Unlocking High Quality AI Adoption in the Workplace

Building the Human Infrastructure
That Makes AI Work

March 2026

Contents

Introduction

Businesses' successful deployment of AI to create long-term value, relies on far more than technological specifications, system integrations and workflow redesign. It relies also on ensuring teams actively engage with, and use, the technology in ways that are valuable for the business and the individual. It relies on building the human-AI relationship.

Yet this human-AI relationship is currently largely neglected, as attention remains on tool and technology roll-out. Typically, the question of the human infrastructure is seen only at the point of capability-building, in the form of training programmes to introduce the technology. Capability, though, is only ever part of the story when it comes to effective behaviour change, and there's no reason to doubt this rule in the context of AI.

There are also consistent signs across industry that point to complex, stalling, or even declining, AI adoption rates amongst employees. In the UK, only 1 in 6 businesses are actively using AI, meaning over 80% of businesses have no plan to use AI[1]. Even among those 'AI adopter' businesses, still only 30% of staff report using the technology[2]. In the US, whilst many employees have 'tried' AI, daily AI use among US employees is a subdued 10%[3], highlighting a 'novelty to utility' gap, with AI remaining a sporadic 'nice to have'. Across Europe, the story is similar; while almost 1 in 3 EU citizens have used GenAI, less than half this number report using the technology in their work, highlighting the gap between personal curiosity and professional adoption.[4]

From adoption rates, to Adoption Quality

Flatlining or falling AI adoption rates - alarming as they are - are only a symptom of the underlying issue for organisations; they are a marker, not the cause. To understand the cause, we believe we need to look at what we're calling Adoption Quality.

We've developed Adoption Quality as a multi-factor concept that recognises the range of factors that influence and shape the human-AI relationship. It captures factors including employee skills ('Means') and organisational permission ('Machinery'), recognising often complex social and organisational factors. Adoption Quality also captures perceptions of how important employees feel AI to be to their business and to their role ('Relevance'), as well as the range of psychological barriers potentially triggered by AI use ('Readiness').

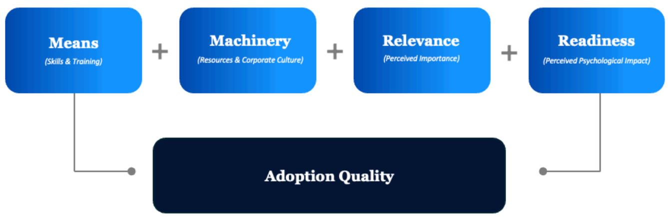


Exhibit 1

Adoption Quality has four components: Means; Machinery; Relevance (of AI); and Readiness (to adopt AI).
Source: Unlocking High Quality AI Adoption in the Workplace, February 2026

To explore this concept of Adoption Quality, we surveyed 1226 full-time employees across the UK and US (data collection, February 2026). Survey respondents worked across a variety of sectors and worked across a range of functions within their organisations.

As a composite measure of a range of factors that can influence AI adoption and use behaviour, we find Adoption Quality has a significant relationship with three important AI metrics:

1. Adoption Quality is a clear indicator of adoption frequency.

2. Adoption Quality is a clear indicator of adoption complexity (the complexity of task where ai is used)

3. Adoption Quality is a clear indicator of adoption avoidance (where employees choose not to use ai even though its use would be beneficial).

In addition, we believe that Adoption Quality – through its focus on employee perceptions – has the characteristics of a lead indicator for businesses, in terms of predicting long-term AI integration success or failure.

The Adoption Quality Score (AQS). Benchmark. Diagnose. Transform.

We measure Adoption Quality on a 0-100 scale (Adoption Quality Score – AQS). A standardised instrument means we can use this scale across geographies, industries, functions, and employee types. AQS – at a headline level - can be broken down to understand each component in more detail (e.g. how are Means, Machinery or Readiness contributing to the overall AQS?). Together, this can lead to and strengthen tailored behavioural interventions that target specific weak-points in AI launch strategies or provide more efficient solutions for course-corrections where businesses have already launched. The AQS can look at AI adoption across an organisation or focus on specific AI tools used in specific situations.

We believe Adoption Quality creates a critical and timely frame through which organisations can more clearly understand what's needed for effective AI strategies that in turn lead to long-term Ai-supported value creation. The Adoption Quality Score (AQS) provides a quantification of the risks and opportunities any business faces as it drives its AI transformation.

By clarifying and quantifying key elements of the human-AI relationship, we believe we can support organisations on what is the most critical, complex and comprehensive organisational change we have faced. We believe we can support organisations in delivering this change and unlocking the human-AI advantage.

The Idea in Brief

The industry has converged on the same diagnosis: AI adoption is stuck, and the problem is human, not technical. What's been missing to this point is a practical way to act on that diagnosis — to identify which human factors are at play, for whom, and what to do about each one. The Adoption Quality Score (AQS) looks to provide this detail and answer these questions. Building a holistic measure of the various drivers and barriers of successful AI adoption, the AQS enables organisations to understand how different mechanisms may be hindering employee AI engagement.

As well as quantifying more traditional drivers of adoption – such as access to training, tools, and leadership support - the AQS explores six specific psychological barriers which typically sit beneath the surface, and out of reach of more traditional surveys, but that have significant influence on important adoption behaviours.

The AQS doesn't replace the insights from the leading large consulting firms, instead, it builds on them by giving organisations a way to measure and segment the problem at the workforce level.

Low adoption is not a single problem to be solved by organisations; adoption rates are held-back by a number of barriers. Organisations need to have better visibility of these barriers to avoid committing resources to solutions that will miss the mark for most employees.

Key Findings

1. Adoption Quality is a measure of how ready and willing employees are to effectively integrate AI use into their roles at work. Adoption Quality has four components: Means (skills & knowledge), Machinery (corporate resources and culture), Relevance (perceptions of AI importance for business and role), and Readiness (psychological impact of AI adoption at work). Measurements of these four components combine to create a 0-100 Adoption Quality Score (AQS).

2. Our research suggests that AQS is a critical measure of the human-AI relationship; it correlates with usage frequency, AI task sophistication, and AI avoidance behaviour.

3. AQS captures employee perceptions which we believe have leading-indicator characteristics, and which typically take time to play-out in terms of actual behaviours seen within the organisation.

4. Across N=1226 employees in the UK and US, we see an AQS of 62.6. This places our survey in the AMBER zone for the AQS but is only the start of the story.

AI readiness is being seen as a *technological* challenge, when it's really a *human infrastructure* challenge. Organisations remain focused on solutions that are categorisable: training, tools and taxonomies.

5. Employees show high levels of confidence in using AI at work (AQS sub-score = 78) but business training and culture trail (AQS sub-scores 59 and 61 respectively). This suggests businesses are behind the curve in making the business case to their teams, and is supported by a relatively low Relevance score (60). This may be important – Relevance shows the strongest correlation with usage frequency and task complexity.

The *social* and *self-concept* barriers are the hardest for teams to express but have the clear potential to drive the human-AI relationship and unlock better - higher quality - AI adoption.

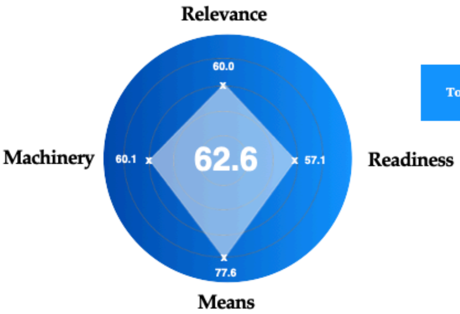
6. AQS reveals that usage frequency, AI task sophistication an AI avoidance are influenced by different factors. AI Relevance has the strongest influence on usage frequency and task adoption, whereas AI Readiness has the strongest influence on avoidance. This challenges the belief that employees only use AI for simple tasks for fear of it 'eating their job'.

7. In our adoption matrix (Relevance vs Readiness), only 41% of employees are showing high levels of Relevance and Readiness. 29% of employees recognise the importance of adopting AI (High Relevance) but have fundamental concerns (Low Readiness) – businesses have work to do on both dimensions.

8. Self-directed negative impacts of using AI at work are felt more currently than social and team concerns (AQS sub-scores 53 v 61). At the same time, AI use avoidance rises fastest with fears of loss of professional identity and relevance in work groups.

9. Organisations need to recognise multiple intervention tracks to drive adoption quality and increase their AQS. With confidence already high, increasing Relevance will drive depth of use and increase AI use for more complex, value-adding processes. Increasing Readiness will decrease time- and resource-consuming AI avoidance and workaround tactics.

10. AQS values vary significantly by role and seniority; the more senior you are, the higher the AQS. Not surprisingly, technology businesses report the highest AQS, and public sector and government, the lowest.



	AQS	Means	Machinery	Relevance	Readiness
Total	62.6	77.6	60.1	60	57.1

AQS >75
AQS 50 - 75
AQS <50

Exhibit 2

Adoption Quality Score (AQS) across sample of US and UK employees (N=1266)
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

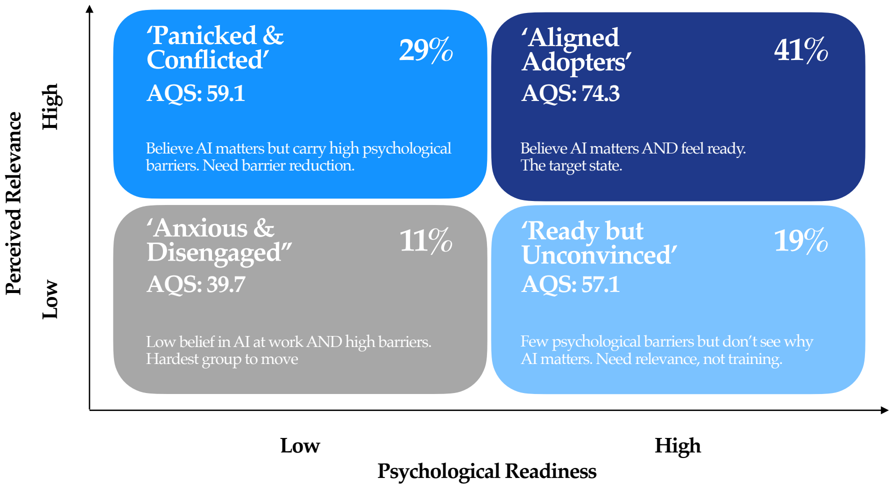


Exhibit 3

Relevance-Readiness Matrix, showing distribution of employees across four quadrants. 59% of those in the study show misalignment with the target state for High Quality Adoption
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

Adoption Quality

Despite the potential of AI to transform business, a more down-to-earth and distinctly analogue challenge sits in the way of this potential – humans using the technology. Forward-looking organisations are realising the potential of AI rests as much with psychology as it does technology. This should be no surprise – successful change management is a process most businesses struggle with - McKinsey's Senior Partner, Jon Garcia, famously gave a 70% failure rate[5]. This is precisely because the focus normally remains on the technical and the process, rather than on the people and teams involved.

AI adoption is more complex still, as the technology arguably transcends our traditional concept of a tool, with considerable – existential, even – consequences for how we work.

With eye-watering levels of investment into the technology and its capability, AI adoption matters. However, in the same way US Surgeon General C Everett Koop pointed out that "…drugs don't work in patients who don't take them.", C-suites across the globe must now reach the same conclusion – AI tools don't work (and won't deliver business value) if employees don't use them.

Adoption Quality looks to quantify and solve this challenge for businesses. We believe that if a company is able to drive high quality AI adoption, this will lead to an increasing willingness amongst its teams to use AI for a range of tasks (from the most basic to the strategic), will reduce deliberate avoidance of the technology, and will deliver high organic adoption rates. We believe building high adoption quality will enable businesses to adapt faster and with greater agility, and with fewer resources committed.

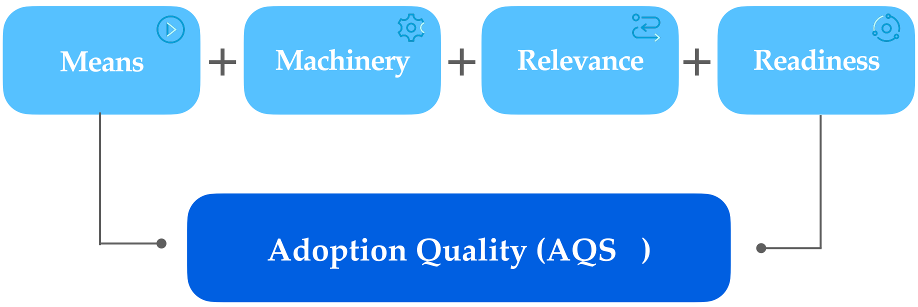


Exhibit 4

The Adoption Quality Score (AQS) - components and weights
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

We define Adoption Quality as having four distinct components:

Means

Means describes the AI skills and knowledge of employees. It includes knowing when and how to use specific tools, and for which tasks within the daily flow of work.

Machinery

Machinery has two dimensions. First, it describes access to the tools and other resources within the business (including training) – we call this 'hard' machinery. It also has a social dimension – the degree to which the organisation supports AI use in terms of culture, leadership communications and manager behaviours ('soft' machinery).

While Means and Machinery sit more comfortably at the organisational level, there's also what sits at the individual level – Perceived Relevance and Psychological Readiness.

Perceived Relevance

A cornerstone of behavioural science is 'salience'; those things that are relevant to us influence our choices and behaviours. We believe that's the case here – that employees need to understand the relevance of AI, in order to effectively engage with AI. Relevance explores employees' perceptions around importance to the sector, the business, and to their specific role within the business.

Psychological Readiness

Beyond recognising the relevance of AI in a role, there's the important question of how AI makes employees feel – what we're calling Psychological Readiness. We've known for decades that there are stable factors that shape our motivation to engage at work – positively or negatively. Self Determination Theory[6] puts forward three key constituents for high motivation: the sense of being in control of one's work ('Autonomy'); the sense of demonstrating or strengthening skills ('Mastery'); and the sense of being a part of a meaningful network of others ('Relatedness'). These three factors feel highly relevant in the age of AI, in that the integration of AI into roles and work-streams could easily cause damage.

We add further dimensions to better understand psychological readiness to use AI: the sense of being able to shape and control decision-making and information flow with AI ('Cognitive'); the sense of being seen as credible and trusted by one's peers when using AI ('Credibility'); and the sense of being able to continue to behave in ways that fit with one's sense of being part of professional body ('Identity').

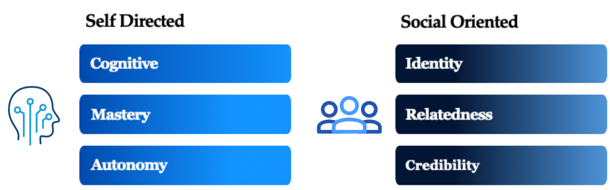


Exhibit 5

Six Psychological Barriers to Readiness to engage and adopt AI in the workplace
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

Together, we believe these six factors provide a holistic and detailed view of individual-level psychological readiness to engage with AI. Critically, by understanding each of these six psychological factors, we can build and test more targeted and efficient interventions to drive-up adoption quality.

The Adoption Quality Score (AQS)

The Adoption Quality Score is a 0-100 composite measure, based on the four components of Means, Machinery, Relevance and Readiness. Measured via a proprietary and validated survey, it allows us to benchmark sectors and regions, as well as provide deep-dive views for individual organisations, including across functions, markets, role-type, and seniority and tenure.

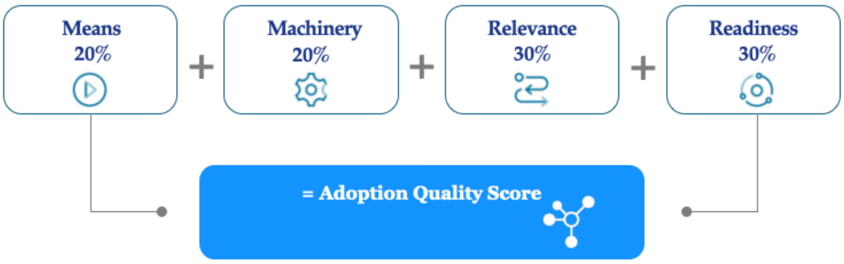


Exhibit 6

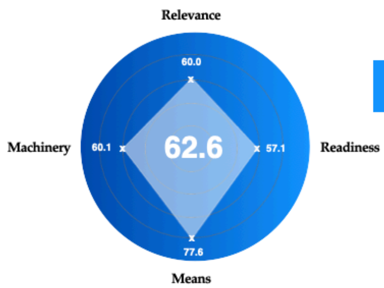
The Adoption Quality Score: components and weights
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

Sample and Methodology

In February 2026 we surveyed 1226 full time employees across the UK and US. Participants completed the AQS survey online via a respected specialist online panel provider, measuring the four components of Means, Machinery, Relevance and Readiness. Participants worked in a wide range of sectors, for businesses of varying sizes, and held various levels of seniority and tenure within their businesses. All participants and their employers remained anonymous. Only demographic and 'firmographic' data were collected in addition to the direct measures for AQS. Participants received a small fee in return for completing the survey.

Results

Adoption Quality Score (AQS)



	AQS	Means	Machinery	Relevance	Readiness
Total	62.6	77.6	60.1	60	57.1

AQS >75
AQS 50 - 75
AQS <50

Exhibit 7

Adoption Quality Score (AQS) across UK/US employees N=1266
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

Across the sample, we record a headline AQS of 62.6. This places our survey sample in the AMBER band of adoption quality. A breakdown to each component shows Means records the highest score (78) and Psychological Readiness, the lowest (57). This suggests we should challenge the prevailing assumption that training to use the tools should be the main focus of organisations in improving adoption quality; it seems employees have high confidence in their skills to use AI. Instead, there appears to be more work to do for businesses, in terms of providing access and support for the use of AI (Machinery: 60.1), making the business case more compelling for employees (Relevance: 60), and to better understand and remove the various worries and concerns employees have about AI adoption (Readiness: 57.1).

AQS and Organisation Size

We see no meaningful difference in AQS and the component scores across organisation size.

AQS and Levels of Experience

Exhibit 8

Variations in Adoption Quality Score (AQS) as a result of years of work experience.
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

	AQS	Means	Machinery	Relevance	Readiness
0-5 years	59.5	74.9	57.8	63.5	46.4
6-10 years	63.9	79.1	62.8	62	56.4
11-20	62.2	77.8	59.8	59.8	56
20+ years	63	76.8	59.6	58.7	60.4

There are differences in AQS across years of experience. AQS climbs alongside seniority, with Psychological Readiness showing the greatest difference between experience levels (34.2 – 60.4). This suggests employees at the start of their careers do perceive the often reported 'hollowing-out' of early career roles as real. Paradoxically, alongside these lower Readiness scores, we see higher Relevance scores for these employees (the score is highest amongst those with 3-5 years' experience). This suggests a difficult position for those in the early stages of their careers – a clear recognition of AI's relevance to their roles, alongside strong concerns and anxiety around what its use may mean for their sense of self in the workplace.[7]

AQS and Sector

	AQS	Means	Machinery	Relevance	Readiness
Technology	72.5	83.7	71.5	76.8	61.3
Real Estate and Property	68.8	81.3	64.1	67.9	64.6
Financial Services	65.4	78.4	66.4	66.3	55.1
Energy and Utilities	62.9	72.6	57.1	68.4	54.8
Manufacturing	62.6	78.4	61.2	56.8	58.9
Retail and Consumer	62.1	78.7	58.7	59.9	55.6
Professional Services and Consulting	61.6	75.6	60.4	62.3	52.3
Education	60.3	77.9	58	56.4	53.8
Healthcare and Life Sciences	59.8	73.7	53.6	55.4	59
Media and Entertainment	59.2	78.9	57	57.7	48.9
Public Sector and Government	57.2	74.2	54.2	50	55.2

Exhibit 9

Variations in Adoption Quality Score (AQS) by sector. Based on UK/US employees
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

There is significant variation in the AQS and its components across sectors. Not surprisingly, Technology (n=167) records the highest AQS (72.5), and records the highest score for Means (83.7) and Relevance (76.8). Psychological Readiness – while low compared to Means and Relevance - is also high for this cohort compared to other sectors (61.3).

The AQS is lowest for those in Healthcare (59.8), Education (60.3) and Public Sector/Government (57.2). Considering the compelling use cases being presented in the media for these sectors, this points to a clear mismatch between opportunity and execution. Psychological Readiness is lowest among those in Media and Entertainment (48.9), and Professional Services and Consulting (52.3), suggesting AI adoption poses specific psychological challenges for those sectors.[8]

From Theory to Impact. AQS and Key Adoption Metrics

The AQS provides a holistic view of overall adoption quality. It also has – we believe – a predictive element, in that it's measuring employee beliefs, perceptions and sentiment which typically lead related behaviours. So a low AQS signals adoption challenges now, and could point to increasing challenges over time.

We also identify three key adoption metrics that are important for any organisation's drive to integrate AI: how often employees are using AI; the complexity of tasks where AI is being used; and the prevalence of avoidance behaviours i.e. where employees recognise using AI would save time and value, but for personal reasons look to avoid it. We find that the AQS has a clear relationship with each of these three key metrics.

A higher AQS is positively associated with higher frequency of AI usage ((ρ = 0.54, p<.001). Those with lowest frequency use (less than once a month) showing significantly lower AQS than those with highest frequency use (multiple times daily (AQS42.7 vs. AQS72.4).

A higher AQS is also positively associated with AI being used for more complex tasks at work ((ρ = 0.39, p<.001). Those using AI for simple tasks record a significantly lower AQS than those using AI for complex and strategic tasks (AQS55.9 vs. AQS72.5).

A higher AQS is negatively associated with AI avoidance behaviours in the workplace ((ρ =-0.3, p<.001). Those who frequently avoid using AI for tasks, even when they know it would be beneficial record a significantly lower AQS than those who never avoid using the technology (AQS51,2 vs AQS68.1)

Together, the relationship between AQS and these three key adoption metrics supports the value of measuring Adoption Quality as a reliable, accessible and actionable proxy for adoption health.

Means, Machinery, Relevance and Readiness - A Deeper Dive

Means

Means describes employees' beliefs in their skills and knowledge to use AI effectively in the workplace. With an AQS of 77.6, Means scores the highest of the four AQS components. At the sector level, employees record the strongest belief in their skills across Technology (83.7), Real Estate (81.3), Retail (78.7) and Financial Services (78.4), with Energy and Utilities recording the lowest Means score (72.6).

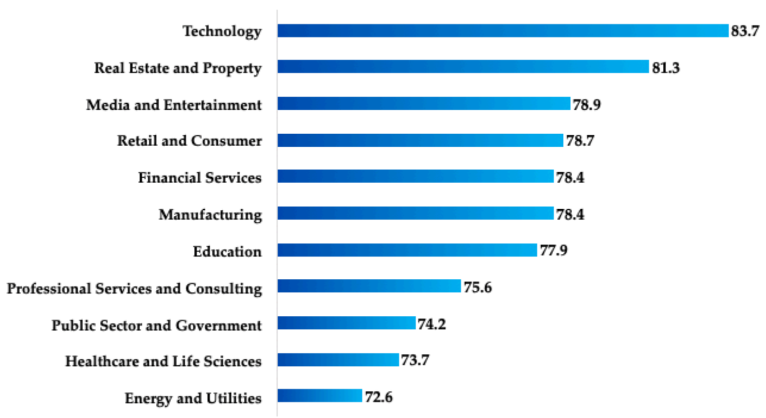


Exhibit 10

Means scores (as a component of the AQS) across sectors.
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

However, this confidence in skills and knowledge is failing to translate into use of AI. When looking at AI usage and task complexity, only 13% of employees are using AI for complex and strategic tasks. 26% of those at manager level with a Means AQS of over 70 only use AI for simple tasks within their work. This number increases to 42% for VPs and Heads of Function, potentially signalling a stress-point at an influential level within organisations.

Means, as a component of the AQS, shows a significant association with key adoption metrics: usage frequency and complexity of use (positive association), and AI avoidance (negative association).

Machinery

Machinery describes employees' perceptions of how well their organisation is enabling their use of AI in their work. Machinery has two components. First, there's Hard Machinery; the actual systems, tools and resources needed to apply AI in work. Second, there's Soft Machinery; the culture, norms, and leadership messages and behaviours that are seen to endorse and encourage AI use.

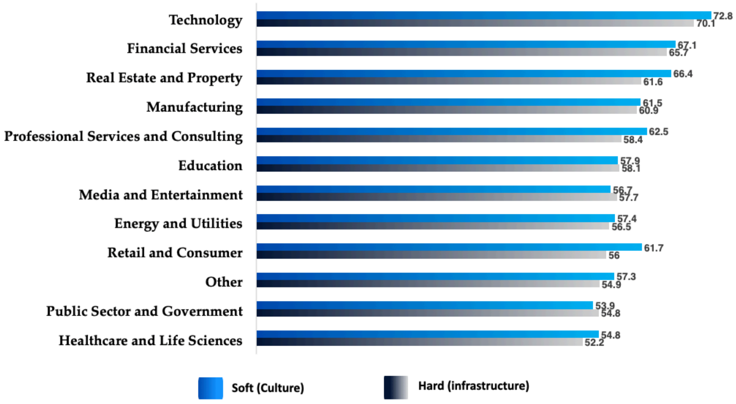


Exhibit 11

Machinery scores (as a component of the AQS) across sectors.
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

With an AQS of 60.1, Machinery scores significantly lower than Means. This suggests employees may sense frustration at the speed and commitment from their organisations to adopt AI. There is a marginal difference between Soft and Hard Machinery scores, although that difference is largest across the Retail, Healthcare, and Professional Services and Consulting sectors. In each case, Soft Machinery scores are higher than Hard Machinery scores, which could point towards employees seeing leadership putting forward a vision for AI without necessarily the appropriate organisational support.

The more senior the employee within the organisation, the higher the Machinery AQS – across both Hard and Soft Machinery. There's a 20-point difference between junior managers or those without direct reports (AQS Machinery: 58), and the C-suite (AQS Machinery: 78).

Machinery, as a component of the AQS, shows a significant association with key adoption metrics: usage frequency and complexity of use (positive association), and AI avoidance (negative association).

Relevance

Relevance describes the level to which employees consider AI to be important to their sector, employer, and to their role. Relevance can be either positive or negative; we measure an absolute level of AI relevance for employees. With an AQS of 60, Relevance is the second lowest of the four components (only Psychological Readiness scores lower).

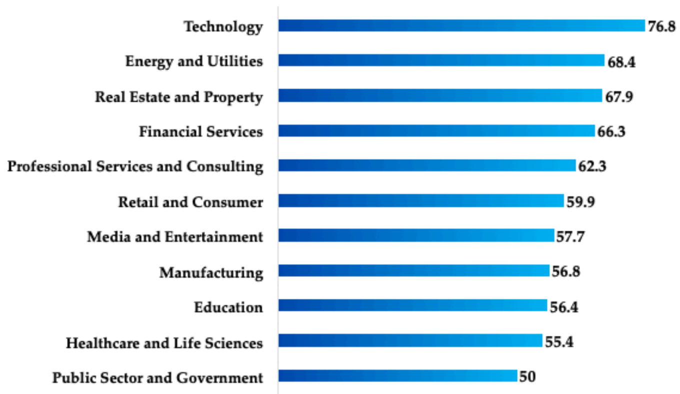


Exhibit 12

Relevance scores (as a component of the AQS) across sectors. N=1266
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

Not surprisingly, Relevance is highest within the Technology sector (Relevance AQS:76.8). It's lowest within the Public Sector and Government (Relevance AQS: 50).

Relevance is highest among those earlier in their careers (2-5 years Relevance AQS: 65 vs. 20+ years Relevance AQS: 59).

Of the four AQS components, Relevance shows the strongest association with AI usage frequency (ρ 0.464, p<.001) and AI complexity of use (ρ 0.356, p<.001). It also shows a significant negative association with AI avoidance (ρ -0.137, p<.001) but displays the lowest correlation of the four AQS components here.

Across our sample, 31% reported low levels of Relevance (Relevance AQS<50).

Readiness

Readiness describes the psychological readiness of employees to adopt AI. This is a six-factor measure, recognising widely reported psychological barriers that can obstruct in-work behaviour and, in this case, specifically, AI adoption. These factors include Cognitive Debt (the perception of losing decision-making skills), loss of control over how to undertake one's work (Autonomy), and a loss of connection with, and importance to, coworkers (Relatedness). It also includes the psychological friction that can occur when AI use is perceived to cut across or damage an employee's sense of professional social identity at work (Identity).

It's important to stress that we are not claiming these six factors are psychometrically independent and, intuitively, it's clear to see how some may influence others affecting how employees may feel towards using AI as part of their work. However, these six factors do offer diagnostic granularity, providing insights into where to focus. They can play a critical role in building-out more targeted and efficient behavioural interventions to improve adoption quality.

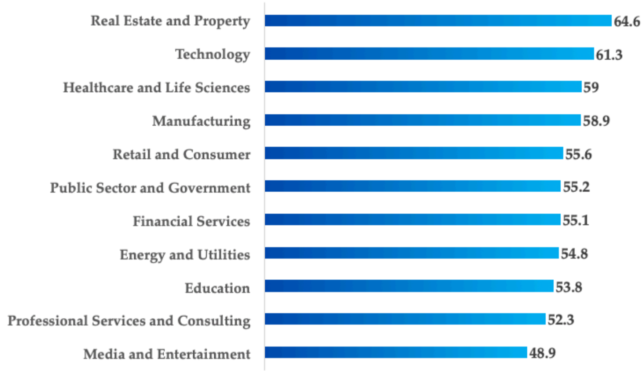


Exhibit 13

Readiness scores (as a component of the AQS) across sectors. N=1266
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

Across all six factors, concerns are higher, the earlier an employee is in their career: for example, potential loss of processing and decision-making skills ('Cognitive') is significantly higher at an early career stage (0-5 years' experience Cognitive Readiness AQS: 76.8) than with 20+ years' experience (Cognitive Readiness: 44.2). Looking across sectors, the perceived risk of loss of autonomy at work is highest among those working in Education (Autonomy Readiness AQS: 50.8), Media (Autonomy Readiness AQS: 50.7ß), and Professional Services and Consulting (Autonomy Readiness AQS: 50.1). Those working in Professional Services and Consulting also record high concerns over loss of key work skills (Mastery Readiness AQS: 51.5), and damage to their decision-making skills (Cognitive Readiness AQS: 55.2).

While these psychological factors that make up Readiness show a significant association with frequency of AI use ($\rho = .203$, $p<.001$) and complexity of task ($\rho = .141$, $p<.001$), it's the association with AI avoidance that is the most interesting. Readiness shows the strongest association with AI avoidance behaviour ($\rho = -.334$, $p<.001$). All six factors increase with increased levels of avoidance behaviour. This points towards a solution space that is largely missed by organisations currently; that understanding and addressing psychological barriers (rather than tool training) could be critical in improving at least one of the key metrics that can lead to AI value creation and ROI.

A finding worth noting here is the distinction between factor prevalence and factor impact. The concern over a loss of decision-making skills (Cognitive) is the most reported barrier in our sample (Cognitive Readiness AQS: mean 48.2), which is consistent with the amount of mainstream and specialist press the concept of 'cognitive debt'[9] has received.

However, when we look at which barriers have the strongest association with actual AI behaviours, the picture changes. The concern over damage to professional identity (Identity) – ranked 4th by prevalence (Identity Readiness AQS: mean 41.1) - shows the highest correlation with all three behavioural outcomes: AI avoidance behaviour ($\rho = +0.34$ [+0.29, +0.40]), frequency of use ($\rho = -0.26$ [−0.31, −0.20]), and complexity of task ($\rho = -0.17$ [−0.22, −0.11]). In other words, a fear of loss of professional identity appears to be a significant driver of destructive AI-related behaviours, yet sits below the surface.

Relatedness 'risk' shows a similar pattern to Identity. This psychological 'risk' is markedly less reported in industry reports but is associated with avoidance behaviour at a comparable level (ρ = +0.33 [+0.28, +0.38]).

Concern over loss of professional identity is rarely brought by employees but looks to be the strongest driver of damaging AI avoidance behaviour. It's a similar story with Relatedness; social oriented barriers are important but beneath the surface.

We acknowledge that these are moderate correlations but we believe they point to meaningful associations that are being missed in the wider conversations around AI adoption, and that can be acted upon in an organisational setting to create more targeted – and potentially more effective - interventions.

These findings raise interesting questions in terms of how organisations need to provide support to reduce or remove these psychological barriers. Far from being conceptual concerns based on academic theory[10], strong associations with key metrics for adoption quality means removing or mitigating for these psychological barriers should be a strategic priority for organisations.

Arguably more importantly, if organisations do not put in place strategies to remove these psychological barriers, and instead push through AI integration 'at all costs', they risk having these barriers deepen over time. In the same way research talks about the rise of Cognitive Debt from AI use, we argue that a broader sense of psychological debt can arise from all of the six factors included in the AQS Readiness score. For example, professional identity debt – which could accrue if an employee is pushed repeatedly to engage in AI-related tasks that conflict with that employee's understanding of what it means to be effective and professional in their role – is as real and potentially damaging as cognitive debt.

We would argue that organisations need to be evolving in terms of AI adoption by amassing as little psychological debt as possible for their employees. Ultimately all debt has to be paid down, one way or another, and we argue AI adoption debt is no different. High psychological debt – as represented by a low Readiness AQS – could result in increasing churn rates, productivity loss and burn-out, alongside ever-increasing training and support budgets.

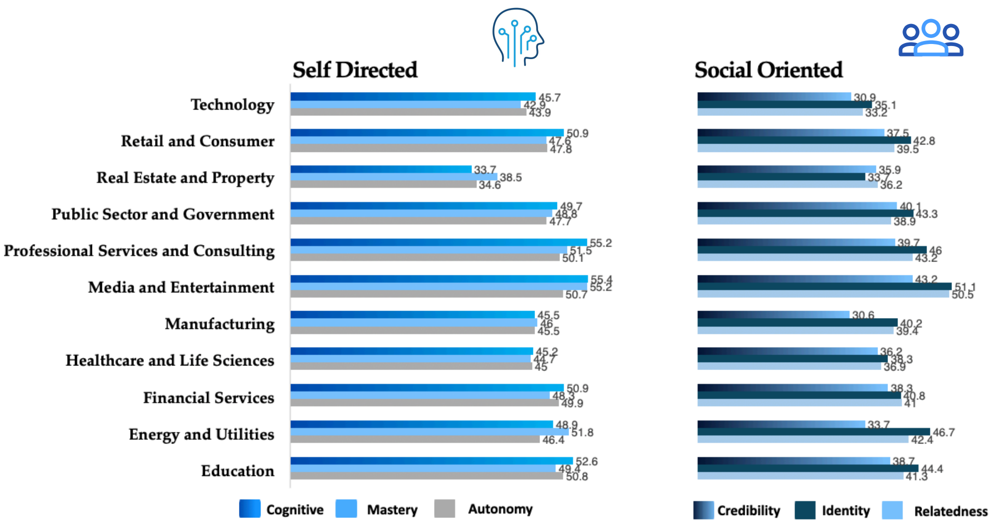


Exhibit 14

Readiness scores (as a component of the AQS) across sectors, broken down by Self Directed Barriers and Social Oriented Barriers. N=1266
Source: Delivering High Quality AI Adoption in the Workplace, February 2026

The Relevance - Readiness Matrix

Means and Machinery are arguably the more tangible, social, and organisation-oriented components within the AQS; they can be more readily adjusted via organisational process, and they receive the majority of press coverage and attention in the debate to drive AI adoption and ROI.

By contrast, perceptions of Relevance and Readiness are more psychological and personal and remain largely in the shadows of current industry reports. We don't believe this puts their adjustment beyond reach of organisational strategy, but we do argue it requires a different, more nuanced approach.

From our data we're able to create what we consider a valuable 2x2 matrix: the Readiness – Relevance Matrix. This matrix shows how the population in our sample are distributed across these two important psychological factors[11].

Understanding levels of Relevance and Readiness is valuable for organisations, as we can see strong associations between these two AQS components and the three key adoption metrics that in turn drive AI ROI. To reiterate, across all four AQS components, Relevance shows the strongest positive associations with frequency of AI use, and complexity of tasks. Readiness shows the strongest negative association with AI avoidance behaviours.

Readiness and Relevance, despite being more psychological than organisational, appear to have a critical part to play in driving high quality AI adoption within organisations and represent, we believe, a clear untapped opportunity for greater value creation.

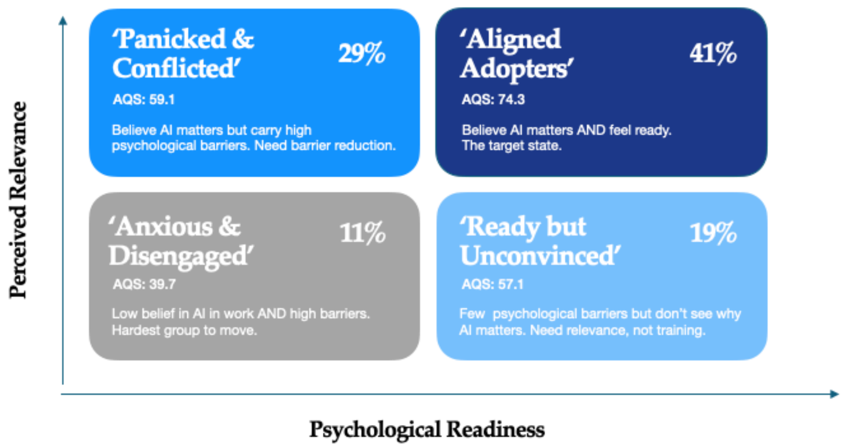


Exhibit 15

The Relevance-Readiness Matrix. Understanding where employees are in terms of perceived Relevance of AI (to sector, business and role) and Readiness to use AI (based on levels of psychological barriers). UK/US employees. N=1266 Source: Delivering High Quality AI Adoption in the Workplace, February 2026

Our matrix identifies four distinct employee cohorts, based on combined levels of Readiness and Relevance. Overall, 59% of those in our survey show some form of misalignment, with 12% showing low levels of both Relevance and Readiness.

'Aligned Adopters': High Readiness – High Relevance (41%)

These are employees who see the importance of AI in their work, and who also display consistently low levels of potential psychological barriers. This is the target state for all organisations, yet in our sample, only 41% of employees are in this quadrant. Aligned Adopters report the highest AQS (AQS: 74). Far from being left alone, organisations should look to learn from and leverage Aligned Adopters as a vital tool to move more of the organisation towards this state.

'Panicked and Conflicted': Low Readiness – High Relevance (29%)

This cohort recognises the importance of AI but also express significant concerns over the psychological impact of AI adoption in their roles. They are as convinced of the importance of AI in their roles as the 'Aligned Adopters' (Relevance AQS: 74.1) but they carry significant psychological barriers (Readiness AQS: 31.9). This cohort represents 29% of those surveyed and reports the second highest AQS (AQS: 59.1). For organisations with employees in this quadrant, there's work to in terms of reducing or removing these potential psychological barriers to adoption, such as co-design of tools, low-stakes experimentation and clear identity support (see next section).

'Ready but Unconvinced': High Readiness – Low Relevance (19%)

These are employees who report low psychological barriers to adoption (Readiness: 75.8) but are failing to see the relevance for AI in the roles (Relevance: 28.8). 19% of those surveyed fall into this category. This cohort has an AQS of 57.1. For organisations with teams in this cohort, the focus needs to be on leadership and management supporting a more compelling narrative for the role of AI in the business.

'Anxious and Disengaged': Low Readiness – Low Relevance (11%)

Those in this cohort show the high levels of concern for what AI may mean for their role, alongside little recognition of how important it may be for their role. This cohort represents 11% of those we surveyed and is the hardest group to move towards the target state. This cohort records the lowest AQS at 39.7– approximately half of that recorded by those in the target quadrant. For organisations finding their employees in this quadrant, the AI adoption strategy needs to combine building a more effective narrative around AI use, with clear steps to remove the psychological threat along the adoption journey.

This segmentation and 2x2 provides a different perspective to the established archetypes from the large consulting firms. These firms identify low adopters, but don't distinguish between an employee who is sceptical but psychologically ready, and someone who believe in the AI but is blocked by various forms of anxiety. The practical consequence here is that a single adoption programme design would be addressing the wrong dimension for a substantial portion of the workforce. For example, a population that skews towards Panicked and Conflicted would call for solutions that focus on change management and psychological barrier removal. Conversely, a population that skews towards Ready but Unconvinced would call for a solution that includes clear demonstrations of use-cases. It's most likely different areas of the same organisation would be seen across different quadrants, with the AQS clearly informing strategy and ensuring resources are allocated effectively and efficiently.

From Insight to Strategy

We believe the AQS serves a number of purposes. First, it allows for clear benchmarking, whether that's across sectors, geographies or competitor sets. It's also valuable to remember that the employee-level perception within the AQS likely gives it a predictive quality, indicating the trend in adoption quality.

Second, it enables organisations to understand their own state of AI adoption with a level of granularity, and - in our initial analysis - shows consistent and meaningful links to key established adoption metrics (use frequency, complexity of use, and avoidance of use), all of which impact on AI ROI.

Third, its multi-factor composition means organisations can take insights from the AQS and create bespoke and targeted interventions to improve relevant factors, to increase overall adoption quality. Organisations are under immense pressure to move quickly with AI adoption and want to maximise results while also minimising risks. We believe the AQS can offer unique support to organisations in meeting this ambition.

How the AQS can fuel targeted behaviour change and improve Adoption Quality

The AQS will be different for every organisation but, in each case, it can act as the jumping-off point to design and test targeted interventions that effectively increase adoption quality.

Our Adoption Quality framework is built on decades of experience using established behaviour change models and frameworks – even including those used in healthcare (the quote from US Surgeon General Everett. C. Koop at the beginning, on drugs not working in patients that don't take them, was not added without reason!). A key benefit of this approach is we also have access to a comprehensive range of proven behaviour change techniques; specific mechanisms that can stimulate and support targeted intervention designs. While the correct interventions for an organisation depend on its unique AQS analysis, we share a few of these potential techniques here.

Means

It's worth remembering that Means was the strongest performing of the four components of the AQS, and this may be the result of the considerable training budgets that are being moved to focus on AI use within businesses. Training and capability building – in terms of tool knowledge and understanding – is the obvious intervention to improve Means.

However, it should also be remembered that despite a high Means score within the AQS, actual AI use remains largely superficial - only 13% of respondents report using AI for complex and strategically important tasks. This suggests training programmes to date are inadequate and not focused on delivering key outcomes. This is further supported in our data, which shows that the Means AQS has little variation from simple AI use (Means AQS: 73.2) to complex AI use (Means AQS: 83.1). One solution here is to take a more behavioural approach to training design, with a clear focus on target behavioural outcomes together with a detailed understanding of the potential barriers to those outcomes. This often involves shifting focus from increasing skills, to increasing motivation to use those skills.

Machinery

Machinery has two forms within the AQS – Hard Machinery and Soft Machinery. Hard Machinery describes physical access to AI tools. This can be improved through careful environmental design and understanding the context-specific triggers needed for AI tool use at the right moment. We should keep in mind that access is also shaped by time, so environmental redesign in this regard could involve signposting and ring-fencing specific moments for AI use (including experimentation).

Soft Machinery, by contrast, describes corporate culture and leadership behaviours. Culture can be shaped by introducing and reinforcing new social norms within the organisation, for example, through constructively describing incidences of AI use (descriptive norms) and their positive outcomes (injunctive norms). Leaders and senior managers can also go beyond communicating the benefits of AI adoption and demonstrate the targeted behaviours, showcasing their successes, and - arguably just as importantly - sharing their uncertainties and failures.

Relevance

Increasing Relevance involves developing a more compelling business case for the use of AI within the business. This in turn relies on leadership narratives that engage and deliver cut-through, with clear use-cases. How the use of AI is framed is likely important here – positive, or 'gain', frames can encourage employees to see the benefits of adopting AI. However, negative, or 'loss', frames can also be highly effective; communicating the consequences of not adopting the technology. Use-cases (from within the business and beyond), demonstrations, and clear impact measures are all likely important to help build relevance amongst employee cohorts.

Readiness

With six factors within the Readiness component, the opportunities for targeted intervention design are many. Here we provide some potential intervention types, based on specific barriers.

To remove or reduce the fear of loss of Autonomy, management can consider involving key team members in the co-design of AI tools and how they're integrated into roles; seeking input in terms of when and how the AI can be used can ameliorate concerns around loss of control. For Mastery, the organisation can ensure team members recognise the clear boundaries of AI's value in their roles, carefully drawing attention to the importance of the 'human in the loop'. Training can highlight and celebrate new skills, in terms of learning how to most effectively deploy AI in a role. Use-cases can also be shaped by direct employee feedback, recognising the importance of employee- and role-specific skills and ability.

With professional identity threat (Identity), leadership is critical in redefining what it means to be a member of that organisational group, with membership and status clearly being attached to using AI. We often hear of AI needing to be positioned as 'augmenting' roles, but in this instance, leadership teams need to effectively augment the professional group with AI and the skills needed to effectively use it.

Specific attention can also be given to understanding where and when in a specific role there's a risk of identity damage as a result of using AI – not all use-cases may risk professional identity threat in the same way. For example, for certain software engineers, identity conflict may happen when being asked to outsource some forms of coding to AI, but not when using AI to draft reports. The focus can then shift to designing around these points of friction (e.g. modifying or removing AI for that part of the task), or potentially working with the individual to reframe AI use as being identity-supporting e.g. reframing the prompting process as a sign of higher technical or specialist knowledge.

Conclusion

In this report we've introduced the idea of Adoption Quality and the Adoption Quality Score (AQS). As a diagnostic, the AQS provides a detailed, novel and intuitive view of the state of adoption across an organisation.

Unlike other measures of adoption and proficiency, the AQS recognises key psychological factors that shape adoption behaviour. The psychological factors sit beneath the surface and so are still largely absent from wider consulting services and solutions. Yet they also appear to have significant influence on behaviour and behaviour change, so to marginalise or ignore their existence threatens organisational agility and effectiveness, at a moment when these qualities have never been more critical.

Note about the authors

Dr Guy Champniss is a consultant, educator, and visiting professor with IE Business School (Madrid), where he designs and delivers courses on behavioural science, business transformation and sustainable innovation. His research in applied social psychology has been published in leading journals including Harvard Business Review. His work as a consultant has been recognised in the UK and US for sustainable innovation, business impact, and market transformation potential. The AQS methodology has been developed by Dr Champniss and a behavioural data science specialist.

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End Notes

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[7] Note: Sample size for those at the early stage of their career is relatively small (n=118).

[8] Note: Sample sizes for sectors can be small in this dataset (e.g. Technology sector, n=167).

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[11] Relevance and Readiness show no correlation within our framework.

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