly entering the **software lifecycle**, rather than remaining only inside the developer's coding window.

IT service management and technical support

AI is also becoming embedded in service desks and IT-support workflows.

Current applications include summarising support cases, categorising incidents, retrieving relevant knowledge, recommending resolutions, generating response material and providing conversational self-service for employees.

More advanced systems can undertake portions of the workflow. ServiceNow's 2026 IT-service-management capabilities, for example, include agentic workflows for categorising incidents, investigating incidents, generating resolution recommendations, preparing post-incident reviews, assisting change requests and undertaking selected administrative tasks.

These capabilities establish what commercially deployed platforms can now support, rather than proving uniform customer adoption.

IT operations, infrastructure and observability

Technology teams are using AI to interpret the enormous volumes of logs, metrics, traces, alerts and configuration information generated by modern digital infrastructure.

Applications include anomaly detection, alert correlation, performance analysis, capacity and cost analysis, incident investigation and root-cause analysis. Generative interfaces can summarise technical evidence and explain possible causes in ordinary language.

Google's Gemini Cloud Assist investigations, for example, can examine logs, configurations and metrics, rank relevant observations and support root-cause investigation. Importantly for Status purposes, the investigation capability remained a **preview offering** at the reference date rather than an example of universally established autonomous cloud operations.

A more ambitious development is AI-supported remediation, where systems progress from identifying an operational problem towards proposing or undertaking corrective action. Commercial products supporting such activity existed by August 2026, but supervised autonomy remains materially more mature than unrestricted autonomous infrastructure management.

Cybersecurity operations

AI is increasingly intertwined with cybersecurity because security teams confront large volumes of alerts, events, vulnerabilities and threat information.

Applications include identifying suspicious patterns, summarising incidents, prioritising alerts, supporting threat investigation, analysing potentially malicious material and assisting security analysts with queries and reports.

Agentic security applications are emerging as well. Microsoft's Phishing Triage Agent, for example, can combine analysis of reported messages with threat intelligence, file and URL analysis and advanced hunting across security data.

Cybersecurity also illustrates an important dual effect: Technology & Information functions are using AI to defend systems while simultaneously having to secure AI systems and defend against AI-enabled threats.

Data engineering, analytics and data management

AI is increasingly used to help build and maintain the information foundations on which organisations operate.

Data professionals can use natural-language instructions to generate SQL or Python, explore datasets, explain queries, transform and clean data, create data pipelines and troubleshoot pipeline failures.

By April 2026 Google's BigQuery Data Engineering Agent was generally available. It could translate natural-language requirements into pipeline code and assist with pipeline creation and maintenance. Microsoft Fabric and other major data platforms similarly incorporated conversational and AI-assisted data capabilities during 2026.

This matters because AI is no longer applied only **to analyse data**. It is increasingly being used to help create and maintain the systems that prepare data for analysis.

Information and knowledge retrieval

Generative AI is changing organisational information retrieval.

Traditional enterprise search generally required users to formulate searches, inspect results and identify relevant documents themselves. AI-enabled retrieval systems can instead interpret a question, search authorised information sources, combine relevant material and produce a conversational response.

Within data environments, similar interfaces allow people without specialist query-language knowledge to interrogate governed organisational information. Microsoft Fabric Data Agents, for example, allow natural-language questions over authorised enterprise data sources, while BigQuery's conversational analytics similarly supports dialogue with organisational data.

The usefulness of these systems depends heavily on the quality, accessibility, permissions and context of the underlying information.

2. What activities are changing?

The clearest change is a movement from **manual production towards human direction, AI production and human verification**.

In software development, a developer may increasingly describe an intended outcome, ask AI to generate an initial implementation, review the result, request changes and then test or integrate it. The human role therefore shifts partly from writing every element manually towards specifying, evaluating, integrating and accepting or rejecting machine-generated work.

This can substantially accelerate code creation, but it can also move bottlenecks elsewhere. GitLab's 2026 research found respondents reporting faster code production while also identifying growing demands around review, security, compliance, traceability and

maintainability. Its survey of 1,528 developers and technology buyers across six countries found 79% agreeing that individual developer productivity had improved while overall software delivery had not accelerated at the same rate.

DORA research reaches a related conclusion. AI can increase development speed, but organisational results depend on the wider delivery system. Its 2025 research found positive relationships with throughput and product performance but continuing negative association with software-delivery stability, particularly where testing, feedback and underlying engineering practices were weaker.

IT operations are becoming more **investigation-oriented and exception-oriented**. Instead of engineers manually examining numerous dashboards and logs before forming a hypothesis, AI can correlate information, summarise what appears unusual and identify likely areas for investigation.

Service management is undergoing a comparable change. Initial classification, summarisation, knowledge retrieval and routine response preparation can increasingly occur before a human service professional becomes involved. Agentic systems extend this by allowing selected incidents or administrative workflows to progress automatically.

Data engineering is beginning to move from manually constructing every transformation towards expressing requirements and reviewing AI-generated pipelines. Google's Data Engineering Agent can generate a plan, create pipeline code, validate it and correct compilation errors.

Across these activities, the common pattern is therefore not simply "automation". AI increasingly sits between **intent and technical execution**. People can express requirements in ordinary language while AI translates those requirements into code, queries, configurations, investigations or workflow actions.

That changes which technical skills consume time, but it does not remove the need for technical understanding. In many circumstances, understanding architecture, security, data, systems and operational consequences becomes more important precisely because producing an initial technical artefact becomes easier.

3. What can AI currently do?

As at 30 August 2026, demonstrated applications show that AI can undertake several materially different types of Technology & Information work.

It can **generate**: producing code, queries, scripts, tests, configurations, documentation and technical explanations.

It can **interpret**: explaining existing code, error messages, logs, system behaviour, datasets and technical documents.

It can **search and retrieve**: locating relevant information across repositories, knowledge stores, documentation, data platforms and other authorised sources.

It can **analyse and detect**: identifying anomalies, vulnerabilities, suspicious events, patterns, likely defects and relationships within large technical datasets.

It can **investigate**: combining information from several technical sources to support debugging, incident analysis, security investigation and root-cause analysis.

It can **build and modify**: generating or changing software components and data pipelines, sometimes across multiple files or steps.

It can **review**: assessing code changes, identifying possible defects and applying repository-specific instructions and contextual information. By July 2026, GitHub's generally available code-review capabilities could incorporate organisational tools, coding standards and external contextual sources into reviews.

Increasingly, it can **act**. Agentic systems can call tools, run tests, interact with repositories, progress service-management workflows or execute other permitted technical actions.

What it cannot currently be assumed to do is operate complex organisational technology reliably without constraints, context or oversight.

AI output can be technically plausible but wrong. Stack Overflow's 2025 global developer survey found more developers distrusting than trusting the accuracy of AI tools, while AI agents themselves were not yet mainstream among respondents.

The ability to generate a technically convincing answer and the ability to produce a production-safe answer are therefore different capabilities.

4. How established is its use?

AI use in Technology & Information is substantial, but establishment differs markedly across activities.

AI-assisted software development is comparatively established. DORA's international 2025 research reported AI use by almost 90% of respondents. Stack Overflow reported that 84% of developers in its 2025 survey were using or planning to use AI tools. These populations and definitions differ, so the figures should not be combined into a single supposed global adoption rate. They nevertheless indicate that AI-assisted development has become a mainstream part of the developer-tool environment.

AI-assisted documentation, code explanation, testing and developer information retrieval are similarly well established as available capabilities, although organisational policies and individual usage vary.

AI in IT operations, service management and cybersecurity is established in selected applications and growing in others. Machine learning for anomaly detection, monitoring, security detection and service classification predates the current generative-AI wave. Generative interfaces and agents are now extending those systems into investigation, explanation and workflow execution.

Data-oriented generative AI is growing rapidly. Conversational analytics and AI-assisted query generation are increasingly incorporated into mainstream data platforms. Agentic data engineering moved further into commercial deployment during 2026, including generally available pipeline-building capabilities.

More autonomous agentic operation remains earlier. Commercially available systems can already perform bounded multi-step technical workflows, but evidence does not support treating autonomous software engineering, cybersecurity or IT operations as the normal organisational model.

The distinction between individual AI use and workflow integration is particularly important. Atlassian's 2026 global research covering 12,035 knowledge workers reported 85% using AI at work but only 29% saying it was embedded in their flows of work. The survey was not confined to Technology & Information, although 2,375 respondents worked in IT, development and other technical functions. It illustrates the broader adoption problem: frequent AI use and organisational process transformation are not the same phenomenon.

5. What appears to be driving adoption?

Productivity and speed are major drivers.

Technology functions face persistent demand to build, maintain, secure and improve growing digital estates. AI can reduce the effort involved in writing routine code, preparing tests, searching documentation, analysing incidents, constructing queries and producing technical material.

DORA's respondents overwhelmingly reported perceived productivity benefits from AI-assisted development, while GitLab's 2026 research similarly found faster code production among organisations using coding AI.

A second driver is **technical complexity**. Modern organisations operate interconnected applications, cloud environments, data platforms, networks, security systems and software dependencies that generate volumes of information beyond what individuals can inspect

manually. AI's ability to retrieve, correlate and summarise technical information makes it attractive in operations and cybersecurity.

Skills and capacity constraints also contribute. AI can make specialist technical capabilities more accessible—for example, allowing a user to formulate a data question without writing SQL or helping a developer work with an unfamiliar framework. This does not eliminate specialist knowledge, but it can reduce the time required to perform some technical activities.

Another important driver is **integration into mainstream technology platforms**. Organisations increasingly encounter AI as functionality inside tools already used for development, cloud management, service management, security and data rather than as a separate experimental system.

Finally, **the rise of AI systems elsewhere in the organisation creates additional work for Technology & Information itself**. Technology teams increasingly need to provide infrastructure, data access, identity, integration, monitoring, security and governance for AI applications and agents. Microsoft's generally available Agent 365, for example, reflects the emerging requirement to discover and govern agents that possess delegated or independent access to organisational systems.

AI adoption within Technology & Information is therefore partly driven by the function's own productivity needs and partly by its responsibility for enabling and controlling AI adoption elsewhere.

6. What are the present limitations?

Reliability remains fundamental

AI-generated technical output can be incorrect even when it appears convincing.

In software development this may mean faulty logic, insecure code, inappropriate dependencies or changes that work locally but fail within the wider system. Developer scepticism remains significant: Stack Overflow's 2025 survey found 46% of respondents distrusting AI-tool accuracy compared with 33% trusting it.

Faster generation can move rather than remove work

Generating code faster does not automatically make the entire software-delivery system faster.

Additional output still requires testing, review, integration, security checking and maintenance. GitLab's 2026 accountability research found 73% of respondents concerned

about maintainability of AI-generated code and 82% concerned that it could create a new form of technical debt.

This is particularly important when evaluating productivity claims. Individual task acceleration should not automatically be interpreted as equivalent improvement in organisational technology performance.

Context is difficult

Technical work depends on organisational architecture, historical decisions, security rules, undocumented dependencies, operational constraints and business requirements.

An AI system that lacks this context may produce an answer that is technically reasonable in isolation but inappropriate for the organisation concerned. The growing effort by coding and operational systems to retrieve repository, infrastructure and organisational context itself demonstrates the importance of this limitation.

Data and information foundations constrain performance

AI retrieval, analytics and operational systems are only as useful as the information they can access.

Fragmented data, inconsistent definitions, outdated documentation, inaccessible repositories and weak metadata can all reduce output quality. Permissions also matter: greater AI access to organisational information can improve usefulness while simultaneously increasing security and confidentiality exposure.

Security risks expand as systems become agentic

An assistant that suggests code presents a different risk from an agent authorised to execute code, call APIs, query databases or modify infrastructure.

AWS noted in July 2026 that coding agents can extend beyond development environments through tool connections to databases, APIs and infrastructure, increasing the resources that security teams must protect.

Agent identity, permissions, credential management, sandboxing, auditability and monitoring therefore become more consequential as autonomy increases.

Integration and organisational readiness remain uneven

Technology estates often span legacy systems, multiple clouds, proprietary applications, spreadsheets, databases and numerous specialist tools.

Connecting AI securely to sufficient organisational context can therefore be much more difficult than demonstrating an AI assistant independently.

The DORA findings are relevant here: AI appears to amplify the characteristics of the wider technology system. Organisations with strong platforms, testing, feedback loops and engineering practices are better positioned to convert individual AI assistance into system-level performance.

Regulation and governance are becoming part of the operating environment

Technology functions increasingly have to understand not only what AI systems can do but how they handle information, permissions, generated material and automated decisions.

In the European Union, AI Act transparency provisions became applicable on 2 August 2026, while enforcement of general-purpose AI model obligations also entered a new phase. Not every internal Technology & Information use falls within the same obligations, and source code itself has specific treatment under Article 50 guidance, but the broader point is that AI systems increasingly operate inside developing legal and governance frameworks rather than a regulatory vacuum.

7. What you should be aware of

Technology & Information is unusual among Business Functions because it is both **a major user of AI and a principal organisational enabler of AI elsewhere**.

Its AI Status therefore extends beyond whether developers use coding assistants. Technology teams increasingly build, integrate, operate, secure and monitor the AI systems being adopted throughout organisations.

Coding nevertheless deserves substantial attention because adoption there is unusually visible and advanced. What should not be assumed is that extensive coding-assistant use means software engineering has become autonomous. Current evidence instead suggests a reallocation of work: AI can produce more technical output more quickly, while human effort becomes increasingly important in specifying intent, evaluating results, integrating systems, managing exceptions and determining whether outputs are suitable for production.

The same distinction applies elsewhere. An AI system that summarises an incident, an agent that investigates it and an agent authorised to change production infrastructure represent materially different levels of capability, responsibility and operational risk.

Adoption statistics also require caution. Surveys may measure access, occasional use, daily use, organisational deployment or embedded workflow integration. Developer populations are particularly exposed to AI tools, so their adoption levels should not automatically be

treated as representative of every Technology & Information activity or every organisation globally.

Much evidence about newer agentic applications comes from technology providers. It establishes that significant capabilities existed by 30 August 2026, but does not by itself establish how widely customers had implemented them. Generally available products, previews, customer pilots and routine production deployment should therefore remain distinct.

There is also an important feedback effect. AI is helping Technology & Information teams manage complexity while simultaneously adding new complexity. Organisations now have AI-generated code to review, AI applications to observe, agents to identify and govern, new security exposures to manage and rapidly increasing volumes of AI-related operational information. Dynatrace's 2026 research, for example, found human verification remaining common in agentic deployments and reliability and resilience continuing to constrain autonomous operation.

Human involvement consequently remains substantial. Current AI is particularly capable where technical work can be expressed as information, code, patterns, queries, tests or bounded actions and where results can subsequently be checked. It is less dependable where success depends on complete organisational context, ambiguous requirements, complex trade-offs or consequences that cannot readily be reversed.

The clearest Status conclusion is therefore that **AI has already become deeply relevant to Technology & Information, particularly in software development, technical knowledge work, data activity and operational assistance. Its role is expanding from helping professionals produce and interpret technical information towards undertaking bounded portions of technical workflows. More autonomous operation is now real enough to matter, but reliability, context, integration, security, governance and organisational readiness continue to limit how far that autonomy can safely and consistently extend.**

Evidence Notes

1. **Google Cloud / DORA — State of AI-Assisted Software Development, September 2025.** International research drawing on nearly 5,000 technology professionals. Reports AI adoption around 90%, widespread perceived productivity improvement and a more complex relationship between AI adoption, software-delivery throughput and stability.
[DORA State of AI-Assisted Software Development](#)
2. **Stack Overflow — 2025 Developer Survey, AI section, 2025.** Large international developer survey. Particularly useful for evidence concerning trust, AI-agent adoption and perceived productivity: more

respondents distrusted AI accuracy than trusted it, and agents were not yet mainstream.

[Stack Overflow Developer Survey — AI](#)

3. **GitHub — Copilot Code Review, March–July 2026.** Provider evidence establishing available and operational coding capabilities. GitHub reported more than 60 million Copilot code reviews by March 2026 and more than one in five GitHub code reviews involving the system; agentic repository-context retrieval and later organisational skills/MCP context were generally available.
[GitHub — 60 million Copilot code reviews](#)
[GitHub — Agentic code review architecture](#)
[GitHub — Code-review agent skills and MCP](#)
4. **GitLab / Harris Poll — AI Accountability Report, June 2026.** Survey of 1,528 developers and technology buyers across six countries. Reports strong adoption of AI coding tools alongside governance, traceability, maintainability and technical-debt concerns; useful evidence that faster code generation does not necessarily translate proportionately into faster end-to-end software delivery.
[GitLab AI Accountability Report announcement](#)
5. **GitLab — Global DevSecOps Report, 2025/2026.** Global survey of 3,266 DevSecOps professionals covering software development, IT operations and security. Provides broader evidence of AI's spread across the software lifecycle and continuing toolchain and process bottlenecks.
[GitLab Global DevSecOps Report](#)
6. **ServiceNow — IT Service Management documentation, updated March–July 2026.** Provider evidence of commercially available AI-supported ITSM capabilities, including incident categorisation, investigation and resolution support, change-management activities and agentic workflows. Appropriate as evidence of capability, not of universal customer deployment.
[ServiceNow IT Service Management](#)
[ServiceNow agentic AI in ITSM](#)
7. **Google Cloud — BigQuery Data Engineering Agent, April 2026.** Provider evidence that agentic data-engineering capabilities had moved from experimental release to general availability. Supports natural-language pipeline generation, modification and maintenance.
[Google Cloud Data Engineering Agent](#)
8. **Google Cloud — BigQuery release notes, June 2026.** Evidence that conversational analytics in BigQuery was generally available by the reference date, including contextual citations and conversational interaction with governed data.
[BigQuery release notes](#)
9. **Microsoft — Fabric developments, 2026.** Provider documentation showing generative and agentic AI extending into data engineering and organisational data access, including data agents and AI functions. Some related capabilities remained in preview while others were generally available, reinforcing the need to distinguish maturity levels.
[Microsoft Fabric — What's New](#)
[Microsoft Fabric Data Agents](#)
10. **Google Cloud — Gemini Cloud Assist investigations, 2026.** Provider evidence for AI-assisted infrastructure and application investigation using logs, metrics and configuration information. The capability remained subject to pre-GA/preview terms at the reference date, making it particularly useful for distinguishing demonstrated capability from established deployment.
[Gemini Cloud Assist investigations](#)
11. **Microsoft — Security Copilot / Phishing Triage Agent, July 2026.** Provider documentation showing AI-agent application to cybersecurity triage and investigation, including threat intelligence, file/URL analysis and security-data correlation.
[Microsoft Phishing Triage Agent](#)
12. **Microsoft — Agent 365, May 2026.** Provider evidence of the emerging Technology & Information requirement to discover, secure and govern organisational AI agents with delegated or independent

permissions. Generally available for commercial customers by May 2026.

[Microsoft Agent 365](#)

13. **GovTech Singapore — STACK Conference 2026 / engineering productivity, 21 August 2026.** Public-sector evidence from Singapore that AI-assisted software engineering is not solely a US phenomenon. GovTech identifies AI-assisted scanning and testing within its SHIP-HATS pipeline and describes AI becoming embedded across the software lifecycle.
[GovTech Singapore — STACK Conference 2026](#)
 14. **Atlassian Teamwork Lab — State of Teams 2026, April–May 2026.** Double-blind research involving 12,035 global knowledge workers and 173 Fortune 1000 executives; the technology brief included 2,375 respondents from IT, development and other technical functions. Particularly useful for distinguishing widespread individual AI usage from embedding AI into organisational workflows.
[Atlassian State of Teams 2026](#)
[Atlassian Technology Leadership Brief](#)
 15. **Dynatrace — Pulse of Agentic AI 2026, January 2026.** Vendor-sponsored global survey of 919 senior leaders involved with agentic AI. Provides evidence of production activity alongside continuing human verification, reliability and resilience concerns. Findings are useful as adoption evidence but should be interpreted in light of the surveyed population and vendor sponsorship.
[Dynatrace Pulse of Agentic AI 2026](#)
[Dynatrace survey announcement](#)
 16. **AWS — Control framework for AI coding agents, July 2026.** Provider security analysis illustrating how coding agents can extend through APIs, databases and infrastructure and why increasing technical agency creates security and governance issues beyond conventional code generation.
[AWS — Balancing speed and safety for AI coding agents](#)
 17. **NIST — Secure Software Development Practices for Generative AI and Dual-Use Foundation Models, SP 800-218A, July 2024; updated supporting material through 2026.** Institutional evidence that AI-related software development introduces additional security considerations across the development lifecycle rather than replacing conventional secure-development requirements.
[NIST SP 800-218A](#)
 18. **European Commission — AI Act transparency and GPAI implementation, July–August 2026.** Primary regulatory evidence. Article 50 transparency requirements became applicable on 2 August 2026, while the Commission also moved into enforcement of applicable general-purpose AI obligations. The Commission's Article 50 guidance specifically clarifies circumstances and exceptions relevant to AI-generated material, including source code.
[European Commission — Article 50 transparency guidelines](#)
[European Commission — Article 50 questions and answers](#)
[European Commission — GPAI obligations guidance](#)
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9. Legal & Compliance

Status as at 30 August 2026

Artificial intelligence has become a material part of Legal & Compliance work, although its penetration remains highly uneven between organisations, jurisdictions and activities.

Its strongest present foothold is in work involving large quantities of text or data: legal research, document summarisation and review, contract analysis, drafting, regulatory monitoring, compliance risk assessment, investigations and knowledge retrieval. Generative AI has broadened these applications by allowing professionals to search and interrogate information in natural language, generate first drafts, compare documents and synthesise material that previously required substantial manual review.

There is also an important difference between legal and compliance use. In legal departments, much current AI remains centred on assisting professionals with research, contracts, documents and knowledge work. Compliance functions also employ predictive and analytical techniques to identify anomalies, assess risk, monitor transactions and prioritise matters for investigation. Generative AI is increasingly being added to these established analytical applications.

More autonomous systems are beginning to appear. Agentic AI can potentially progress portions of research, contract and compliance workflows rather than merely generating an answer. As at the reference date, however, this is substantially less established than AI assistance and remains particularly sensitive where actions could affect legal rights, regulatory obligations or consequential organisational decisions.

The resulting Status is neither one of experimental technology awaiting practical use nor one of autonomous legal and compliance functions. AI is already being used meaningfully, and adoption accelerated sharply through 2025–26, but human verification, professional judgement and accountability remain central.

1. What is AI currently being used for?

Legal research and information retrieval

Legal research is one of the clearest applications of generative AI.

Current systems can search legal material using ordinary-language questions, identify potentially relevant cases, statutes and regulatory materials, summarise lengthy sources and synthesise information from multiple documents. The Singapore Ministry of Law's 2026 legal-sector guidance, which expressly covers in-house counsel, identifies plain-language searching, jurisdiction and topic filtering, interactive research and synthesis of legal material among current applications.

This can change the initial stages of research considerably. Instead of identifying search terms, locating numerous documents and reviewing each individually, a professional can use AI to identify potentially relevant material and produce an initial synthesis.

The distinction between assistance and legal authority remains important. An AI-generated research response is not itself authoritative legal material, and the reliability of underlying sources, jurisdiction, currency and interpretation still requires examination.

Contracts and commercial legal work

Contracts are another major area of organisational use.

AI can identify and extract clauses, compare contractual wording against templates or playbooks, highlight unusual or missing provisions, summarise obligations, suggest alternative language and produce first drafts. It can also help search an organisation's contract portfolio for renewal dates, commitments, liabilities or provisions affected by changes in regulation or policy.

The 2026 AI in Professional Services research identifies contract drafting among common legal GenAI applications, while Singapore's Ministry of Law describes in-house applications extending across the contract lifecycle, including drafting, policy checking, obligation tracking and responding to internal questions about contract terms.

This is beginning to extend beyond pre-signature review. Contract-management research in 2026 shows growing interest in using AI to analyse contractual information after execution, identify risk and extract commercial insights. However, post-signature integration appears less mature than document review and drafting.

Document review, due diligence and investigations

AI is being used to process document populations that would otherwise require extensive manual review.

Systems can classify material, extract facts, identify relevant passages, find relationships between documents, construct initial chronologies and summarise findings. These capabilities support transaction due diligence, internal investigations, litigation preparation, e-discovery and responses to regulatory inquiries.

Within organisations, this can mean reviewing internal records against company policies, identifying inconsistencies or potentially significant events and directing professionals towards material warranting further examination.

AI is particularly suited to first-pass review because large document populations can be screened much faster than a person could read them sequentially. The significance of what is found — or missed — remains a separate question.

Drafting and everyday legal productivity

A substantial portion of present use is comparatively ordinary.

Legal professionals use general-purpose and specialist AI to summarise documents, draft correspondence, prepare first versions of memoranda, policies, board papers and contractual provisions, improve wording, prepare meeting material and answer internal questions.

Thomson Reuters' 2026 professional-services study identifies legal research, document review, summarisation, memo drafting, correspondence and contract drafting among prominent legal uses.

Such activities may spread faster than major legal-system transformation because they can be introduced into existing work without completely redesigning the underlying process.

Regulatory monitoring and interpretation support

Legal and compliance teams must follow legislation, regulations, regulatory guidance, enforcement developments and other external requirements across potentially numerous jurisdictions.

AI can monitor large volumes of regulatory material, classify developments, summarise changes, identify potentially affected parts of an organisation and assist professionals in assessing what a new requirement may mean.

This is especially relevant to multinational organisations, where the difficulty is not simply locating a new rule but determining its jurisdiction, effective date, applicability and relationship with existing obligations.

AI can reduce the information-handling burden. Determining the organisation's actual legal obligations may nevertheless require interpretation of the relevant authoritative material.

Compliance risk assessment, monitoring and investigations

Compliance applications extend beyond generative AI.

Machine learning and other analytical systems are already used in areas such as fraud detection, anti-money-laundering monitoring, transaction surveillance, sanctions and adverse-media screening, risk scoring and anomaly detection.

Generative AI adds capabilities including summarising alerts, extracting information from documents, producing initial investigation narratives, assisting risk assessments and retrieving policy or regulatory information.

KPMG's 2026 international survey of chief ethics and compliance officers found AI most commonly being used among respondents for compliance risk assessment and management, data visualisation and predictive analytics, and employee training and awareness.

The practical pattern is therefore often one of AI helping prioritise attention rather than making the final compliance determination: systems identify transactions, documents or circumstances warranting examination, while people investigate the resulting exceptions.

Legal and compliance knowledge management

Organisations possess large quantities of potentially useful legal and compliance knowledge in policies, prior advice, contracts, regulatory interpretations, investigation files, templates and other internal material.

AI-enabled retrieval can make this material easier to access by allowing professionals to ask questions in natural language rather than knowing precisely where information is stored.

This is potentially important because part of the value of AI in these functions comes not from generating new legal knowledge but from making existing organisational knowledge more readily usable.

2. What activities are changing?

The most visible change is the compression of information-intensive work.

Legal research, for example, traditionally involves constructing searches, locating authorities, reading multiple documents, extracting relevant propositions and producing a synthesis. AI can now perform portions of this sequence rapidly, leaving the professional to verify sources, assess interpretation and apply the law to the organisation's circumstances.

Contract review is changing similarly. Rather than reading every provision sequentially before identifying departures from an accepted position, professionals can increasingly begin with AI-generated identification of clauses, deviations and potential issues. Human attention can then concentrate more heavily on ambiguity, negotiation, material risk and unusual circumstances.

Document-intensive investigations and due diligence are becoming more exception-oriented. AI can screen larger populations of material, organise information and identify items meeting specified criteria. This changes where human effort enters the process, although it does not establish that the machine has identified every relevant fact.

Compliance monitoring is also shifting from manual observation towards machine-assisted prioritisation. Regulatory information, transactions, communications or other data can be processed continuously, with potentially significant events escalated for examination.

Another change is the interface through which professionals access organisational information. A lawyer or compliance professional increasingly can ask a system a question rather than manually locate a policy, precedent, contract or database entry. This makes retrieval conversational and can reduce dependence on knowledge of underlying information structures.

Generative AI is also reducing the effort involved in producing first drafts. The activity consequently moves from creating every word to instructing, reviewing, correcting and refining machine-generated material.

The more consequential development is the early movement from **AI that assists** towards **AI that progresses work**. Agentic systems can potentially perform sequences of tasks: retrieve information, analyse it, prepare a document, update a system, route an item or trigger another action.

That development remains much less mature. Thomson Reuters' 2026 study found organisational agentic-AI use substantially below GenAI use, including within corporate

legal functions. Regulators are simultaneously emphasising the additional issues created when AI systems move from producing information to acting with greater autonomy.

Legal & Compliance therefore illustrates an important current transition: AI is increasingly performing the preparatory, searching, organising and first-draft portions of professional work, while consequential interpretation and decision-making remain considerably more human-dependent.

3. What can AI currently do?

As at 30 August 2026, demonstrated applications show that AI can perform several materially useful kinds of Legal & Compliance work.

It can **search and retrieve**: locating relevant material across legal databases, contracts, policies, regulatory publications and organisational knowledge repositories.

It can **read and extract**: identifying clauses, dates, obligations, parties, regulatory requirements, facts and other information within large document collections.

It can **summarise and synthesise**: reducing lengthy cases, regulations, contracts, investigation material or multiple sources into more manageable explanations.

It can **compare**: identifying differences between contractual wording and approved positions, comparing versions of documents or assessing material against policies and specified criteria.

It can **classify and prioritise**: sorting documents, alerts, transactions or regulatory developments and directing attention towards matters assessed as more relevant or higher risk.

It can **detect patterns and anomalies**: supporting fraud, transaction monitoring, surveillance and other compliance activities where suitable data is available.

It can **draft**: producing initial versions of contracts, memoranda, correspondence, policies, investigation summaries, reports and other legal or compliance text.

It can **support analysis**: identifying possible issues, generating questions, structuring arguments, assisting risk assessments and presenting potentially relevant considerations for professional review.

Increasingly, it can **progress portions of workflows** through agentic systems that combine information retrieval, analysis and permitted actions.

These are substantial capabilities. They should not be confused with reliable autonomous legal judgement.

Legal and compliance questions frequently depend on facts that are incomplete, jurisdiction-specific law, competing interpretations, commercial objectives, privilege, precedent,

regulatory expectations and assessments of materiality or risk. Generative systems can also produce convincing but incorrect information.

The Federal Court of Australia, in its April 2026 practice note, specifically warned that generative AI can produce fictitious cases or quotations, incorrect statements of law and factual errors while presenting them persuasively. Similar concerns have prompted regulatory and professional guidance internationally.

The demonstrated capability is therefore best understood as powerful information processing, generation and analytical assistance — not the transfer of professional accountability to the system.

4. How established is its use?

AI use is now clearly established enough to be part of the normal Legal & Compliance environment, but the depth of deployment varies substantially.

Some earlier forms of AI are comparatively mature. Compliance monitoring, anomaly detection, fraud analytics, document classification and technology-assisted document review pre-date the recent generative-AI wave and are established in relevant sectors.

Generative AI adoption accelerated particularly quickly during 2025–26.

Thomson Reuters' 2026 AI in Professional Services study, covering more than 1,500 professionals across 27 countries, reported organisational GenAI use of 47% among corporate legal respondents, compared with 23% in the previous year's study. Corporate risk respondents reported still higher use. The same research found that more than 80% of current GenAI users across the professional-services sample used the technology at least weekly.

Association of Corporate Counsel research based on 657 in-house professionals across 30 countries likewise describes a shift from planning towards active implementation.

These figures should not be converted into a single global legal-adoption rate. Studies use different definitions of AI, different populations and different questions. “Use” may also describe anything from individual drafting assistance to integration into core legal workflows.

That distinction is significant. A 2026 vendor-sponsored survey of 452 in-house legal professionals found 52% already using or evaluating AI for contract review. Such evidence demonstrates substantial market activity, but a provider-sponsored sample and the inclusion of organisations merely evaluating technology do not establish universal operational deployment.

Compliance shows a similarly mixed picture. KPMG's 2026 global chief ethics and compliance officer survey records material AI use across several compliance activities, while a separate industry survey of 204 legal, risk and compliance professionals reported 59.3% of teams using AI in some capacity. Both point towards growing deployment, but neither should be treated as a measurement of every compliance function globally.

Agentic AI remains earlier. Thomson Reuters reported 18% organisational agentic-AI usage among corporate legal respondents in its 2026 sample, compared with 47% for GenAI. Current agentic applications therefore belong in the Status picture, but not as the prevailing legal operating model.

Overall, AI assistance in Legal & Compliance is now established and growing. Integration into end-to-end controlled workflows is much less uniform, and consequential autonomous operation remains emerging.

5. What appears to be driving adoption?

Workload and capacity pressure are major drivers.

Legal and compliance teams face expanding volumes of contracts, regulations, organisational information and business requests. The Association of Corporate Counsel's 2026 benchmarking across 576 legal departments in 45 countries found that the median number of company employees supported by each lawyer had continued to rise. Thomson Reuters similarly identifies staffing and resource constraints as a major concern for corporate legal departments.

AI offers a way to process more information without increasing professional effort proportionately.

Speed and productivity are therefore prominent motives. ACC research found efficiency identified as the leading GenAI benefit by 91% of surveyed in-house legal professionals. Research across professional services similarly identifies saving time, streamlining processes and automating routine work among the principal reasons professionals support AI adoption.

The volume and complexity of regulation is an additional compliance driver. Organisations must monitor changing requirements across areas including privacy, financial crime, cybersecurity, employment, sustainability, trade and AI itself. KPMG's 2026 compliance research found new regulatory requirements among leading challenges facing participating chief compliance officers.

Integration into professional and enterprise software is lowering the practical barrier to use. AI capabilities increasingly appear within research platforms, contract-management systems, document repositories, productivity tools and enterprise applications rather than requiring users to develop standalone systems.

Improved access to organisational knowledge also matters. Legal departments often possess extensive precedent, policy and contractual information but cannot retrieve it efficiently. Natural-language AI interfaces make such repositories potentially more usable.

Business expectations are increasing. Legal teams are expected to respond at the speed of the wider organisation while also helping address the legal and regulatory consequences of AI being deployed elsewhere in the enterprise. This gives Legal & Compliance a dual relationship with AI: it is simultaneously a user of the technology and frequently part of the organisational governance surrounding its use.

Finally, **professional experience itself is driving further experimentation**. As individuals discover that AI can materially reduce time spent searching, summarising or drafting, demand can develop from practitioners as well as from management. This has also produced a less desirable form of adoption: unsanctioned or “shadow” AI use where organisational provision and governance lag behind employee behaviour.

6. What are the present limitations?

Reliability remains fundamental

Generative AI can provide inaccurate, incomplete or fabricated information while expressing it confidently.

This is particularly material in Legal & Compliance because a false authority, omitted contractual obligation, incorrect regulatory interpretation or missed compliance issue can have consequences well beyond the quality of a draft.

The problem is not theoretical. Courts in several jurisdictions have encountered AI-generated fictitious authorities. The Solicitors Regulation Authority's August 2026 warning notice referred to English cases involving unchecked AI hallucinations and reiterated that professional responsibility remains with the regulated person.

Legal information is jurisdictional and time-sensitive

A generally plausible answer may be legally wrong because it relies on another jurisdiction, superseded legislation, incomplete facts or an authority that does not support the proposition asserted.

Regulatory requirements can also change rapidly. AI's usefulness therefore depends heavily on access to appropriate, current and authoritative information.

Confidentiality, privilege and data protection constrain use

Legal work routinely contains commercially sensitive, privileged, personal or otherwise confidential information.

Entering such information into an unsuitable external AI system can create issues involving confidentiality, data processing, retention, cross-border storage and potentially legal professional privilege.

Singapore's 2026 legal-sector guidance places confidentiality alongside professional ethics and transparency as a core principle. The SRA similarly warned in August 2026 that both free and paid AI systems can create confidentiality risks depending on their contractual terms, settings and architecture.

This helps explain why access to a general-purpose chatbot does not automatically make it suitable for organisational legal work.

Integration and organisational information remain difficult

The most valuable legal or compliance information may be dispersed across contract repositories, document-management systems, email, policies, regulatory databases, case-management tools and business applications.

An AI system that cannot securely access the relevant material may produce a technically impressive answer from an incomplete picture.

Human judgement remains difficult to reproduce

Legal and compliance work involves more than identifying rules.

Professionals assess ambiguity, credibility, proportionality, materiality, precedent, organisational objectives, regulatory expectations and competing risks. They also communicate advice and assume responsibility for consequential decisions.

Current AI can support these activities but cannot be presumed to exercise dependable context-complete judgement across unrestricted circumstances.

Governance is developing unevenly

AI use can spread faster than formal organisational controls.

Thomson Reuters' 2026 Future of Professionals research found 34% of respondents using AI tools not sanctioned by their organisations. Its government legal-department study similarly found adoption increasing faster than governance, with one-fifth of participating agencies reporting no AI-use policy.

This matters because uncontrolled use can make it difficult to know what information has been entered into external systems, what outputs influenced decisions or whether appropriate review occurred.

Agentic AI introduces additional control questions

The risks become more significant when AI is permitted to act rather than merely advise.

FINRA's 2026 regulatory oversight material identifies issues including agents exceeding intended authority, handling sensitive data, limited domain knowledge, difficult auditability and autonomous action without human validation.

An assistant producing a draft compliance assessment and an agent authorised to update a case, communicate externally or progress a regulated process therefore represent materially different levels of operational risk.

Demonstrating value remains incomplete

High adoption or frequent usage does not itself demonstrate better legal outcomes.

Thomson Reuters reported that only 18% of professionals in its 2026 professional-services study said their organisations tracked AI return on investment, while many did not know whether it was measured.

Time saved on research or drafting is comparatively easy to perceive. Demonstrating improvements in legal risk, compliance effectiveness, contract outcomes or decision quality is considerably harder.

7. What you should be aware of

Legal & Compliance provides an unusually clear illustration of why **AI capability, AI use and delegation of responsibility are different questions.**

AI can already undertake substantial portions of information-intensive professional work. It can search, summarise, compare, classify, draft and identify potential issues at a speed that materially changes some workflows. There is credible evidence that organisations are using these capabilities, and adoption accelerated significantly through 2025–26.

That does not mean that legal or compliance judgement has been automated.

Professional and regulatory authorities across jurisdictions continue to emphasise human responsibility. Singapore's Ministry of Law states that legal professionals remain ultimately responsible for their work product. The American Bar Association has connected AI use with existing duties involving competence, confidentiality, communication and candour. Australia's Federal Court requires responsible use consistent with existing legal and professional obligations. England and Wales' Solicitors Regulation Authority states expressly that AI does not transfer professional responsibility.

Jurisdictional differences also matter. Rules concerning professional conduct, privilege, disclosure, privacy, recordkeeping and permissible AI use are not globally uniform.

The regulatory environment surrounding AI itself is changing. In the European Union, significant provisions of the AI Act became applicable and enforceable by August 2026, including transparency requirements for certain systems, while revised implementation dates mean important high-risk-system obligations will apply later. Legal and compliance teams therefore increasingly have to understand AI both as a tool they use and as a technology their organisations may need to govern.

Compliance AI also has two sides. AI is being used to detect fraud, anomalies and suspicious activity, while regulators and international bodies are simultaneously addressing criminals' use of AI, deepfakes and other emerging technologies. The technology can therefore change both the compliance control environment and the risks being controlled.

Adoption evidence requires particular care. Surveys showing that a legal department “uses AI” may describe an employee using an assistant, a specialist contract-review system, enterprise-wide deployment or an experimental pilot. These are not equivalent states of adoption.

The same applies to emerging agentic systems. Commercial availability demonstrates capability; it does not establish routine organisational delegation of consequential legal or compliance decisions.

The clearest Status conclusion as at 30 August 2026 is therefore that **AI has moved into substantive Legal & Compliance work, particularly where the work involves searching, reviewing, extracting, summarising, drafting, monitoring and prioritising large quantities of information. Its use is growing rapidly and is beginning to alter workflows, but deployment remains uneven and human professional responsibility remains fundamental. More autonomous and agentic applications are developing, but they should not yet be mistaken for the normal operating model of organisational Legal & Compliance functions.**

Evidence Notes

1. **Thomson Reuters Institute — 2026 AI in Professional Services Report, February 2026.** Global research covering more than 1,500 professionals across 27 countries. Principal evidence for GenAI and agentic-AI adoption, current legal and corporate-risk usage and workflow applications. Corporate legal organisational GenAI use was reported at 47%, compared with 23% in the prior study; corporate legal agentic-AI use was substantially lower at 18%.
[2026 AI in Professional Services Report](#)
2. **Thomson Reuters Institute — State of the Corporate Law Department Report 2026, March 2026.** Evidence concerning corporate legal departments, resource pressure, technology priorities and the accelerating importance of AI. The research reports that almost half of surveyed corporate legal departments had some form of enterprise-wide GenAI tool while measurement of outcomes remained limited.
[State of the Corporate Law Department Report 2026](#)
3. **Thomson Reuters Institute — Future of Professionals Report 2026, June 2026.** Global survey of 1,816 professionals across 62 countries covering legal, tax, audit, accounting, compliance, risk and global trade. Important evidence for frequency of AI use, professional workflow integration and shadow AI: 34% reported using tools their organisation had not sanctioned.
[Future of Professionals Report 2026](#)
4. **Association of Corporate Counsel — Generative AI's Growing Strategic Value for Corporate Law Departments, 2025/26.** Survey of 657 in-house legal professionals across 30 countries. Supports the assessment that in-house GenAI adoption was accelerating and that efficiency was the dominant reported benefit.
[ACC GenAI corporate law department survey](#)
5. **Association of Corporate Counsel / Major, Lindsey & Africa — 2026 Law Department Management Benchmarking Report, June 2026.** Based on 576 legal departments across 45 countries. Supports evidence of increasing workload pressure, including a median 367 company employees supported per in-house lawyer in 2026.
[ACC 2026 legal department benchmarking findings](#)
6. **Singapore Ministry of Law — Guide for Using Generative AI in the Legal Sector, 6 March 2026.** Government guidance explicitly covering in-house counsel as well as private practice. Provides detailed evidence of available use cases including legal research, contract review, drafting, document review, due diligence, internal investigations and knowledge management, together with professional ethics, confidentiality and transparency considerations.
[Singapore Guide for Using Generative AI in the Legal Sector](#)

7. **KPMG — 2026 Global Chief Ethics and Compliance Officer Survey.** International compliance evidence. Among respondents, AI was most commonly used for compliance risk assessment and management (50%), data visualisation and predictive analytics (44%), and employee training and awareness (44%); 68% described their experience as mixed but leaning positive.
[KPMG 2026 Global CCO Survey](#)
8. **Regology — 2026 State of Regulatory Compliance Survey.** Industry survey of 204 compliance, legal and risk professionals. Reported 59.3% of teams using AI in some capacity while continuing to identify accuracy, privacy and bias concerns. Used as supplementary rather than population-wide evidence because it is provider-sponsored.
[2026 State of Regulatory Compliance Survey](#)
9. **FINRA — 2026 Annual Regulatory Oversight Report: GenAI Continuing and Emerging Trends.** Regulatory evidence concerning actual observed GenAI uses among financial-sector member firms. FINRA identifies summarisation and information extraction as a leading use and discusses governance, testing, monitoring, accuracy, bias and emerging agentic-AI risks including autonomy, authority, auditability and sensitive-data handling.
[FINRA 2026 GenAI regulatory oversight material](#)
10. **Solicitors Regulation Authority — Misuse of AI Warning Notice, 17 August 2026.** Particularly current regulatory evidence concerning hallucinations, supervision, confidentiality, privilege and accountability. The SRA states that AI use does not reduce or transfer professional responsibility and specifically addresses considerations for in-house solicitors.
[SRA Misuse of AI Warning Notice](#)
11. **Federal Court of Australia — Use of Generative Artificial Intelligence Practice Note, 16 April 2026.** Judicial guidance documenting the ability of GenAI to produce fictitious authorities, incorrect law and factual errors, while recognising possible efficiency and access-to-justice benefits.
[Federal Court of Australia GenAI Practice Note](#)
12. **American Bar Association — Formal Opinion 512 / ABA material on generative AI ethics, 2024–25.** Supports treatment of competence, confidentiality, communication, supervision, candour and continuing lawyer responsibility when using generative AI.
[ABA ethics material on generative AI](#)
13. **European Commission / EU AI Act Service Desk — AI Act implementation, July–August 2026.** Primary regulatory evidence for the position at the reference date. Enforcement of applicable AI Act provisions began on 2 August 2026, including transparency provisions, while revised dates defer significant high-risk AI requirements to December 2027 and August 2028 depending on category.
[EU AI Act implementation timeline](#)
14. **Financial Action Task Force — AI/deepfake and financial-crime material, December 2025–2026.** Provides international context for compliance functions: AI and machine learning can support risk and transaction analysis, while AI and deepfakes simultaneously create emerging illicit-finance and fraud risks.
[FATF Horizon Scan on AI and Deepfakes](#)
15. **World Commerce & Contracting — AI in Contracting 2026, February 2026.** Survey evidence from 518 contract and commercial-management professionals. Supports the conclusion that AI use in contracting has progressed beyond initial experimentation but remains short of institutional maturity, with expected effects concentrated on repetitive work, drafting, review, analytics and risk identification.
[AI in Contracting 2026](#)
16. **LegalOn / In-House Connect — State of AI for In-House Legal 2026.** Vendor-sponsored survey of 452 in-house legal professionals. Used cautiously as supplementary evidence concerning contract-review adoption: 52% reported using or evaluating AI for contract review and respondents strongly favoured supervised rather than unrestricted agentic workflows.
[2026 State of AI for In-House Legal](#)

10. Risk & Assurance

Status as at 30 August 2026

Artificial intelligence is becoming a material part of Risk & Assurance, but its position differs considerably according to what the technology is being asked to do.

The most visible current use is AI **supporting risk and assurance professionals**: helping identify risks, analyse large datasets, prepare audit work, search documentation, draft reports, summarise evidence and investigate exceptions. Generative AI has made these activities more accessible because professionals can interact with information in natural language rather than relying entirely on specialist analytics tools.

A second, more established strand involves **analytics, anomaly detection and automated monitoring**. Organisations have long used statistical and machine-learning techniques to identify unusual transactions, potential fraud, control failures and other patterns. These techniques increasingly sit alongside continuous controls monitoring and broader data-driven assurance.

A third development is newer: AI becoming part of the **control or assurance mechanism itself**. Systems can continuously monitor transactions or AI assets, assess them against defined conditions, identify exceptions and assemble evidence. More agentic systems are beginning to undertake portions of risk and controls workflows. Commercial capability is advancing rapidly, but evidence does not support treating autonomous AI-led assurance as normal organisational practice.

Risk & Assurance also occupies an unusual position because the function increasingly has two AI responsibilities simultaneously. It can **use AI to perform risk and assurance work**, while also being asked to **assess the risks, controls and governance of AI used elsewhere in the organisation**. The second responsibility is growing as enterprise AI deployment expands and regulatory, cybersecurity, fraud, operational and governance concerns become more significant.

The resulting Status is therefore mixed. AI-assisted professional work is growing quickly; analytics and automated monitoring are established in some environments; AI-supported testing and continuous assurance are developing; and more autonomous risk and assurance processes remain comparatively early.

1. What is AI currently being used for?

Risk identification and assessment

AI is being used to help organisations identify, organise and assess risk information.

Risk professionals can use generative AI to summarise internal reports, incidents, policies, audit findings, external information and other material; identify recurring themes; compare risks; draft risk descriptions; and prepare initial risk assessments. More advanced approaches combine structured organisational data with external or operational signals to support risk sensing.

This can widen the information considered in risk assessment, but it does not mean that AI independently determines an organisation's risk position. Risk significance depends on organisational objectives, risk appetite, context, dependencies and management judgement that may not be fully represented in the information available to the system.

The movement towards more dynamic assessment is nevertheless visible. PwC's 2026 research into internal audit risk assessment describes more mature approaches combining dynamic risk inputs, stronger alignment with enterprise risk management, continuous planning and AI-enabled risk sensing, while also finding that relatively few organisations had fully embedded such capabilities by the reference date.

Audit planning and preparation

Internal audit is one of the clearest areas of current adoption.

AI can assist with background research, understanding a process, reviewing prior findings, identifying relevant risks and controls, preparing interview questions, developing work programmes and producing preliminary documentation.

The Internal Audit Foundation and AuditBoard reported in February 2026 that, among more than 370 senior North American internal audit leaders surveyed, 35% described AI use in audit planning as extensive and another 33% as occasional. Risk assessment showed 25% extensive and 39% occasional use. These figures apply to the surveyed population rather than internal audit globally, but demonstrate meaningful operational use.

Audit fieldwork, evidence analysis and testing

AI and analytics can examine transactions, documents, system records and other evidence to identify anomalies, inconsistencies or items warranting investigation.

This changes the possible scale of audit analysis. Instead of selecting only a small sample because examining the complete population manually would be impractical, technology can sometimes analyse much larger populations and direct auditors towards exceptions.

Generative AI adds capabilities such as document comparison, summarisation, extracting information from evidence and helping explain identified patterns. However, use in substantive testing remains less established than drafting and planning. Gartner's August 2026 poll of 743 audit professionals found 30% using AI for audit testing, compared with 60% using it to draft audit issues, ratings or reports.

Reporting and communication

Drafting is among the strongest present generative-AI use cases.

AI can organise observations, summarise supporting evidence, draft findings, improve consistency of language, prepare executive summaries and help produce presentations or stakeholder communications.

The same Gartner research found 60% of respondents using generative AI to draft audit issues, ratings or reports, 41% to review drafts and 35% to prepare stakeholder communications. This illustrates an important feature of current adoption: AI is often more established in **producing and refining audit material** than in making the underlying assurance judgement.

Fraud and anomaly detection

Machine learning and other analytical techniques are used to identify unusual transactions, behavioural patterns, network relationships and other indicators associated with fraud or misconduct.

AI can help prioritise large numbers of transactions or alerts for human investigation and can recognise combinations of characteristics that would be difficult to detect through simple rules.

At the same time, AI is changing the fraud being investigated. Generative systems can support convincing phishing, fabricated documents, impersonation and synthetic audio or video. The Internal Audit Foundation's 2026 research found 85% of surveyed North American internal audit leaders regarded AI-enabled fraud as a moderate or high risk, while fewer than 40% believed their functions were adequately prepared to detect or respond to it.

Internal controls and continuous monitoring

AI increasingly sits alongside rules-based automation and analytics in controls monitoring.

Systems can monitor transactions, user activity, access rights, configuration changes and other operational information, compare events with control conditions and identify exceptions more continuously than periodic manual testing permits.

Commercial risk platforms in 2026 were also offering continuous monitoring of controls relating specifically to AI systems, including risk assessments, control effectiveness, regulatory classification and ongoing compliance status. These offerings establish that the capability exists; they do not establish that continuous AI-driven control assurance has become widespread organisational practice.

Assurance over organisational AI

An increasingly important Risk & Assurance activity is examining AI itself.

Internal audit and risk teams are assessing matters such as AI inventories, governance, data, model performance, access, cybersecurity, privacy, human oversight, third-party dependencies, monitoring, explainability, incident management and accountability.

A 2026 case study concerning a large global financial institution describes an internal audit of AI across the lifecycle, including autonomous and agentic systems, covering issues such as prompt manipulation, data leakage, model drift, third-party AI, auditability and human oversight. It provides evidence of advanced organisational practice, although one case should not be interpreted as representative of the market generally.

2. What activities are changing?

The most important change is the movement from **periodic, sample-based and manually intensive assurance towards more data-driven, continuous and exception-oriented work.**

Risk assessment has traditionally depended heavily on interviews, workshops, previous audit findings, risk registers and periodic planning exercises. AI makes it increasingly practical to process a larger flow of internal and external information and continuously identify possible changes in risk. PwC's 2026 research nevertheless indicates that many functions still rely substantially on traditional inputs, so dynamic AI-supported risk sensing remains a direction of development rather than a universal operating model.

Audit preparation is changing more quickly. Tasks such as summarising previous reports, researching an area, drafting planning documents, formulating questions and preparing initial risk-control material can be compressed substantially.

Fieldwork is also becoming more exception-oriented. Analytics can scan larger transaction populations and identify unusual items for examination. This does not eliminate testing; it changes where professional attention is concentrated.

Reporting is experiencing a similar shift. The effort involved in producing a first draft can fall substantially when AI converts findings and evidence into an initial narrative. The auditor's work consequently moves towards determining whether that narrative is complete, balanced and supported by evidence.

Continuous monitoring changes the timing of assurance. A control exception that previously emerged during a quarterly review or annual audit may potentially be identified shortly after

it occurs. This creates the possibility of assurance becoming more continuous, although the extent of actual implementation remains considerably behind the technical possibility.

A further change is occurring in the **risk universe itself**. Internal audit increasingly has to assess AI governance and AI-related operational risks alongside conventional technology, financial, operational and conduct risks. The IIA's Risk in Focus 2026 research, based on 4,073 senior internal auditors across six world regions, placed digital disruption including AI as the second-highest-ranked global risk, behind cybersecurity.

This creates a dual transition: Risk & Assurance is changing because it **uses AI**, while its workload is also changing because **AI creates new organisational risks requiring assurance**.

3. What can AI currently do?

Current systems demonstrate several useful capabilities.

AI can **read and retrieve**: searching policies, audit reports, risk registers, control descriptions, contracts, incident records and other organisational information.

It can **summarise and organise**: condensing large volumes of material, identifying themes and structuring information for risk assessment or audit preparation.

It can **compare**: examining documents, transactions or control information for inconsistencies and differences.

It can **detect**: identifying anomalies, unusual behaviour, relationships and patterns that may indicate fraud, control failures or emerging risks.

It can **classify and prioritise**: assigning information to risk categories, grouping findings and directing attention towards items judged more likely to require investigation.

It can **generate**: drafting risk descriptions, audit programmes, interview questions, findings, reports, executive summaries and stakeholder communications.

It can **analyse larger populations**: applying rules, statistical methods and machine learning across datasets that would be impractical to examine manually.

Increasingly, it can **monitor continuously**: comparing ongoing events or system states against defined controls and generating exceptions or evidence when conditions change.

And emerging systems can **undertake portions of workflows**: collecting information, applying defined procedures, progressing tasks and escalating exceptions.

These capabilities are materially different from reliable independent assurance.

AI does not automatically know whether evidence is genuine, complete or appropriately interpreted. It may infer relationships that do not exist, miss relevant context or generate convincing explanations unsupported by evidence. The increasing presence of AI-generated documents, images, audio and other information makes evidence authenticity itself a growing assurance issue. The IIA highlighted this problem in 2026, noting that AI-generated content requires auditors to place greater emphasis on verifying information at its source.

AI can therefore perform substantial portions of the **information-processing component** of risk and assurance work. It cannot be assumed to possess the independence, professional scepticism, organisational understanding or accountability required for an assurance conclusion.

4. How established is its use?

AI use in Risk & Assurance is now substantial enough that it can no longer reasonably be described as principally experimental. But adoption statistics require particularly careful interpretation.

Gartner's August 2026 poll found 93% of participating audit leaders reporting some AI use. Yet only 38% reported having an AI strategy, and the most common applications were relatively contained activities such as pre-planning, drafting findings and reviewing documents. Gartner consequently characterised current use as concentrated more on productivity than transformation.

Other research produces lower figures because populations and definitions differ. Wolters Kluwer reported in earlier research that 39% of surveyed internal auditors were already employing AI, while another 41% intended to adopt it within the following year. These figures should not be combined with Gartner's into a single adoption rate: one may count relatively limited individual AI use while another captures different tools, respondents or definitions.

The direction is nevertheless clear.

Generative AI for **research, summarisation, drafting, planning and general productivity** is growing rapidly.

Data analytics, anomaly detection and automated monitoring are more mature technologies and in some organisations are established components of assurance and control environments.

AI-supported **risk assessment and audit testing** are developing but less uniformly embedded.

AI used to provide **continuous or substantially autonomous assurance**, or agents authorised to progress significant portions of audit and control workflows, remains earlier.

Regional evidence reinforces rather than removes this unevenness. KPMG's 2026 Nordic internal audit research reports increasing adoption while identifying data quality, fragmented systems and skills as important constraints. New Zealand internal audit research similarly reports increasing use and strong intentions to expand it. The IIA's global research shows that digital disruption is important across regions but its perceived significance and audit response differ materially.

The current position is therefore better described as **broad exposure to AI with uneven depth of integration**, rather than universal transformation of Risk & Assurance.

5. What appears to be driving adoption?

Productivity and capacity pressure are major drivers.

Risk and audit functions routinely process large quantities of documents, evidence, transactions, findings and reports. Automating portions of research, analysis and drafting can allow limited teams to examine more information or redirect effort towards investigation and judgement.

Gartner reported in January 2026 that more than 70% of surveyed chief audit executives regarded building an innovation culture and better use of data analytics and generative AI as important or extremely important priorities for 2026, in a context of pressure for greater audit coverage and constrained resources.

Coverage is another driver. Analytics can examine substantially more information than manual sampling permits, potentially allowing assurance teams to identify exceptions across larger transaction populations.

Speed matters as risk environments change more quickly. Organisations increasingly want risk information and assurance closer to the time events occur rather than only after periodic audit cycles.

Improved access to organisational knowledge is also important. Generative interfaces make policies, prior audits, methodologies and risk information easier to search and interrogate.

The changing risk environment itself is driving adoption. AI-enabled cyber threats, fraud, misinformation and increasingly autonomous systems create risks that conventional periodic methods may struggle to monitor. Gartner's second-quarter 2026 emerging-risk research, for example, identified AI-enabled discovery of cyber vulnerabilities as the leading emerging risk among its surveyed risk executives and managers.

Enterprise AI adoption creates demand for assurance over AI. As organisations deploy AI into business processes, risk and audit functions are increasingly expected to understand whether appropriate governance, controls and accountability exist.

Regulatory and standards developments reinforce this pressure. ISO/IEC 42001 provides an international AI management-system framework, while parts of the EU AI Act became enforceable on 2 August 2026, increasing the significance of documented risk management, transparency, governance and monitoring in affected organisations.

Finally, AI functionality is increasingly being incorporated into mainstream audit, governance, risk and controls platforms. This lowers the practical barrier to use because Risk & Assurance teams do not always need to build separate AI systems themselves.

6. What are the present limitations?

Reliability and evidence integrity

Risk and assurance work depends on evidence.

Generative AI can produce incorrect statements, unsupported conclusions and invented details while sounding authoritative. An AI-generated audit finding or risk assessment therefore cannot be regarded as reliable merely because it is coherent.

The problem is becoming two-sided: auditors must verify **AI output they themselves use**, while increasingly questioning whether **evidence supplied to them may also have been generated or manipulated by AI**.

Data quality and access

AI is only as useful as the information it can appropriately access and interpret.

Risk information often sits across audit systems, enterprise applications, spreadsheets, incident databases, risk registers, emails and specialist platforms. Inconsistent definitions, inaccessible data and poor-quality records constrain analysis.

KPMG's Nordic research identifies data quality, access and fragmented systems as continuing obstacles to advanced AI-enabled assurance.

False positives and context

Anomaly detection can identify what is unusual without determining whether it is wrong.

Large numbers of alerts can create additional work if systems cannot distinguish genuine risk from legitimate exceptions. Conversely, models trained on historical patterns may fail to recognise genuinely new forms of misconduct or risk.

Skills

Risk professionals require sufficient understanding to question AI output rather than simply accept it.

The skills involved extend beyond prompting. They include data analysis, model limitations, technology risk, evidence evaluation, cybersecurity, AI governance and the professional judgement needed to determine when automated conclusions are inappropriate.

The IIA's professional guidance increasingly reflects this development; in May 2026 it released updated data-analytics guidance covering AI and emerging technologies, and in August added prompting tools for internal auditors.

Governance and control of the assurance technology

Using AI inside a control or assurance process creates a circular issue: **the mechanism used to provide assurance may itself require assurance.**

Questions arise about who authorised the system, which data it uses, how changes are controlled, whether its output can be reproduced, how exceptions are escalated and who remains accountable if it fails.

This becomes more important as AI moves from recommending an action to taking one.

Independence and professional judgement

Internal audit has formal responsibilities concerning independence, objectivity and professional judgement. AI does not remove those responsibilities.

A system may assist an auditor in analysing evidence or drafting a conclusion, but responsibility for the assurance provided remains human and organisational. The Global Internal Audit Standards, effective from January 2025, continue to provide the worldwide professional framework within which technology-enabled internal audit operates.

Assurance capability is lagging enterprise AI adoption

Risk & Assurance must understand increasingly sophisticated AI while simultaneously developing its own AI capabilities.

This gap is visible internationally. ISACA's March 2026 European research found significant uncertainty around organisations' ability to halt AI systems during incidents, while the IIA's global Risk in Focus research shows AI-related digital disruption rising rapidly as an organisational risk.

The difficulty is therefore not simply adopting AI faster. It is maintaining credible assurance over an organisational technology environment that is itself changing rapidly.

7. What you should be aware of

Risk & Assurance illustrates especially clearly why **AI use, AI capability and AI reliance are different things**.

An auditor using AI to summarise a document presents a different risk from a monitoring system automatically identifying control failures. Both differ again from an AI agent authorised to investigate exceptions or progress assurance procedures.

Similarly, high reported AI adoption can coexist with limited transformation. Gartner's 2026 findings demonstrate this directly: AI use among participating audit professionals was very high, yet much of it remained concentrated in discrete productivity activities and only a minority of respondents reported an AI strategy.

The word **assurance** also requires care. A technology provider may describe a system as continuously testing controls or producing audit-ready evidence. That establishes a technical capability or commercial offering; it does not establish that an independent assurance professional has accepted the system's output as sufficient evidence or that organisations are routinely relying upon it without further examination.

Risk & Assurance is also becoming part of the wider organisational response to AI. COSO published guidance in 2026 applying its established internal-control framework to generative AI, while ISO/IEC 42001 and the EU AI Act provide additional governance and risk-management reference points. These developments indicate that assurance over AI is becoming more structured, but regulatory requirements and organisational practices differ by jurisdiction and sector.

Global evidence should not be interpreted as geographically uniform. The IIA's 2026 research spans six regions and shows differing risk priorities. European organisations are responding to the EU AI Act; financial institutions face sector-specific model and

operational-risk expectations; and organisations with mature data and audit infrastructures can deploy capabilities that may be impractical for smaller or less digitised organisations.

There is also an important distinction between **AI as a risk** and **AI as a response to risk**. The same broad technology can help detect fraud while making fraud easier to create, strengthen cybersecurity analysis while increasing cyberattack capability, and improve evidence analysis while making fabricated evidence more convincing.

Human involvement therefore remains central to the current Status. AI can search, classify, compare, detect, analyse, monitor and draft at a scale that materially changes risk and assurance work. But assurance ultimately involves determining whether evidence is sufficient, whether controls are appropriately designed and operating, what uncertainty remains and what conclusions can responsibly be communicated.

As at 30 August 2026, AI has become a meaningful and expanding component of Risk & Assurance. Its strongest current footholds are in professional productivity, data analysis, anomaly detection, risk assessment support, audit planning and reporting. More continuous AI-enabled monitoring and control testing are developing, while assurance over organisational AI is becoming an increasingly important responsibility in its own right. More autonomous forms of AI-led assurance exist as capabilities and early deployments, but should not yet be mistaken for the normal operating model of the function.

Evidence Notes

1. Gartner — “Audit Teams' AI Use is Common, But Most Teams are Lacking Strategic Adoption and Application”, August 2026. Webinar poll of 743 audit professionals. Principal evidence for the distinction between high reported use and limited strategic integration; reports 93% some AI use, 38% with an AI strategy, 60% using GenAI for drafting audit issues/reports and 30% for testing. [Gartner — Audit Teams' AI Use, August 2026](#)

2. Internal Audit Foundation / AuditBoard — “Internal Audit and AI-Enabled Fraud”, February 2026. Survey of more than 370 senior internal audit leaders in North America. Supports current AI use across planning, reporting, risk assessment and fieldwork and evidence concerning preparedness for AI-enabled fraud. [The IIA — AI-Enabled Fraud Research](#)

3. The Institute of Internal Auditors — Risk in Focus 2026 Global Summary. Survey responses from 4,073 senior internal auditors across six world regions. Principal global evidence concerning the rising importance of digital disruption including AI and differences in regional risk environments. [The IIA — Global Risk in Focus 2026](#)

4. PwC — “Risk Assessment, Reimagined”, August 2026. Research into internal audit risk assessment practices. Supports the developing movement towards dynamic risk inputs, continuous planning and AI-enabled

risk sensing while noting that relatively few organisations have fully embedded these capabilities. [PwC — Risk Assessment, Reimagined](#)

5. KPMG — Nordic Internal Audit Survey 2026, June 2026. Regional evidence from Nordic internal audit leaders concerning AI adoption, data-driven assurance, data constraints and skills. [KPMG — Nordic Internal Audit Survey 2026](#)

6. Grant Thornton New Zealand — AI and Internal Audit in New Zealand, 2026. Provides regional evidence of increasing AI use by New Zealand internal audit teams and continuing resource and emerging-risk pressures. [Grant Thornton New Zealand — AI and Internal Audit](#)

7. The Institute of Internal Auditors — Global Internal Audit Standards. Issued 2024 and effective January 2025. Provides the current international professional framework within which AI-enabled internal audit activities operate. [The IIA — Global Internal Audit Standards](#)

8. The Institute of Internal Auditors — IPPF Documents, 2026 additions. Evidence of current professional guidance covering data analytics, AI and emerging technology, including May 2026 data-analytics guidance and an August 2026 AI-prompting tool. [The IIA — Standards and Guidance Documents](#)

9. Gartner — 2026 Audit Priorities, January 2026. Survey of chief audit executives supporting technology, data analytics and GenAI as significant priorities amid pressures for wider audit coverage and resource constraints. [Gartner — Audit Innovation Priorities 2026](#)

10. Gartner — Quarterly Emerging Risk Report, August 2026. Survey of 316 senior executives and risk managers across sectors and regions; identified AI-enabled discovery of cyber vulnerabilities as the leading emerging risk in Q2 2026. [Gartner — Q2 2026 Emerging Risks](#)

11. ISACA — 2026 AI Pulse Poll, Europe, March and June 2026. Evidence concerning gaps between organisational AI adoption and governance, incident-response capability and visibility over AI-enabled threats. [ISACA — AI Governance and Enterprise Risk Research](#) [ISACA — AI-Powered Cyberattack Research](#)

12. COSO — Achieving Effective Internal Control Over Generative AI, 2026. Applies COSO's Internal Control—Integrated Framework to generative AI and provides evidence of the increasing formalisation of AI-related controls and assurance. [COSO — Internal Control Guidance](#)

13. ISO — ISO/IEC 42001:2023, Artificial Intelligence Management Systems. International management-system standard addressing governance and responsible management of organisational AI. [ISO — ISO/IEC 42001](#)

14. European Commission — EU AI Act Service Desk and transparency guidance, 2026. Primary regulatory evidence. Relevant provisions and enforcement powers became applicable from 2 August 2026, while other high-risk-system provisions have later application dates. [European Commission — AI Act Enforcement Timetable](#) [European Commission — Article 50 Transparency Guidance](#)

15. ServiceNow — AI Risk and Compliance documentation, 2026. Provider evidence establishing commercially available capability for AI risk assessment, control management, regulatory classification and continuous controls monitoring. Used as capability evidence, not evidence of widespread customer adoption. [ServiceNow — Continuous Controls Monitoring](#)

16. Grant Thornton — Global Financial Institution AI Lifecycle Audit case study, 2026. Organisational case evidence concerning internal audit of a substantial enterprise AI portfolio and emerging agentic AI risks.

Useful as evidence that advanced practice exists, not as evidence of general adoption. [Grant Thornton — AI Lifecycle Audit Case Study](#)

17. Wolters Kluwer TeamMate — Internal Audit AI Adoption Survey. Earlier survey evidence showing 39% of respondents already using AI and 41% intending adoption in the following year. Used primarily to illustrate differences between survey populations and definitions rather than to establish a universal adoption rate. [Wolters Kluwer — Internal Audit AI Adoption Survey](#)

18. The IIA — “AI Truth Decay”, June 2026. Professional evidence concerning the effect of AI-generated material on the reliability and authentication of audit evidence. [The IIA — AI Truth Decay](#)

11. Leadership & Governance

Status as at 30 August 2026

Artificial intelligence has entered Leadership & Governance through two related but distinctly different routes.

The first is **AI being used by leaders and governing bodies themselves**: to find and synthesise information, analyse reports and performance data, prepare meetings, summarise discussions, generate communications, explore alternatives and provide input into management or Board decisions.

The second is **AI becoming an object of leadership and governance**. As organisations deploy AI more widely, executives and Boards are increasingly involved in approving investments, assigning accountability, monitoring AI-related risks, receiving information on deployment and establishing organisational policies, controls and oversight arrangements.

These two developments are progressing at different speeds. AI assistance for individual executives is increasingly accessible through mainstream productivity and enterprise software, and senior leaders show considerable willingness to use AI-generated information. IBM's 2026 survey of approximately 2,000 CEOs globally found 64% comfortable making major strategic decisions based on AI-generated input. That indicates substantial acceptance of AI as decision support, but not that strategic decisions are routinely delegated to AI.

Formal Board use is less established. Deloitte's July 2026 research describes AI as moving from an agenda item towards a Boardroom tool, but finds use still new, uneven and largely concentrated in administrative and analytical tasks. Governance of organisational AI, meanwhile, has become a significant leadership issue even where Boards themselves make little direct use of AI.

The resulting Status is therefore not one of AI replacing organisational leadership or corporate governance. It is one in which AI increasingly influences the **information environment around leadership decisions**, while the growth of organisational AI is simultaneously creating a new and expanding field of executive and Board oversight.

1. What is AI currently being used for?

Executive information and research

One of the most straightforward applications is helping senior managers handle large volumes of information.

Generative AI can search permitted information sources, summarise reports and correspondence, compare documents, extract important points and produce initial explanations. Leaders can use natural-language questions to interrogate information that previously might have required several reports, searches or analyst requests.

This is particularly significant at executive level because leadership work often involves integrating information from different parts of an organisation rather than performing a single specialist process. AI can help assemble financial, operational, customer, workforce, market or project information into a more concise initial picture.

The capability does not establish that the synthesis is complete or that the significance attributed to particular information is correct. Its present role is principally one of information assistance rather than authoritative organisational interpretation.

Decision preparation and analysis

AI is increasingly used to support the preparation surrounding decisions.

Applications include analysing datasets, comparing performance, identifying unusual movements, generating alternative interpretations, investigating questions and supporting scenario analysis. IBM's global CEO research indicates that almost two-thirds of surveyed CEOs were comfortable using AI-generated input for major strategic decisions.

There is an important distinction between **informing a decision** and **making it**. Much leadership use remains in the former category: AI can expand the information available, shorten analytical preparation or offer alternative perspectives, while executives retain decision authority.

At lower levels of operational management, the boundary is beginning to move further. IBM's 2026 CEO study reports respondents estimating that 25% of operational decisions were being made by AI without human intervention. Because this is a CEO survey estimate spanning organisations and decision types, it does not establish that one quarter of consequential corporate decisions globally have been automated. It does, however, indicate that automated decision-making has progressed materially in some operational environments.

Meeting and Board preparation

AI can assist with agendas, document summaries, meeting briefs, questions, minutes and follow-up material.

Deloitte's 2026 Board research identifies current applications including analysing reports, summarising materials, preparing for discussions and identifying important meeting topics. These are among the clearest present Board-specific uses because they supplement information processing without necessarily transferring formal decision authority.

Board members may also use general-purpose AI independently for research, explanation or preparation. Norwegian research conducted in early 2026 found three in four surveyed Board members using AI in some form in their Board work. The same study, however, found more than four in five operating without formal organisational AI guidelines, illustrating that individual adoption can run well ahead of institutional governance.

Management and governance reporting

AI is increasingly capable of producing first drafts of performance commentary, executive summaries, briefing notes and governance reports from underlying organisational information.

Where AI is connected to enterprise data, it can also help interrogate performance indicators and identify exceptions requiring management attention. This can make reporting more interactive: rather than receiving only a fixed report, a manager may be able to question the underlying information conversationally.

The strongest current capability is still generally the preparation and interpretation of information rather than the independent determination of what a Board or executive team ought to conclude from it.

Executive communications

Leadership teams are using the same generative capabilities appearing across other knowledge-work functions: drafting emails, speeches, internal announcements, presentation material, summaries and explanations.

These uses can be important even though they do not constitute automated leadership. They reduce preparation effort and allow rapid adaptation of communication for different audiences, but the organisational position being communicated remains a human responsibility.

Oversight of organisational AI

A rapidly growing governance use is not AI performing governance but leadership **governing AI**.

Activities include approving AI strategies and investments; assigning executive responsibility; establishing policies; considering material risks; determining permitted and prohibited uses; receiving reporting on AI implementation; overseeing incidents; and considering implications for workforce, data, cybersecurity and business strategy.

Three-quarters of respondents to Grant Thornton's 2026 survey of 950 C-suite and senior business leaders reported that their Boards had approved major AI investments. Yet 48% said their Boards had not established AI-governance expectations, and 46% had not integrated AI

risk into continuing oversight. The figures demonstrate both the rise of AI as a governance matter and the uneven maturity of that governance.

2. What activities are changing?

The clearest change is occurring in **how leadership information is assembled and consumed**.

Senior managers traditionally depend upon chains of analysts, reports, dashboards, presentations and meetings to bring organisational information upwards. AI can compress portions of this sequence. A leader can increasingly ask a question, retrieve relevant information, request a summary or comparison and explore a follow-up question through the same interface.

This does not eliminate the underlying functions that produce reliable organisational information. It changes the point at which interpretation begins and potentially reduces the effort involved in navigating between information sources.

Meeting preparation is changing similarly. Large packs and background papers can be summarised; potential questions can be generated; previous discussions can be searched; and meeting records can be converted into summaries and actions. Deloitte's Board research indicates that these practical, administration-adjacent activities are among the places where Board use is presently concentrating.

A further change is the **speed of analytical iteration**. Executives can explore additional questions without every iteration becoming a new analyst request or spreadsheet exercise. AI can produce an initial interpretation, be challenged, examine another scenario and reformulate the output. That makes exploratory analysis easier, although ease of generation does not establish reliability.

Decision workflows are also beginning to develop a new division between human and machine roles. Some operational decisions can increasingly be performed automatically within defined systems. More consequential leadership decisions generally remain human, but AI is becoming another participant in the preparation process: retrieving evidence, testing alternatives, identifying patterns and producing arguments or summaries.

Governance itself is changing because organisations now have an additional technology requiring cross-enterprise oversight. AI can involve strategy, technology, data, cybersecurity, employment, legal obligations, operations, reputation and risk simultaneously. This is encouraging new governance arrangements, including executive AI leadership roles, management committees and Board oversight responsibilities.

IBM's global CEO survey reported 76% of responding organisations having a Chief AI Officer in 2026, compared with 26% in the previous year's study. The size of that reported shift warrants caution because titles and responsibilities vary, but it provides strong evidence that explicit executive accountability for AI has become much more prominent.

The regulatory environment is reinforcing this governance activity. In the European Union, major portions of the AI Act became applicable on 2 August 2026, while AI-literacy requirements had already applied since February 2025. Singapore, meanwhile, updated its Model AI Governance Framework for Agentic AI in May 2026 using feedback from more than 60 organisations and case studies of operational deployments. These developments do not mean organisations worldwide use the same governance model, but they show organisational AI governance moving from a largely voluntary discussion towards more formalised management activity in multiple jurisdictions.

3. What can AI currently do?

Within Leadership & Governance, demonstrated systems can **read, retrieve and condense** substantial quantities of textual and structured information.

They can **compare and analyse**, identifying differences between reports, periods, alternatives or datasets and surfacing matters that may warrant attention.

They can **generate**, producing draft briefings, presentations, executive summaries, Board materials, communications, minutes, questions and explanatory text.

They can **converse with information**, enabling leaders to explore organisational material through successive natural-language questions rather than relying only upon predefined reports.

They can **support scenarios and decision preparation**, generating alternatives, analysing assumptions and helping a decision-maker explore possible implications.

Where sufficiently connected to organisational systems, AI can **monitor and act**, detecting events or changes and, within permitted boundaries, initiating or completing parts of operational workflows. The emergence of agentic systems means the Leadership & Governance issue is consequently moving beyond what AI can say towards what an organisation allows AI to do.

AI can also support AI governance itself. Systems can assist with inventories, documentation, monitoring, policy analysis, control evidence and reporting, although these applications overlap materially with Risk & Assurance, Legal & Compliance and Technology & Information.

What current capability does not demonstrate is that an AI possesses complete organisational context or can reliably substitute for executive or Board judgement. Strategic and governance decisions frequently depend upon ambiguous objectives, values, stakeholder interests, incomplete evidence, organisational history and consequences that are difficult to reduce to available data.

AI can produce an impressively coherent answer without necessarily knowing that information is missing, that an assumption is inappropriate or that an apparently rational option conflicts with circumstances not represented in its inputs.

4. How established is its use?

Leadership & Governance presents a particularly uneven adoption picture.

General executive productivity and information assistance are increasingly established. Senior managers have access to AI through mainstream workplace platforms and general-purpose systems, and the global IBM CEO findings indicate considerable acceptance of AI-generated decision input.

Direct formal Board use is growing but less mature. Deloitte's July 2026 research found nearly half of participating public companies had not formally enabled or standardised AI or generative AI for Board activities. Where use was occurring, it concentrated largely on analysis, summarisation, meeting preparation and identifying issues for discussion.

Survey findings differ substantially by population. PwC reported that 35% of directors in one survey said their Boards had integrated AI into oversight activities. Norwegian research found approximately three-quarters of surveyed Board members personally using AI in some way. An Australia/New Zealand-oriented BoardPro survey of 485 directors, executives and governance professionals found 79% personally using AI at least weekly while 44% of Boards had no agreed organisational position on AI and only 2% had what the survey defined as a formal governance framework with clear accountability and regular reporting. These findings describe different things—Board integration, individual Board-member use and governance maturity—and therefore cannot sensibly be combined into a single Board-adoption percentage.

AI oversight is becoming substantially established as an agenda issue, even though governance mechanisms remain uneven. Deloitte's global study of 700 Board directors and executives across 56 countries found 31% saying AI was still not on their Board agenda, down from 45% in the earlier survey. NACD's mid-2026 surveys similarly placed AI among leading agenda issues for both US public and private company Boards.

Delegation of substantial leadership authority to AI remains much earlier. Automated operational decisions exist, and agentic technology is expanding the range of actions systems

can undertake. Evidence does not establish autonomous executive management or autonomous corporate governance as a normal organisational model as at the reference date.

5. What appears to be driving adoption?

The first driver is **information volume and complexity**. Leadership functions must absorb material from across an organisation and from a changing external environment. AI offers a way to search, condense and interrogate more information without proportionately increasing preparation effort.

A related driver is **speed**. Leadership decisions frequently occur under time constraints. AI can reduce the time between receiving information and producing an initial analysis, comparison or briefing.

Accessibility matters as well. Generative AI permits a non-specialist user to request analysis in ordinary language. Senior managers do not need to construct every database query, spreadsheet calculation or analytical workflow personally.

Organisations are also increasingly embedding AI into the software and information environments leaders already use. This lowers the barrier between deliberately undertaking an "AI project" and simply encountering AI as another feature of normal organisational technology.

Pressure surrounding **enterprise AI transformation** is itself driving leadership engagement. IBM's study found 69% of surveyed CEOs saying AI was already changing aspects of their businesses they regarded as core. BCG's 2026 survey of 625 CEOs and Board members globally illustrates the intensity of this pressure: 60% of CEO respondents believed their Boards were too impatient with the pace of AI transformation, while 35% thought their Boards overestimated what AI could replace.

Governance adoption is being driven by risk and accountability as well as opportunity. Morgan Stanley's April 2026 survey of 200 executives involved in AI governance at global corporations found 90% regarding data-related risks—including privacy, cybersecurity and discrimination—as material. Regulation, standards and national governance frameworks are adding further impetus. ISO/IEC 42001 provides an international AI-management-system standard, while jurisdictions including the EU and Singapore have created increasingly concrete governance expectations or frameworks.

6. What are the present limitations?

Information quality remains fundamental. AI cannot reliably compensate for incomplete, outdated or misleading organisational information. An executive summary can be concise and well written while still being based on the wrong data or omitting material context.

Reliability remains variable. Generative systems can produce incorrect facts, unsupported interpretations or invented material. The problem is particularly important in leadership settings because polished language can give uncertain analysis an appearance of authority.

Context is difficult to capture completely. Executive and Board judgement often depends upon informal organisational knowledge, stakeholder relationships, competing objectives, historical commitments and circumstances that are not recorded in accessible data. AI analysing only the available information may therefore solve a narrower problem than the one leadership is actually facing.

Confidentiality and information security impose constraints. Leadership and Board materials commonly contain commercially sensitive, personal, strategic or legally privileged information. Norwegian Board research is notable because it found substantial individual AI use occurring despite widespread absence of formal organisational guidelines, including Board members sharing strategic and financial information with AI tools.

Governance maturity has not kept pace uniformly with adoption. Morgan Stanley's 2026 findings describe organisations assigning accountability and controls at different speeds. Grant Thornton found 78% of its surveyed executives lacking strong confidence that their organisation could pass an independent AI-governance audit within 90 days. IBM's separate global technology-leadership study found two-thirds of surveyed CIOs and CTOs reporting accountability for AI systems they did not fully control and 70% saying business teams were deploying technology faster than IT could track.

Leadership understanding is uneven. The Conference Board's 2026 work, based principally on US public-company evidence, found only 23% of surveyed executives describing their Boards as highly fluent in AI. BCG's global evidence also indicates differences between CEOs and Boards in perceptions of capability, pace and replacement potential.

AI-generated decision support can introduce automation bias. A plausible analytical recommendation may receive more weight than its evidential quality warrants. Singapore's 2026 Agentic AI governance framework specifically added material addressing automation bias, reflecting its practical importance as systems acquire greater autonomy.

Demonstrating value remains difficult. Faster preparation is relatively easy to observe; improved leadership judgement is much harder to measure. A shorter Board paper or quicker analysis does not necessarily result in a better decision.

Finally, accountability does not transfer simply because AI participates in a workflow. Current governance frameworks continue to place humans and organisations at the centre of responsibility. Singapore's framework, for example, explicitly emphasises meaningful human accountability when agents are deployed.

7. What you should be aware of

Leadership & Governance is particularly susceptible to confusion between **AI being discussed by leaders** and **AI being used to perform leadership work**.

AI has unquestionably become a major Board and executive subject. That does not mean Boards themselves extensively use AI in their proceedings. Deloitte's evidence is especially useful on this point: organisational attention to AI is now substantial, while formal Boardroom adoption remains comparatively new and uneven.

Likewise, **AI-informed decisions are not the same as AI decisions**. A CEO reading an AI-generated briefing, an executive team asking AI to analyse alternatives and an automated system independently taking an operational action represent materially different forms of reliance.

Individual and institutional adoption can also diverge sharply. Directors and executives may personally use AI even where their organisation has no formal framework governing that use. Evidence from Norway and Australia/New Zealand makes this distinction particularly visible.

Much of the available evidence consists of executive surveys, professional-services research and technology-provider material. These sources are valuable for establishing what senior leaders report doing and what systems can perform, but they have limitations. A CEO saying that AI informs strategic decisions does not reveal how heavily AI output actually influences those decisions. A Board describing AI as an agenda priority does not demonstrate mature governance. A commercially available executive assistant does not establish routine Board deployment.

The rapid growth of AI governance also needs careful interpretation. Formal policies, committees, management systems and regulatory obligations are evidence that governance activity is becoming institutionalised. They do not by themselves establish that organisations can see every AI system they use, assess every risk or enforce their policies consistently. The substantial governance gaps reported in 2026 surveys demonstrate this difference.

There is also an important distinction between ordinary AI assistance and agentic AI. An assistant that summarises a Board paper presents principally information-quality, confidentiality and reliance questions. A system permitted to initiate actions, make

operational decisions or coordinate other systems introduces additional questions of authority, monitoring, escalation and accountability.

As at **30 August 2026**, the strongest conclusion is therefore not that AI has become an autonomous participant in corporate leadership.

AI has become a material component of the information and analytical environment surrounding organisational leadership. It is increasingly used to research, summarise, analyse, prepare meetings, draft communications and inform decisions. Direct formal Board use is growing but remains uneven, while substantial delegation of consequential leadership authority remains limited. At the same time, overseeing organisational AI has itself become an increasingly significant executive and governance activity. The central feature of the current Status is therefore augmentation and expanding oversight—not the displacement of human leadership or governance accountability.

Evidence Notes

1. **Deloitte — “How boards are using AI today,” 21 July 2026.** Board Practices Quarterly research on formal Board use of AI; supports findings that Boardroom adoption remains new and uneven and currently concentrates on report analysis, summarisation, discussion preparation and related tasks. [Deloitte — How boards are using AI today](#)
2. **Deloitte Global — “Governance of AI: A critical imperative for today's boards,” second edition, 2026.** Survey of 700 Board directors and executives in 56 countries; principal evidence on AI entering Board agendas, including the finding that 31% reported AI was still not on the Board agenda. [Deloitte Global — Governance of AI](#)
3. **IBM Institute for Business Value — 2026 CEO Study, May 2026.** Global survey of approximately 2,000 CEOs conducted with Oxford Economics. Supports findings concerning CEO acceptance of AI-generated strategic input, emergence of Chief AI Officer roles and reported use of AI in operational decision-making. [IBM — 2026 CEO Study](#)
4. **IBM Newsroom — “CEOs are Reshaping C-suite Roles for the AI Era,” 4 May 2026.** Reports 64% of surveyed CEOs comfortable making major strategic decisions based on AI-generated input and 76% reporting a Chief AI Officer. Figures are survey reports and are not treated as universal adoption measures. [IBM — CEO study announcement](#)
5. **IBM Institute for Business Value — technology leadership study, 8 June 2026.** Global study of 2,000 C-level technology executives; supports evidence of governance/visibility gaps, including accountability for systems not fully controlled and decentralised technology deployment. [IBM — AI control gap study](#)
6. **Boston Consulting Group — “CEOs and Boards Are Aligned on AI in Theory, but Divided in Practice,” 4 May 2026.** Survey of 351 CEOs and 274 Board members from leading companies globally. Used principally as evidence of disagreement about implementation pace, capability and replacement expectations between Boards and CEOs. [BCG — CEOs and Boards survey](#)
7. **Morgan Stanley Institute for Sustainable Investing — corporate AI governance analysis, 27 August 2026.** Combines S&P 500 Board-composition analysis with an April 2026 survey of 200 AI-governance

executives at global corporations. Supports findings on governance structures, data risks, human oversight and uneven maturity. [Morgan Stanley — State of Corporate AI Oversight](#)

8. **NHH Norwegian School of Economics — “AI in the Norwegian Boardroom,” 2026.** National survey of Norwegian Board members conducted in early 2026. Particularly useful non-US evidence on direct director use of AI and the gap between individual usage and formal organisational guidelines. [NHH — AI in the Norwegian Boardroom](#)
 9. **BoardPro — “AI Governance Pulse: A Benchmark Report,” 2026.** Survey of 485 directors, executives and governance professionals across Australia, New Zealand and elsewhere. Supports regional evidence concerning high individual AI use alongside low levels of formal Board governance. Population and methodology differ from other Board surveys, so its percentages are not combined with them. [BoardPro — AI Governance Report 2026](#)
 10. **The Conference Board — “Governing AI: S&P 500 Disclosure of AI Risks,” 22 April 2026.** Based on S&P 500 disclosure data and a survey of 130 executives, principally from US public companies. Supports findings concerning growing AI risk visibility and uneven Board AI fluency. Its US focus is explicitly recognised. [The Conference Board — Governing AI 2026](#)
 11. **Grant Thornton — 2026 AI Impact Survey.** Survey of 950 C-suite and senior business leaders. Supports evidence on Board approval of AI investment, governance expectations, integration of AI into continuing oversight and confidence in governance maturity. Findings are respondent reports rather than independent verification of control effectiveness. [Grant Thornton — 2026 AI Impact Survey](#)
 12. **NACD — Q2 2026 Public and Private Company Quarterly Surveys, 15 July 2026.** US director evidence showing AI among leading Board agenda priorities. Used as supplementary evidence rather than as a global proxy. [NACD — Governance surveys and benchmarking](#)
 13. **Singapore Infocomm Media Development Authority — Model AI Governance Framework for Agentic AI, launched January and updated 20 May 2026.** Primary public-authority evidence on organisational governance of agentic AI, human accountability, risk bounding, lifecycle controls and automation bias. The May update incorporated feedback from more than 60 organisations and operational case studies from Singaporean and international organisations. [IMDA — Updated Model AI Governance Framework for Agentic AI](#)
 14. **European Commission — EU AI Act implementation material, current to August 2026.** Primary regulatory evidence. The AI Act became broadly applicable on 2 August 2026, subject to staged exceptions, while AI-literacy obligations had applied since February 2025 and rules concerning governance and general-purpose AI had begun applying in August 2025. [European Commission — AI Act framework and implementation](#)
 15. **International Organization for Standardization — ISO/IEC 42001:2023.** Primary standards source establishing the existence and scope of an international AI management-system standard covering organisational policies, objectives, processes, risks and opportunities. Its existence demonstrates an available governance architecture, not the extent of organisational certification or implementation. [ISO — ISO/IEC 42001 Artificial Intelligence Management Systems](#)
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12. Research & Knowledge Management

Status as at 30 August 2026

Artificial intelligence has become a significant part of Research & Knowledge Management, but its position differs considerably according to what information is being searched, how consequential the resulting synthesis is and whether AI is connected to an organisation's own information environment.

At the most accessible level, general-purpose AI systems and specialist research assistants are already being used to find information, summarise documents, investigate subjects, compare sources and prepare initial research outputs. Specialist research platforms increasingly support literature discovery, screening, extraction and evidence synthesis. Elsevier's 2025 international research found that 84% of researchers surveyed had used AI tools in their work, although only 22% said they trusted existing tools.

A second development is potentially more important to organisational knowledge management. AI is increasingly being connected to internal repositories such as document-management systems, collaboration platforms, knowledge bases, email, intranets and enterprise applications. Instead of requiring employees to know where information is stored or which keywords were originally used, current systems can interpret ordinary-language questions, search across several sources, retrieve relevant material and generate a consolidated answer. Microsoft, Google, OpenAI, Anthropic and specialist enterprise-search providers all offered such capabilities by the reference date.

This does not mean that an organisation's scattered information has automatically become reliable institutional knowledge. Generated synthesis can misrepresent underlying evidence; relevant documents may not be retrieved; outdated material can be surfaced; access permissions and confidentiality remain important; and knowledge that was never documented cannot simply be recovered from a repository. The present Status is therefore one of rapidly expanding research and retrieval capability, genuine organisational deployment in some environments, but continuing dependence on source quality, information architecture and human judgement.

1. What is AI currently being used for?

One of the broadest applications is **information discovery and research assistance**. General-purpose AI systems with web search or research functions can investigate questions across multiple public sources, identify relevant material, summarise findings and produce reports with citations or links to underlying sources. Specialist research tools provide more structured access to scholarly literature. These capabilities are increasingly used for preliminary research, horizon scanning, subject familiarisation and finding potentially relevant publications before deeper examination.

AI is also being used for **literature and document review**. Systems can summarise individual papers and reports, compare several documents, extract specified information and identify common themes, differences or apparent gaps. In structured research workflows they can help formulate questions, classify papers against inclusion criteria, populate evidence

tables and prepare initial synthesis. A 2025 systematic review of generative AI in health evidence synthesis found promising performance for activities including question formulation and data extraction, while finding reliability insufficient for treating literature search or study selection as fully dependable automated processes.

An increasingly important organisational application is **enterprise search and internal knowledge retrieval**. Microsoft Copilot Search, for example, provides AI-based search across Microsoft 365 and connected organisational sources. Google's enterprise offering similarly combines intranet search and AI assistance across organisational data and supports connectors to systems including SharePoint, Jira, Confluence and ServiceNow. OpenAI's connected-app capabilities can retrieve material from third-party services and use connected sources during deeper research, while Anthropic's integrations allow research across connected organisational services.

This changes the nature of a knowledge query. An employee looking for a policy, previous project decision, product specification or piece of internal research may no longer need to identify the correct repository and construct separate searches. The AI layer can search across permitted information sources, interpret the question semantically and present a consolidated answer or set of relevant documents.

There is evidence of actual deployment rather than product capability alone. Confluent, for example, has described deploying AI-powered enterprise search to give employees access across documents, support material and Slack conversations. Duolingo similarly describes adopting enterprise search where organisational information had previously been dispersed across Google Drive, Slack, Confluence and Zendesk. These remain vendor-published customer cases and should not be treated as representative adoption statistics, but they establish that cross-system internal knowledge retrieval is operational in real organisations.

AI is also being applied to **knowledge organisation and classification**. Documents can be tagged, grouped, classified or related semantically rather than only through manually assigned categories. Information can be extracted from unstructured material and converted into structured records. Semantic search, embeddings and knowledge graphs can help identify relationships among documents, people, concepts and organisational entities that may not share identical terminology.

Knowledge capture and institutional memory are emerging applications. Meeting transcripts, discussions, correspondence, technical documents and project records can be summarised and made more searchable. AI can help transform large volumes of previously difficult-to-reuse material into information that later employees can interrogate conversationally. Research published in 2026 also points towards experimentation with using generative AI to integrate forms of expertise and tacit organisational knowledge, although this remains much less mature than retrieval from already documented information. A study based on interviews across 52 organisations described emerging attempts to capture context-action patterns from expert work and make them more broadly available.

Another application is **expertise discovery**. By analysing documents, communications, projects and recorded contributions, systems can help identify people with relevant experience or locate earlier work concerning a particular problem. In practice this can complement rather than replace conventional employee directories because much

organisational expertise remains undocumented or ambiguously represented in digital records.

Finally, AI increasingly supports **research drafting and communication**. Researchers and knowledge workers use it to prepare outlines, summaries, briefing papers, comparison tables, explanatory material and first drafts. This is often less technically demanding than building an enterprise knowledge system and can therefore diffuse quickly through individual work even where formal organisational knowledge-management transformation remains limited.

2. What activities are changing?

The clearest change is that **finding information is becoming more conversational and less dependent on knowing where information resides**.

Conventional organisational search commonly requires users to know which repository to visit, select appropriate keywords and inspect numerous documents. AI-enabled search increasingly allows the user to describe the information sought in ordinary language. The system can search across sources, interpret meaning rather than exact wording and provide either relevant material or a synthesized response. Microsoft describes Copilot Search as a universal search layer across Microsoft 365 and connected content, while Google similarly combines organisational data sources behind a unified search interface.

Research workflows are changing in a related way. A researcher can increasingly move from a question directly to a preliminary evidence landscape without manually performing every intermediate operation. Search, document triage, summarisation, extraction and initial synthesis can be compressed into a shorter interactive sequence.

This does not eliminate the underlying research stages. Instead it changes where effort occurs. Less time may be spent manually reading every potentially relevant document simply to establish what it contains. More attention can instead be directed towards assessing source relevance, methodological quality, contradictions, omissions and whether the generated synthesis actually follows from the evidence.

Document review is therefore shifting from **reading everything sequentially towards machine-assisted triage and targeted human examination**. AI can identify documents or passages apparently relevant to a question and provide initial summaries. The human researcher can then examine important sources in greater depth. This can be valuable where document populations are large, but it also creates the possibility that material not retrieved or incorrectly summarised will escape attention.

Knowledge-management work is changing from maintaining repositories alone towards making their contents **queryable as organisational context**. Traditional knowledge bases depend substantially on deliberate categorisation, documentation and navigation. AI can reduce some of the burden of finding material even where taxonomy is imperfect. That does not remove the need for information management: poor, duplicated or outdated repositories can simply produce poorer AI-grounded answers.

The relationship between documented knowledge and individual expertise is also beginning to change. Generative systems can help convert conversations, work products and experience into reusable summaries or explanations. Conversely, employees can interrogate accumulated organisational material without locating the original author. The result is a potentially broader circulation of organisational knowledge, although evidence for large-scale capture of genuinely tacit knowledge remains much earlier than evidence for document retrieval.

A further change concerns **research continuity**. Connected systems can maintain access to project records, past analysis and earlier decisions that might otherwise be rediscovered through colleagues or recreated from scratch. This creates the possibility of a more accessible institutional memory, but only to the extent that the relevant information was retained, is readable by the system and remains within the user's permitted access.

3. What can AI currently do?

Current systems demonstrate that AI can search large bodies of text using meaning and context rather than exact keyword correspondence. They can accept ordinary-language questions and identify apparently relevant documents, passages or records.

They can **read and extract** information from reports, research papers, correspondence, presentations, transcripts and other documents; identify specified facts or attributes; and arrange extracted information into structured forms.

They can **summarise and compare**, producing concise accounts of lengthy material, identifying similarities and differences among documents and assembling information concerning a subject from several sources.

They can **classify and organise** material by subject, meaning, relationship or requested criteria, assisting document tagging, screening and information triage.

They can **synthesise**, combining retrieved information into explanations, briefing material or preliminary research reports. Modern research systems can perform multiple searches, examine sources and produce extended cited outputs rather than merely answer from model memory. OpenAI's deep research, for example, could by February 2026 work with connected sources and restrict web investigation to selected trusted sites.

They can increasingly **reason across public and private information together** where access is authorised. Connected applications permit a system to investigate material in organisational repositories alongside other available information rather than treating internal knowledge as an entirely separate search environment.

AI can also assist with structured research activities such as paper screening, data extraction and evidence comparison. Demonstrated performance can be substantial in defined tasks. One 2025 study of systematic-review screening in obstetrics found both Claude and ChatGPT approaching human screening performance under the tested conditions, although performance differed by model, stage and prompting method.

That capability should not be generalised into dependable autonomous research. A systematic review published from evidence searched in January 2025 found that generative AI systems missed large proportions of studies when used for literature searching and produced material error rates in screening, extraction and risk-of-bias assessment. Its conclusion was that the evidence did not support generative AI undertaking evidence synthesis without human involvement or oversight.

Current capability is therefore strongest when described as **accelerating discovery, retrieval, organisation and first-stage synthesis**, rather than reliably determining what the complete evidence base means in every research context.

4. How established is its use?

The use of AI for everyday research, search, summarisation and drafting is already substantial. Elsevier's international 2025 research, covering approximately 3,200 researchers across 113 countries, reported that 84% had used AI tools in their work. This does not establish that AI is embedded in formal institutional research workflows, but it shows that researcher-level use is no longer a marginal activity.

AI-assisted scholarly research is also becoming an identifiable product category rather than merely an experimental use of general chatbots. Research platforms now offer paper discovery, document analysis, extraction, synthesis and increasingly structured review workflows. Elsevier, for example, was offering an AI-assisted research environment incorporating source information, evidence comparison and contradiction surfacing by 2026.

Enterprise knowledge retrieval is growing but is less uniformly established. Major productivity and cloud platforms now provide enterprise-search and organisational-data connections, and specialist enterprise-search deployments provide evidence of operational use. Microsoft, Google, OpenAI and Anthropic had all developed mechanisms for bringing authorised enterprise information into AI interactions by the reference date.

Availability, however, is ahead of demonstrated organisation-wide adoption. Connecting an AI assistant to SharePoint or Google Drive does not show that an organisation's workforce routinely depends upon it for knowledge retrieval, still less that its knowledge-management processes have been redesigned around AI.

Evidence from adjacent information-management institutions illustrates this mixed position. Clarivate's 2025 survey of 2,032 librarians across 109 countries and regions found 67% reporting that their libraries were exploring or implementing AI. The majority nevertheless remained in relatively early stages. The survey also found geographical differences, with 37–40% of respondents in Asia and Europe described as being at initial implementation or beyond. These figures concern academic, public and national libraries rather than corporate knowledge-management departments, but they demonstrate internationally that AI adoption in organised information environments is both substantial and still uneven.

More ambitious applications involving automated capture of organisational expertise, dynamic knowledge creation or agents that continuously maintain knowledge environments remain earlier. Academic work in 2026 was still describing many of these organisational

configurations as developing approaches requiring changes in knowledge-management capabilities and systems rather than as established practice.

The present picture is consequently one of **established individual AI-assisted research, growing enterprise retrieval and knowledge integration, and substantially earlier development of AI-managed institutional memory and more autonomous knowledge processes.**

5. What appears to be driving adoption?

Information volume is a fundamental driver. Organisations possess growing quantities of documents, messages, recordings, research, project material and application data. The difficulty is increasingly not simply storing information but finding the relevant part at the time it is needed.

AI offers a way to reduce the friction created by fragmented repositories. Search that works across documents, email, collaboration systems and enterprise applications is attractive because users no longer need to understand every underlying filing structure. Google's and Microsoft's enterprise-search offerings explicitly address this cross-source information problem.

Speed and researcher capacity are also major factors. Searching literature, screening documents, extracting information and producing initial summaries can consume substantial professional time. Elsevier's research found 58% of surveyed researchers saying AI tools were already saving them time, although this was self-reported rather than independently measured productivity.

A related driver is the desire to make accumulated organisational knowledge more useful. Information may technically exist yet remain functionally inaccessible because employees do not know that it exists, where it is located or how it was described. AI-powered semantic retrieval can surface material that conventional keyword search might not readily reveal.

Integration into existing workplace platforms is lowering adoption barriers. Employees increasingly encounter AI search and retrieval inside productivity suites, collaboration systems and established enterprise software rather than through separate experimental applications. This makes adoption possible without rebuilding the entire knowledge environment at once.

Research organisations also face pressure to process an expanding evidence base quickly while preserving traceability. Specialist research products are consequently placing increasing emphasis on citations, source-linked synthesis and mechanisms that expose underlying evidence rather than supplying an unsupported generated answer. Elsevier's 2026 research environment, for example, was designed to show sources, citation reasoning and contradictions alongside generated findings.

Finally, organisational interest is driven by the prospect of making expertise reusable. If lessons from previous projects, specialist work and internal decisions can be retrieved more readily, knowledge becomes less dependent on finding the particular person who remembers

it. This potential is important, although the practical ability to capture and reproduce tacit expertise remains much less established than retrieval from recorded information.

6. What are the present limitations?

Source reliability remains fundamental. AI can summarise weak evidence as fluently as strong evidence. A source-grounded answer is therefore not necessarily a correct answer; it may faithfully reproduce information that is outdated, incomplete, biased or wrong.

Retrieval is not completeness. Enterprise and research systems may provide highly relevant results without finding every relevant item. This distinction becomes critical in systematic reviews, legal research, safety research or other activities where missing evidence can materially change a conclusion. The systematic-review evidence showing high omission rates for general-purpose generative AI literature searches demonstrates why a convincing synthesis cannot itself establish that the underlying search was comprehensive.

Synthesis remains fallible. AI can misunderstand documents, remove qualifications, merge findings that should remain separate or assign excessive confidence to ambiguous evidence. Research on reference hallucinations published in 2026 further demonstrates that generated academic-style references and unsupported claims remain possible even in modern systems.

Organisational knowledge quality is uneven. Enterprise AI cannot reliably recover knowledge that was never recorded. Nor can it automatically determine that one of several conflicting policies is current unless the underlying information environment allows that distinction to be made. Duplicate files, obsolete versions, inconsistent terminology and poorly maintained repositories remain knowledge-management problems even when the search interface becomes intelligent.

Permissions and confidentiality matter considerably. Enterprise knowledge is often intentionally fragmented by access rights. A useful AI system must retrieve broadly while respecting those boundaries. Microsoft describes enterprise protections around prompts, responses and tenant data, while Google describes permissions-aware access to connected information. These capabilities are important precisely because connecting AI to organisational information creates new consequences if access controls are poorly implemented.

Provenance can become harder to inspect when synthesis is convenient. A user receiving a coherent answer may be less inclined to open the underlying documents. Citations and source links improve traceability but do not prove that a cited source supports every statement made from it. The ease of synthesis can therefore increase the importance of verification rather than remove it.

Tacit knowledge remains difficult. Much expertise consists of experience, judgement, relationships and contextual understanding that has never been fully written down. Research into AI-mediated tacit-knowledge integration is emerging, but it should not be mistaken for evidence that organisations can currently convert all human expertise into a searchable AI knowledge base.

Finally, **integration remains an organisational as well as technical problem**. Research on generative AI and knowledge management published in 2026 emphasises that technology adoption alone is insufficient; organisational knowledge systems, processes and capabilities affect whether AI can create useful value from information.

7. What you should be aware of

Research & Knowledge Management is one of the organisational functions in which AI can appear more mature than it actually is because the immediate user experience is so persuasive. Asking a question and receiving a well-written answer across several documents can feel substantially more advanced than conventional search.

The important distinction is between **information retrieval and knowledge assurance**. Current AI can find, organise and explain information remarkably quickly. That does not establish that it has found everything relevant, selected the best evidence, recognised every contradiction or correctly interpreted what the evidence means.

The distinction between public and organisational information also matters. A public research assistant searches material available through the web or selected external databases. An enterprise system may instead retrieve confidential reports, project records, policies and communications available only to authorised users. These are materially different knowledge environments even though the conversational interface may look similar.

Similarly, an AI system that can technically connect to an organisational repository does not establish that the organisation has achieved an integrated knowledge-management environment. Permissions, information quality, repository coverage, metadata, version control and employee practices continue to determine what the system can actually retrieve.

Adoption evidence needs corresponding care. Large numbers of researchers using AI do not mean that formal research processes have been automated. A library exploring AI does not mean that AI manages its collections. A vendor customer case establishes operational deployment in that organisation, not the normal position globally.

Human involvement therefore remains particularly important where research must be exhaustive, evidence has to be evaluated rather than merely located, or resulting conclusions carry significant consequences. Current empirical evidence supports meaningful AI assistance with several stages of evidence synthesis but not an assumption that the entire research process can reliably be delegated.

There is nevertheless a substantive change underway. Until recently, organisational knowledge management depended heavily on employees knowing what to search for and where to search for it. By 30 August 2026, AI systems could increasingly search across heterogeneous organisational sources, interpret natural-language questions and turn retrieved material into a usable first synthesis.

The clearest Status conclusion is therefore that **AI has moved beyond being merely a better search box**. It is becoming an interface through which people research public information and interrogate their organisations' accumulated knowledge. Individual research assistance

and document synthesis are already widespread enough to be material; enterprise knowledge retrieval is growing; and more ambitious attempts to capture expertise and orchestrate knowledge processes are emerging.

What remains unresolved is whether the apparent coherence of AI-generated knowledge can be made consistently as dependable as the sources and decisions for which organisations use it. As at the reference date, source provenance, completeness, permissions, information quality, synthesis reliability and human judgement remain central to that question.

Evidence Notes

1. **Elsevier / Researcher of the Future 2025**, international research covering approximately 3,200 researchers across 113 countries. Reported 84% having used AI in their work, 58% saying AI already saved time and only 22% trusting existing tools. The Elsevier figures are also reproduced in its corporate R&D trends material. [Elsevier research-assistant material](#)
2. **Clarivate, Pulse of the Library 2025**, 30 October 2025. Survey of 2,032 respondents across 109 countries/regions; 67% reported exploring or implementing AI, with most still in early stages and material regional variation. Particularly useful as international evidence from organised information-management environments, although not a corporate-KM adoption measure. [Clarivate Pulse of the Library 2025](#)
3. **Microsoft, Copilot Search / Copilot connectors documentation**, including material current to August 2026. Establishes commercially available AI-powered universal enterprise search across Microsoft 365 and connected organisational content; Microsoft states that indexed connector content can be included in search responses. Capability evidence rather than proof of universal customer adoption. [Microsoft Copilot Search documentation](#)
4. **Google Cloud, Agentspace/Gemini Enterprise**, 2025–2026. Establishes unified enterprise search, synthesis and permissions-aware retrieval across organisational sources, with connectors to systems including Microsoft 365, Jira, Salesforce, ServiceNow, Confluence and SharePoint. Google's April 2025 announcement also named organisations engaging with Agentspace, but this was treated as evidence of market activity rather than an adoption rate. [Google enterprise-search documentation](#)
5. **OpenAI, deep research and connected applications**, 2025–February 2026 updates. Establishes multi-source research with citations, connections to third-party services and, by February 2026, the ability to connect deep research to external applications/MCP sources and constrain searches to selected trusted sites. [OpenAI deep research](#)
6. **Anthropic, Research and enterprise integrations**, April–May 2025 and August 2026 documentation. Establishes research across web, Google Workspace and connected services, together with organisational connectors including Microsoft 365 resources. Again used as capability evidence, not as evidence that customers routinely deploy all such functions. [Anthropic Research and integrations announcement](#)
7. **Generative artificial intelligence use in evidence synthesis: A systematic review**, 2025. Review of 19 studies reporting substantial variation and material error rates across searching, screening, extraction and risk-of-bias tasks; concluded that available evidence did not support GenAI evidence synthesis without human involvement or oversight. This is a principal source for the limitations and capability-versus-reliability distinction. [PubMed record](#)
8. **Rashid et al., Role of Generative Artificial Intelligence in Assisting Systematic Review Process in Health Research**, *Value in Health*, 2025. Systematic review of 30 experimental studies; found promising performance for question formulation and data extraction but inconsistent reliability in literature searching and study selection. [PubMed record for Rashid et al.](#)

9. **Insuk et al., How Well Do ChatGPT and Claude Perform in Study Selection for Systematic Review in Obstetrics**, *Journal of Medical Systems*, 2025. Demonstrates comparatively strong model performance under a defined screening experiment while also illustrating model-, task- and prompt-dependent variation. Used to avoid presenting limitations evidence as implying that AI cannot perform research-assistance tasks effectively. [PubMed record for Insuk et al.](#)
 10. **Hussinki, Mikalef & Ritala, Generative artificial intelligence and organizational knowledge management: four alternative configurations**, published 17 June 2026. Academic analysis of the relationship between generative AI, organisational KM systems and organisational readiness; useful particularly for the proposition that AI technology alone does not establish effective knowledge-management integration. [Organizational knowledge-management study](#)
 11. **Xu et al., Beyond Codification: Generative AI and the Integration of Tacit Knowledge in Organizations**, *Academy of Management Proceedings*, July 2026. Based on 66 interviews across 52 organisations implementing generative AI in knowledge-intensive work. Provides evidence that organisations are experimenting with broader AI-mediated integration of expertise while also identifying important boundary conditions. [Academy of Management study](#)
 12. **FPZ/Gellify CESARE case study research**, *Journal of Knowledge Management*, March 2026. A research case examining implementation of generative AI within knowledge-management processes at an Italian manufacturing company, providing non-US empirical evidence of organisational implementation. [CESARE organisational KM study](#)
 13. **Glean customer cases — Confluent and Duolingo**. Vendor-published organisational examples showing operational use of AI-powered search across fragmented internal information systems. These establish real deployments but have deliberately not been used to infer wider adoption or independently verified productivity benefits. [Confluent customer case](#)
 14. **Davis & Mahmoud, Citation Constraints and Reference Hallucinations in Large Language Models**, *Canadian Conference on Artificial Intelligence*, 2026. Tested academic-style generation across several contemporary systems and found continuing invalid/inconsistent references and unsupported claims, supporting the continuing need to distinguish citation presentation from source verification. [Reference-hallucination study](#)
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The Status Across Business Functions

Viewed together, the twelve Business Functions reveal an organisational AI landscape that is already substantial but remains highly uneven.

AI is no longer confined to specialist technology teams or isolated experimentation. It is being used across financial work, recruitment, marketing, customer interaction, operations, strategic analysis, projects, technology management, legal and compliance work, risk and assurance, leadership activities and organisational research.

Yet the existence of AI across all these functions should not be mistaken for uniform maturity.

One of the clearest patterns across the Status is the difference between **AI assistance and deeper organisational integration**.

Generating, summarising, searching, classifying, analysing, drafting and supporting human work are increasingly visible across many functions. These applications can often be introduced without transferring substantial organisational authority to an AI system.

More deeply integrated uses are also developing. AI can increasingly interact with enterprise information, participate in multi-stage workflows, monitor changing conditions and, within defined environments, initiate or execute actions.

The movement from **answering to acting** is therefore real.

It is not, however, equivalent to widespread autonomous operation.

Across functions, consequential authority generally remains more constrained than the technological capability to generate analysis or perform bounded actions. Human review, organisational permissions, established controls and accountability continue to matter particularly where decisions affect people, money, legal obligations, operational safety or institutional responsibility.

A second pattern is that **capability is often ahead of adoption**.

AI providers and research systems can demonstrate capabilities that are not yet routinely embedded within organisations. Technical possibility, commercial availability, pilot deployment and scaled operational use frequently coexist at the same time.

This helps explain why apparently contradictory descriptions of organisational AI can all contain some truth. AI may simultaneously be widespread as an individual productivity tool, growing as an integrated organisational capability, emerging in more agentic workflows and experimental where substantial autonomy is involved.

A third pattern is that AI is changing not only the execution of work but also the **distribution of work within activities**.

Producing a first draft may become faster while verification becomes more important. Finding information may become easier while determining whether retrieval is complete remains difficult. Analysis may be generated more quickly while judgement about its significance remains human. Monitoring may become more continuous while responsibility for responding to what is detected remains organisational.

Efficiency in one part of a workflow does not necessarily remove work from the system. It can move the work elsewhere.

The Status also demonstrates that **organisational information is becoming increasingly important to AI use.**

General-purpose AI can provide substantial assistance without access to an organisation's internal environment. Deeper organisational applications, however, increasingly depend upon enterprise data, documents, systems, permissions, workflows and institutional knowledge.

That integration can increase usefulness while simultaneously making questions of information quality, confidentiality, provenance, access control and governance more significant.

Several functions also reveal a dual relationship with AI.

Strategy and transformation teams may use AI while simultaneously helping organisations respond to AI-driven change. Legal & Compliance functions may use AI in their own work while addressing legal and compliance questions created by AI elsewhere. Risk & Assurance functions can use AI while also assessing risks and controls surrounding AI. Leaders and governing bodies can use AI-generated information while simultaneously overseeing organisational AI.

AI is therefore becoming both **a tool used within organisations and an object of organisational management and oversight.**

The evidence also shows why simple global adoption statements should be treated cautiously.

Organisations differ substantially in scale, digital maturity, data infrastructure, regulatory environment, resources, skills and willingness to integrate AI into consequential activities. Survey populations and definitions of “AI use” also differ.

There is consequently no single organisational adoption rate that adequately describes the Status across all twelve functions.

What can be said more confidently is that AI has become a material part of the working environment across a broad range of organisational activities, while the depth, maturity and consequences of that use vary considerably.

The overall Status as at **30 August 2026** is therefore neither one of isolated experimentation nor one of comprehensive AI transformation.

It is a more complex position.

AI assistance is increasingly established across many forms of knowledge work. Integrated applications are growing. Bounded AI action is becoming more visible. More autonomous consequential operation remains considerably less established. Human judgement, organisational authority, evidence, controls and accountability continue to surround much of the activity that matters most.

That unevenness is not incidental to the Status.

It is part of the Status.

AISTatus — Continuing the Exploration

Artificial intelligence can be examined from several perspectives.

This publication considers AI through the **Business Functions** lens: where and how AI is currently being applied across the functions and activities of organisations.

The wider AISF AISTatus series also examines the current AI landscape through two other complementary lenses.

Industries & Sectors considers where and how AI is currently being applied across economic and societal sectors.

Technology Landscape considers the significant AI technologies, system forms and enabling developments that currently constitute the applied AI landscape.

The three perspectives form the **AISTatus Tripod**:

Business Functions — Industries & Sectors — Technology Landscape

Each lens produces a standalone publication.

Readers do not need to read one AISTatus publication in order to understand another. The same development may legitimately appear through more than one lens because each asks a different question of the current landscape.

Together, the lenses provide complementary ways of discovering what is happening in artificial intelligence at a defined point in time.

AISTatus forms one part of the wider AISF educational architecture.

AISTatus helps readers DISCOVER what is happening.

AIGuides help readers NAVIGATE AI and the questions surrounding its use.

AISF Insight Books help readers UNDERSTAND important AI developments and their implications in greater depth.

Each serves a different primary reader purpose while contributing to the wider AISF objective of supporting clearer understanding of artificial intelligence.

Future Status Updates & User Submissions

Artificial intelligence continues to change rapidly.

New capabilities emerge. Existing technologies improve. Organisational applications develop. Experiments become deployments, some deployments expand, and others may be modified or discontinued. Evidence of adoption also becomes more complete over time.

AIStatus is therefore inherently time-bound.

This edition represents the Status assessed **as at 30 August 2026**. It is not intended to be silently updated so that an earlier Status appears to describe a later environment.

Future editions may reassess the Business Functions landscape using a new reference date.

The functions examined may also change where developments warrant it. Elements may be retained, added, modified, combined, separated or removed according to the circumstances and evidence relevant to a future Status.

The objective is not to preserve a fixed classification indefinitely.

It is to provide as coherent a representation as practicable of the position at each defined point in time.

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Acknowledgements

AI Sourced Facts (AISF) acknowledges the researchers, public institutions, statistical agencies, professional bodies, academic institutions, companies, industry organisations and others whose publicly available work contributes to understanding the continuing development and adoption of artificial intelligence.

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Human oversight remained integral to the determination of purpose, scope, publication architecture, research requirements, evidence standards, substantive acceptance and final editorial position.

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Truth, Clarity & Guidance in the Age of AI.

Publication & Governance Information

Title: AI Across Business Functions

Publication: AISTatus 1

Subtitle: Where and How AI Is Being Applied Across Organisations

Series: AISF AISTatus

Edition: Version 1.0 / 2026 Edition

Status Reference Date: 30 August 2026

Publication Date: September 2026

Published by: AI Sourced Facts (AISF) Pte. Ltd.

Website: www.aisourcedfacts.com

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AISF maintains editorial oversight of this publication.

AIStatus is a point-in-time publication. Future editions may reassess the subject at a later reference date where material developments affect the Status of artificial intelligence across Business Functions.

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AI Across Business Functions

Artificial intelligence is entering almost every major function of organisations.

But where is it actually being used — and how established is that use?

AI Across Business Functions examines the Status of AI across twelve organisational functions, including:

Finance & Accounting • Human Resources & Recruitment • Marketing & Communications • Sales & Customer Experience • Operations & Supply Chain • Strategy, Innovation & Transformation • Project & Programme Management • Technology & Information • Legal & Compliance • Risk & Assurance • Leadership & Governance • Research & Knowledge Management

Across each function, the same seven questions examine current applications, changing activities, demonstrated capability, adoption, drivers, limitations and what readers should be aware of.

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Status as at 30 August 2026

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