

Linking Contemporary Organisational Expectations and AI Adoption: The Case Study of UK Knowledge Workers

Module: Converting Research into Practice (LCDB7010_LON)

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List of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
AIA	AI Adoption
CSR	Corporate Social Responsibility
DOI	Diffusion of Innovation Theory
EI	Emotional Intelligence
HR	Human Resources
ISTAM	Intelligent Systems Technology Acceptance Model
IT	Information Technology
JD-R	Job Demands-Resources Theory
IV	Independent Variable
DV	Dependent Variable
MV	Mediating Variable
MOD	Moderating Variable
PLS-SEM	Partial Least Squares Structural Equation Modelling
SD	Standard Deviation
SME	Small and Medium-sized Enterprise
SPSS	Statistical Package for the Social Sciences
SRQ	Sub-Research Question
TAM	Technology Acceptance Model
TOE	Technology-Organisation-Environment Framework
UK	United Kingdom
UTAUT	Unified Theory of Acceptance and Use of Technology
XAI	Explainable Artificial Intelligence

Executive summary

This study investigates how organisational expectations shape AI adoption outcomes amongst UK knowledge workers, addressing an expectation–readiness gap neglected by TAM, UTAUT, and DOI frameworks. Using a mixed-methods pilot design ($N = 56$; $N = 3$ interviews), it tests 26 constructs and 21 hypotheses across eight theoretical pathways. Findings indicate that sustainable adoption depends on leadership, psychological readiness, and governance infrastructure rather than technology access alone.

Keywords: *AI adoption; knowledge workers; organisational expectations; socio-technical framework; employee well-being; innovative behaviour; UK workplace*

PART 1: THE RESEARCH PAPER

1. Introduction

Artificial intelligence (AI) is transforming the knowledge economy in the UK, prompting organisations to rethink workforce expectations and operating procedures. As AI penetrates professional domains, from law to the civil service, organisations are demanding fast productivity gains while under-investing in the cultural, psychological and governance infrastructure necessary for sustained adoption. These are also ignored by the existing models such as TAM, UTAUT and DOI and often consider adoption as a rational, linear process.

Problem Statement

The central theoretical problem is the absent multi-level socio-technical framework that connects organisational expectations, AI implementation and professional consequences in institutionally bounded contexts.

This thesis develops and empirically tests an integrated socio-technical framework to explain the expectation–readiness gap and its impact on adoption, well-being and innovative behaviour.

Research Questions

The study is guided by a primary research question: *How do contemporary organisational expectations shape AI adoption outcomes amongst UK knowledge workers, and what factors mediate or moderate this relationship?*

To address this, eight sub-research questions (SRQ) are examined:

- **SRQ1-2:** How do organisational expectations and readiness—mediated by performance expectancy—directly influence adoption and well-being?
- **SRQ3-4:** To what extent do leadership support and training provision facilitate acceptance, and how are these moderated by emotional intelligence and learning ability?
- **SRQ5-7:** How do psychological mediators, including stress appraisal, job insecurity, and meaningful work, shape innovative behaviour and engagement?
- **SRQ8:** How do boundary conditions, such as occupational exposure and gender, moderate adoption patterns?

These questions collectively address the micro (individual), meso (organisational), and macro (contextual) levels of the proposed framework.

2. Literature Review

2.1 Theme 1: Theoretical foundations of technology adoption: frameworks and their limitations

The literature on AI adoption (AIA) among knowledge workers has brought forward several foundational theoretical frameworks, each offering distinct yet frequently overlapping perspectives on how and why organisations and individuals adopt new technologies. The Technology Acceptance Model (TAM), proposed by Davis, remains widely employed in contemporary AIA research (Chatterjee & Rana, 2021; Kelly et al., 2022; Ibrahim et al., 2025; Song et al., 2025). It assumes that perceived usefulness and perceived ease of use are primary drivers of technology acceptance. However, this framework demonstrates significant limitations when applied to the complex socio-technical landscape of AI implementation (Qu & Kim, 2025), especially in knowledge-intensive environments. A critical examination reveals that the binary model of

instrumental variables in TAM is misaligned with the multidimensional psychological and organisational dynamics shaping AI adoption paths among knowledge workers (Vorm & Combs, 2022; Ramadan & Alruwaili, 2024; Shrivastava, 2025).

The Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed to extend the TAM with social influence and facilitating conditions. Research on adopting AI by knowledge workers demonstrates that UTAUT model still partially predicts outcomes, but do not influence attitudes toward use as anticipated; instead, new constructs are introduced, particularly innovative behaviour and critical thinking as neutralising factors to perceived risks (Bianchini et al., 2025). Such theoretical shortcoming necessitates a more sophisticated integration of psychological mechanisms and environmental scenarios. The Diffusion of Innovation Theory (DOI) (Rogers, 2023) has been extensively applied to technology adoption contexts. It outlines the characteristics of innovation such as relative advantage, compatibility, complexity, trialability, and observability. Yet, evidence indicates that these attributes behave differently in various professional contexts and cultural settings; and complexity, assumed to negatively influence adoption, shows insignificant effects in educational and professional contexts, challenging the scope of DOI assumptions (Raman et al., 2024; Overbye-Thompson & Hamilton, 2025).

The Technology-Organisation-Environment (TOE) framework extends the depth of analysis beyond individual and organisational factors by including environmental pressures, offering a more comprehensive analytical lens. The integration of TOE with DOI and institutional theory has produced more robust explanatory models for AIA, but these integrative approaches reveal fundamental conflicts in how enterprises interpret the concept of technology adoption as either efficiency-driven or legitimacy-seeking activities (Übellacker, 2025; Wang et al., 2025). Still; a critical challenge persists; most contemporary frameworks treat adoption as a linear, rational decision-making process; whereas empirical evidence increasingly suggests that adoption is deeply reliant on trust, emotional responses, and organisational power dynamics (Mashiah & Avidar, 2025). This distinction has important implications for explaining why organisations with high organisational AI readiness may also experience both employee concealment of AI use and resistance to transparent adoption (Azzahra & Ridzki, 2026).

2.2 Theme 2: The knowledge worker paradox: capabilities, expectations, and performance outcomes

Contemporary organisational expectations regarding AIA among knowledge workers are based on the beliefs of enhanced productivity, more effective decision-making, and accelerated innovation. Nevertheless, growing data implies a negative relationship between AIA and knowledge worker performance and well-being that challenges these basic hypotheses (Ocampo et al., 2024; Leoni et al., 2024; Aljuwaiber, 2021). Specifically, a double-edged sword effect concerning the link between AI implementation and the innovative behaviour of knowledge workers is found, grounding in self-determination theory (Kang & Lee, 2025). While AI assistants can enhance innovative performance by reducing the perceived work intensity, particularly in organisations with high organisational AI readiness; the highly intelligent AI systems simultaneously trigger personal development concerns and competency-related anxiety that prevent innovative behaviour. This suggests that organisational enthusiasm for AI implementation may strengthen the psychological systems that erode knowledge worker innovation (Obenza et al., 2024).

Additionally, the interaction effect of AI awareness and task performance is further complicated by the mediation of psychological mechanisms. It is found that this consciousness negatively determines task performance via its influence on leader-member exchange relationships and organisational commitment in a strong way (Chen et al., 2024). This is the direct opposite of what organisational expect in terms of boosting capability and knowledge. Rather, career uncertainty generated by AI expansion leads to the undesirable work states, involving lower organisational commitment, diminished task engagement, and thoughts of leaving. Such psychological problems are not captured by traditional productivity metrics, thus representing an essential gap between organisational measurement frameworks and the actual knowledge worker experiences.

Subsequently, performance expectancy plays a crucial mediating role between organisational support and social influence and AI usage performance outcomes (Bhachaiyud & Laptaned, 2025). However, knowledge workers those who work in public sector are marked by a large willingness-use gap, as notable variations exist between the reported willingness to employ AI for strategic and analytical tasks

and its actual deployment (Veseli et al., 2025). This gap indicates that motivational and organisational factors moderate adoption in ways unexplained by technology acceptance models — a mismatch reflected even among UK Civil Service HR staff who express personal enthusiasm yet face organisational unpreparedness (Sohoni et al., 2025).

Concisely, when it comes to AIA, the reflexive practitioners deeply concern about deskilling, dehumanization, disconnection, and disinformation (Slavova & Zhauniarovich, 2026). Instead of believing in transformative disruption, the professionals conceptualise AI as performing routine tasks under human supervision, preparing for a reinforcement of existing workplace disorders versus profound change. This established view of AI's probable future direction diverges substantially from organisational narratives which are highlighted by innovation and enhancement, uncovering a considerable communication and expectations gap separating senior leadership and knowledge worker community.

2.3 Theme 3: Organisational readiness, change management, and the implementation infrastructure gap

Success in adopting is less an outcome of technological sophistication and more an indicator of organisational readiness, which are defined as the collective efficiency, commitment, and contextual support for managing technological change (Miake-Lye et al., 2020; Domlyn et al., 2021; Almamega et al., 2025). However, most organisations show substantial deficiencies across several dimensions of readiness. A comprehensive model of change management for technology implementation in public organisations identifies five essential elements, encompassing leadership and governance, organisational culture and readiness, technological infrastructure, training and human capital development, and supportive structures and regulations (Alghamdi et al., 2011; Alghamdi et al., 2014; Wahyudin et al., 2024). A systematic review proves that while there is a remarkable investment in technological infrastructure, cultural transformation is consistently underdeveloped, leading to implementation failures despite technical capability.

Many organisations conflate technological infrastructure scalability with organisational capacity for transformation, resulting in investments in systems and platforms without corresponding attention to cultural change, leadership development, or employee

psychological preparation (Warner & Wäger, 2019; Uren & Edwards, 2023; Hortoványi et al., 2023; Martínez-Peláez et al., 2022; Wahyuni et al., 2024). This pattern is profoundly reinforced by the adoption of Learning Management System in higher education in which 75% of difference in perceived organisational change readiness derives from vision clarity, top-management support, project champion effectiveness, and organisational flexibility (Veseli et al., 2025). In contrast, the factors of organisational history of change, and collective self-confidence exhibit a modest impact. This implies that, in this specific context, strategic and leadership-related variables are more relevant than individual-level psychological variables (Peng et al., 2021). Yet, this does not points out that psychological readiness is unimportant, but rather that its influence may be more indirect or context-dependent (Miake-Lye et al., 2020; Caci et al., 2025).

Besides, digital transformation readiness in manufacturing contexts is rooted in core misunderstandings of the requirements of digitalisation. Senior leadership frequently views digital transformation as primarily technological execution, whereas frontline workers and middle managers consider it fundamentally as human transformation process (Gilli & Lettner, 2025; Machado & Winroth, 2024; Ahmed & Aziz, 2024; Rocha et al., 2024). This conceptual divergence causes the execution plans that target technological accessibility without regard to psychological preparation, cultural transformation, and ongoing support mechanisms. Research focusing on organisational readiness for smart hospital unit projects presents the key barriers, namely unclear timelines, inconsistent training, limited resources, infrastructure constraints, and critically, concerns about overreliance on technology and the decline of clinical judgment (Kumar et al., 2023; Ahmed et al., 2025; Lim et al., 2025)

On top of that, critical change management literature describes that resistance to change does not represent an illness but rather a rational response to genuine threats to professional identity, job security and task autonomy (van Dijk & Dick, 2019; Raval et al., 2021; Caci et al., 2023). Institutional contexts are defined by hierarchical organisational structures, professionalised expertise requirements, and established professional norms where technology adoption perceived as a threat to professional judgment and autonomy is met with higher resistance (Jussupow et al., 2020; Chen et al., 2022; Ackerhans et al., 2024; Ackerhans et al., 2025). For instance, the slow pace

of digitisation in the property valuation sector is not due to technical constraints, but instead due to institutionally conservative principles, outdated regulation and weak data governance. These findings challenge narratives that blame worker ignorance or technological anxiety for adoption resistance, alternatively claiming that resistance stems from sophisticated institutional logics and legitimate concerns about professional integrity.

2.4 Theme 4: Skill requirements, training systems, and the emerging AI literacy imperative

Contemporary AIA demands a reconsideration of the required competencies and skill development frameworks. The expectation that knowledge workers must be trained primarily on operating AI tools which is simply not adequate to meet the ongoing need to cultivate ranging from AI literacy, ethical reasoning, data interpretation to critical evaluation of AI-generated outputs. Intellectual workers themselves identify nine key training topics for safe and effective AI adoption, comprising: basic understanding of what AI is and how it functions, misinterpretation of AI outcomes, bias augmentation, worker rights, and accountability frameworks (Ng et al., 2021; Almatrafi & Johri, 2024; Chee et al., 2025). These needs extend far beyond conventional technical training into philosophical, ethical, and rights-based aspects of AI integration.

Thus, the literature reveals alarming gaps between the training provision and the demands of workers. As mentioned above, most UK Civil Service HR respondents believe that there is inadequate knowledge to effectively integrating AI, even though they are personally ready to do so (Smith et al., 2025). For example, it is a cross-national evidence across 35 European countries that workplace training provision is a strong predictor of the national-level AI adoption rates, but that most organisations lack sufficient training capacity (European Public Health Association, 2025; Muehlemann, 2025; Ionaşcu et al., 2025; IEEE, 2024; Rahman, 2025). This infrastructure deficit seems systematic as opposed to marginal, referring to an organisational failure to recognise that AIA calls for comprehensive reskilling, not marginal capability enhancement.

In that way, the highly-experience professionals demand distinct support frameworks compared to the inexperienced practitioners. In lieu of the uniform training approaches, organisational AI readiness depends on the differentiated development

pathways that are tailored to career stage, domain expertise, and risk tolerance (Vadisetty & Polamarasetti, 2024; Bayly-Castaneda et al., 2024; Tusquellas et al., 2025; Hong, 2025). Organisational systems are centred on quality evaluation which allows expert knowledge workers more effectively evaluate and assess AI-generated outputs. However, organisational training systems are designed based on the assumption of uniform population of knowledge workers, contributing to a misalignment of training content and the diverse skill standards which are set by both occupational groups and career stages.

Research conducted on AIA in the construction industry, supply chain management, and financial auditing consistently points to skill gaps and limitations in technical guidance as the primary barriers to implementation (Kokina et al., 2021; Cannas & Ciano, 2022; Ahatsi & Olanrewaju, 2025; Booyse & Scheepers, 2025). Remarkably, firms that report adopting AI expect major future transformations in skills, but most share the low levels of systematic investment in forward-looking training and capability development. This gap conveys that the complexity of implementation is not considered and that there is overconfidence in the worker's ability to acquire self-directed skill under operational pressure.

2.5 Theme 5: Psychological and well-being dimensions: the human cost of AI transformation

Organisational expectations regarding AIA frequently overlook or minimise the psychological consequences related to anxiety, burnout, skill insecurity, and erosion of professional identity. There is now evidence that AI implementation produces significant negative psychological effects that not only partially offset efficiency gains but also threaten sustainable workforce adaptation. The phenomenon of "technostress" is experienced across multiple professional domains and can be described as high level of stress, anxiety, and perceived incompetence since workers, in parallel, attempt to keep up with their existing workloads while learning emerging technologies and adapting to new work processes (Soulami et al., 2024; Jeong et al., 2024; Shonhe & Min, 2025; Kim et al., 2025)

In other words, this mechanism could be termed a "productivity trap" in which organisational efficiency gains from embracing AI do not translate into a reduction of workload demands or an improvement in work-life balance but rather into increased

performance targets and intensified productivity expectations (Beer & Mulder, 2020; Zacher & Rudolph, 2021; Bîzoi & Bîzoi, 2024). The workers afterwards perceive AI not as a supportive partner but as a tool for surveillance and productivity boost, eventually giving a rise to job displacement anxiety and an organisational desire for the higher-quality output. This perception is particularly noticeable in competitive organisational cultures in which committing to using AI signals both efficiency and organisational justification for their intensified workload expectations.

For instance, longitudinal research from South Korean companies asserts that even as AIA does not directly affect employee depression, it has the substantial indirect effects through job insecurity pathways (Chung et al., 2025). It is important to note that the presence of corporate social responsibility (CSR) programs and organisational support systems moderate these adverse outcomes. Despite this, most firms implementing AI do not, at the same time, strengthen CSR campaigns or build protective psychological safety mechanisms, therefore, vulnerability is exacerbated.

The concept of "meaningful work" accordingly becomes clear as an indispensable mediating mechanism through which AIA shapes worker behaviour and well-being (Smids et al., 2020; Watermann & Kubowitsch, 2023; Ocampo et al., 2024). AI-induced job insecurity lowers perceived work meaningfulness, which in turn reduces engagement in socially and environmentally responsible behaviours even when direct productivity is still maintained. This proves that corporate goals for efficiency improvements and stronger employee engagement are mutually incompatible unless enterprises decide to allocate funds correspondingly in meaning-making frameworks, job redesign to enhance autonomy, and psychological support systems.

Ultimately, despite limited research, there is a necessity to look at generational distinctions between AI acceptance and adaptation. The intelligent workers who are generation Z accepting AI, but also actively seeking careers in fields that are perceived as less automatable with the meaning of the greater stability, dignity, and work-life balance (Anjum, 2024; Ayoobzadeh et al., 2024; Syafani et al., 2025). This adaptive response reveals that while younger workers are more technically proficient with AI systems, they also believe that organisational goals and foreseeable career paths pose a serious threat, contributing to the complicated hybrid adoption patterns in which

technical engagement is combined with strategic career positioning away from AI-intensive roles.

2.6 Theme 6: Contextual factors, national context and the UK knowledge worker landscape

The literature on AIA is becoming globalised, but for the development of the thesis, the specific UK context needs to be considered. A comparative analysis in Europe finds a large cross-national variation in genAI adoption rates (ranging from under 3% to 25% across 35 countries) even though the shares of jobs likely to be affected by AI which is broadly similar across these countries (Georgieff & Hyee, 2022; Manta & Geambaşu, 2024; Brey & van der Marel, 2024). At the worker level, individual abilities, non-routine cognitive job content, and organisational decision-making all predict implementation trend; at the country level, digitalisation infrastructure and workplace training availability have a considerable influence on diffusion rates. The UK's relative standing on these factors is under-explored in current study.

First, the public sector environment in the United Kingdom is unusual for AIA because it imposes certain governance restrictions on digital maturity across agencies and has its own professional cultures. Individual personal willingness for AIA is evidenced by UK Civil Service HR workers despite organisational constraints (Henman, 2020; Madan & Ashok, 2023; Roberts et al., 2024), claiming that individual-level variables may not be sufficient to achieve systematic adoption without parallel organisational restructuring. However, the UK public sector's digital maturity varies per agency, with distinct cultural attitudes toward technology innovation and different levels of stakeholder participation in adoption choices.

Second, the UK's larger digital policy environment, shaped by Vision 2030-equivalent frameworks and legislative activities, drives corporate aspirations for AI deployment. However, there is inadequate investigation on how UK knowledge workers perceive organisational expectations, whether these expectations line with feasible deployment plans and how professional norms within UK knowledge work groups determine adoption results (Fazakarley et al., 2023; Olawade et al., 2024; Stogiannos et al., 2023; Stogiannos et al., 2024). The literature offers minimal UK-specific research on knowledge workers' opinions on AIA, expectations alignment, and experienced consequences.

Third, the professional context significantly moderates AIA patterns. Knowledge jobs encompass diverse professional domains including legal services, accounting, journalism, financial services, recruitment, HR management, and scientific research. Each domain maintains distinctive professional norms, expertise requirements, regulatory constraints, and epistemological frameworks. All these affect the feasibility and desirability when it comes to AIA. Investigative journalism in the Netherlands, for instance, experiences substantial obstacles barriers related to resource constraints, communication gaps between journalists and IT professionals, and structural organisational barriers rather than individual resistance (Fridman & Krøvel, 2024; Dodds et al., 2024; Cools & Diakopoulos, 2024). These sectoral variations imply that UK-specific thesis research should be more professional-contextually focused, versus relying on an identical knowledge worker population.

Fourth, gender dimensions in AIA receive minimal attention in current literature despite emerging evidence of persistent gender gaps which are concentrated in the most exposure-intensive occupations (Cazzaniga et al., 2024; Dorta-González et al., 2024; Humlum & Vestergaard, 2024). Female knowledge workers have been found to prioritise innovation attributes in different ways in comparison to their male colleagues. Put it simply, women put more importance on ease of use, compatibility, relative advantage, and trialability, while men favour compatibility, ease of use, and observability (Jatmiko et al., 2024; Raman et al., 2024). It is under-researched whether these patterns reflect genuine variations in preferences, organisational socialisation, or structural positioning within occupational hierarchies, but the gender-sensitive analysis remains essential for understanding UK knowledge worker populations.

2.7 Theme 7: Ethical dimensions, responsible AI, and the governance imperative

Contemporary organisational expectations on AIA are frequently proceeded with insufficient attention to ethical dimensions, governance requirements, and responsible execution frameworks (Al-Kfairy et al., 2024; Mohammed et al., 2024; Shukla, 2024). The contradiction between AIA enthusiasm and responsibility concerns has become increasingly apparent. According to a global survey of knowledge workers, ethical concerns consisting of algorithmic bias, data privacy, transparency issues, and worker rights were ranked as the top barriers to the safe adoption of AI (Vatankhah et al.,

2024; Mensah, 2024; Goktas & Grzybowski, 2025). Yet, they tend to be delegated to specialised governance functions rather than being embedded in technology adoption decisions in a deliberate way.

Knowledge silos exist between technical specialists, editorial or operational leadership, and worker communities which consistently slow down the deployment of responsible AI practices. A study of Dutch news organisations found that successful ethical AI practice requires bridging technical, editorial, and managerial perspectives through purposeful knowledge-sharing systems, yet most organisations lack such integrative mechanisms (Dodds et al., 2024a; Dodds et al., 2024b). This organisational fragmentation creates disconnects where technical teams design AI systems according to efficiency metrics, operational managers evaluate implementation based on productivity gains, and workers experience AI through narrow windows of direct system interaction, with ethical implications remaining invisible to many organisational participants.

The framework of "consequences-mechanisms-risks" provides a rigorous analytical technique to detect risks in the workplace arising from AI-mediated access to knowledge systems (Gausen et al., 2024). Severe effects that justify ethical attention include commodification of worker knowledge, appropriation of expertise value, concentration of power through algorithmic decision-making, and marginalisation of worker perspectives. Nevertheless, the organisational implementation frameworks fail to interact carefully with these ethical mechanisms. This leads to AI systems that unintentionally (or intentionally) reinforce managerial control and diminish worker autonomy and knowledge valuation.

Algorithmic transparency and explainability become key criteria for enterprises yet remain incompletely carried out in most AI systems. Workers express profound concern about "human likeness" in genAI systems, recognising that anthropomorphic¹ design presents dangers such as overtrust in system outputs, inappropriate reliance on algorithmic recommendations, and confusion about responsibility allocation

¹ **Anthropomorphic** refers to making AI seem human, which can mislead users into over trusting it and misjudging responsibility.

between human judgment and algorithmic advice (Schimmelpfennig et al., 2024; Mathew et al., 2024; Holbrook et al., 2024). Such worries reflect deep understanding of how AI system design choices shape human-AI interaction, in ways that are often invisible to designers and leaders within companies.

In general, "responsible AI" is not only about technical fairness and bias mitigation but also human rights alignment, worker protections, transparent accountability, and democratic participation in technology governance. But most organisational standardisations narrowly aimed at technical performance metrics and operational efficiency, deferring ethical considerations until crises emerge. This imbalance between ethical frameworks and organisational practices is the greatest weakness of current AIA literature to properly guide practice.

2.8 Theme 8: Toward an empirically grounded understanding of expectations-adoption misalignment

Synthesis across studies highlights a consistent pattern: present-day business standards for embracing AI comprehensively differ from empirical evidence of actual integration routes, knowledge worker experiences, and adoption outcomes. When companies go with AI, they generally presume it to deliver gains in productivity, improved decision-making, and maintained or enhanced worker well-being, also occurring relatively rapidly through technology deployment combined with basic training provision. Empirical evidence, however, asserts that successful AIA necessitates a comprehensive organisational transformation which involves culture change, leadership development, psychological safety creation, ethical governance establishment, and ongoing support system development, in other words, a transformation taking up much more time, resources, and attention than most firms currently invest.

The willingness-use gap observed across multiple professional domains and countries represents a crucial finding that should reshape organisational AI adoption strategies. Knowledge workers commonly express their willingness to employ AI tools, but their low actual usage proves that simply making tools available organisationally is insufficient without addressing underlying motivational, contextual, and support constraints. This deficit persists even among workers with high individual technology

readinesss, reflecting that the barriers are at the system-level rather than individual-level.

The further point is that there is a paramount contradiction between the emphasis on "AI fluency" and "digital literacy" training within enterprises and worker-identified needs for ethical reasoning, responsibility frameworks, and critical evaluation of AI restrictions. Organisations habitually approach AI training as technical skill acquisition, whereas workers acknowledge that they must have philosophical frameworks for understanding when it is appropriate, ethical, and aligned with their professional responsibilities in terms of using AI. This mismatch suggests that organisational expectations and worker demands have become conceptually misaligned at the fundamental level.

Concisely, empirical evidence suggests the need to re-evaluate the appropriateness of AIA in all knowledge intensive work, as some professional domains may legitimately prefer human expertise over automation. Organisations typically overlook this point of view, treating adoption as binary rather than task-specific.

2.9 Synthesis: Critical implications for UK knowledge worker research

The misalignments identified in the previous section do not merely represent theoretical gaps; they carry profound implications for how AIA must be studied, particularly within the UK knowledge economy. This thesis, therefore, shifts the focus from traditional technology acceptance to a more sophisticated socio-technical investigation through the following research imperatives:

First, organisational expectations regarding AI adoption need to be recalibrated to acknowledge that adoption constitutes organisational transformation rather than technology deployment, demanding investment in change management, leadership development, and psychological support systems substantially exceeding current practice.

Second, UK-specific research must investigate how national context, professional norms, regulatory frameworks, and occupational cultures shape AI adoption pathways, realising that UK knowledge workers represent distinctive populations

requiring investigation as opposed to the merely application of the globally derived frameworks.

Third, research must attend seriously to whether organisational expectations and knowledge worker interests remain genuinely aligned or whether organisational productivity mandates basically diverge from worker needs for meaningful work, professional autonomy, and psychological well-being.

Fourth, ethical dimensions of AI adoption should have a central instead of the external responsibility, which means embedding responsible AI frameworks into adoption decisions, rather than adding governance structure retrospectively. Finally, research must be aware of that the future of AI adoption for UK knowledge workers is genuinely open, depending primarily on organisational choices, regulatory developments, and worker collective action versus technologically determined outcomes.

The main contribution of this study is to question the assumptions about AI's inevitability, to generate empirically based frameworks that reconcile organisational capabilities with the needs of the workers and ethical demands, also to provide practical guidance to the organisations using AI.

3. Conceptual Framework

3.1 Research Constructs and Hypotheses

Table 1 maps all 26 research constructs, spanning independent, dependent, mediating, and moderating variables onto their theoretical bases, item coding, and associated hypotheses, providing the conceptual backbone for the empirical investigation that follows.

Table 1: Mapping of Research Constructs, Theoretical Bases, and Associated Hypotheses

INDEPENDENT VARIABLES (IVs)						
Variable Name	Coding	Dimensions	Theoretical Basis	Author	Hypothesis	Scale / Instrument
Organisational Expectations (SRQ1)	A1, A3	Perceived Utility Expectations (efficiency, cost reduction, quality improvement)	Expectancy Theory/ Organisational Behaviour	Lawler and Suttle (1973), Mitchell (1982), Isaac et al. (2001)	H1a, H1b, H1c	Likert scale + Qualitative
	A4, A6	Timeline Expectations (pace of adoption and implementation)				
	A2, A5	Performance Outcome expectations (productivity gains, innovation increases)				
Organisational Readiness (SRQ2)	B1, B2	Technological Infrastructure Readiness	Change Management Theory, TOE Framework	Weiner (2009), Rafferty et al. (2013), Satyro et al. (2022),	H2a, H2b, H2c	5-dimensional model
	B3, B4	Culture and Psychological Readiness				
	B5, B6	Leadership and Governance Readiness				
	B7, B8	Human Capital and Skill Readiness				

	B9, B10	Structural and Regulatory Readiness		Chittipaka et al. (2023)		
Leadership Support (SRQ3)	C3	Change Vision Clarity and Strategic Communication	Leadership Theory/ Change Management	Gill (2002), Mansaray (2019), Mouazen and Hernández-Lara (2021), Peng et al. (2021)	H3a, H3b, H3c	Likert scales
	C1, C2	Emotional Support & Psychological safety creation and Instrumental Support (resources, training, technical assistance)				
	C4	Participatory Decision-Making and Employee Voice				
	C5	Transformational Leadership Behaviours (role modelling, inspiration)				
	C6	Communication Frequency and Bidirectionality				
Training Provision (SRQ4)	D1	Pre-implementation training provision	Adult Learning Theory / Training Transfer	Burke and Hutchins (2007), Merriam (2008), Nafukho et al. (2017),	H4a, H4b	Attendance, satisfaction, impact
	D3	On-the-job training during implementation				
	D6	Post-implementation support and continuous learning				
	D2	Training depth (basic literacy vs. advanced competence)				

	D4	Training alignment with actual task requirements		Nafukho et al. (2022)		
	D5	Trainer competence and credibility				
Organisational Support	E1	Technical support availability and quality	Social Support Theory / UTAUT	Kurtessis et al. (2017), Lee et al. (2023), Sheikh et al. (2023)	H7a, H7b, H7c	Multiple indicators
	E6	Help desk responsiveness and expertise				
	E3	Job redesign to enhance autonomy and meaning				
	E4	Mental health and psychological support services				
	E2	Peer support and communities of practice				
	E5	Resource adequacy for implementation				
DEPENDENT VARIABLES (DVs)						
AI Adoption	F1	Frequency of AI tool usage (daily, weekly, occasional)	Diffusion of Innovation / TAM / UTAUT	Rogers (2003); Venkatesh and Davis (2000), Venkatesh et al. (2003)	H1a-c, H2a-c, H3a-c	Frequency, breadth, quality
	F2	Breadth of usage (number of different tasks/applications)				
	F3a	Depth of usage (sophisticated use vs. basic functionality)				
	F3b	Integration with work processes				

	F3c	Sustained engagement vs. abandonment				
	F3d	Quality of implementation (appropriate, inappropriate use)				
Employee Well-being (SRQ6)	H1	Job Satisfaction	Stress Process Theory / Conservation of Resources / Commitment Theory / Social Exchange Theory	Pearlin et al. (1981), Vera et al. (2016), Meyer and Maltin (2010), Ahmad et al. (2022)	H6a, H6b, H1c, H7a, H7b	Multiple validated instruments
	H2	Work Engagement (vigour, dedication, absorption)				
	H3	Burnout				
	H4	Anxiety				
	H5	Organisational Commitment				
	H6	Work-Life Balance				
	H7	Career Anxiety				
Innovative Behaviour	I1	Idea generation and creativity	Innovation Theory / Work Design Theory	Kwon and Kim (2020), Waheed et al. (2023), Gagné et al. (2024)	H1c, H5a-c	Innovative Behaviour
	I3	Idea development & experimentation				
	I2	Idea championing & implementation				
	I4	Collaboration on innovation				
MEDIATING VARIABLES (MVs)						

Stress Appraisal (SRQ5)	G1	Perceived Excitement of learning AI systems	Cognitive Appraisal Theory (Lazarus)	Lazarus and Folkman (1984)	H5a, H5b, H5c	Quantitative + qualitative
	G2	Perceived anxiety to job loss				
Job Insecurity (SRQ6)	G3	Cognitive job insecurity	Job Demand-Resources Theory	Kwon and Kim (2020)	H6a, H6b	Likert + qualitative
	G4	Perceived technology impact on role				
Performance Expectancy (G)	G5	Perceived usefulness for job tasks	Social Cognitive Theory, Expectation-Confirmation	Bandura (1977, 1986, 1997, 2001), Darley and Fazio (1980), Venkatesh and Davis (2000), Brown et al. (2012)	H2b	Likert scale
Meaningful Work (SRQ7)	G6	Task significance and impact	Job Characteristics Theory,	Hackman & Oldham (1975, 1976, 1980)	H7a	Likert scale

			Meaning-Making			
Trust in AI	G7	Perceived reliability and consistency	Social Trust Theory, System Design Literature	Luhmann (1979, 1995), Mayer, Davis & Schoorman (1995), Kaur et al. (2022)	H3b	Likert + qualitative
	G8	System predictability and comprehensibility				
MODERATING VARIABLES (MODs)						
Learning Ability	J2	Cognitive flexibility and adaptability	Learning & Adaptation Theory	Bandura (1977, 1986, 1997), Kolb (1984), Nafukho et al. (2017/2022)	H4b	Multiple scales
Organisational AI Readiness	J6a	Innovation culture strength	Organisational Culture Theory, Digital Maturity	Schein (2010), Kane et al. (2017), Lopes et al. (2026)	H2c, H5c	Likert scales
	J6b	Digital Maturity Focus				

Corporate Social Responsibility	J5a	Ethical AI governance, Transparency and accountability	Stakeholder Theory, Institutional Theory	Freeman (1984), DiMaggio & Powell (1983), Scott (1995)	H6b	Likert + documentary
	J5b	Employee welfare initiatives, Job security protection programs				
	J5c	Community and environmental responsibility				
Emotional Intelligence	J1	Self-awareness of emotions	Emotional Intelligence Theory (Mayer-Salovey)	Salovey & Mayer (1990), Mayer & Salovey (1997)	H3c	Validated instruments
Occupational Exposure (SRQ8)	J3	Task-level AI exposure (frequency of AI system engagement)	Innovation Diffusion Theory	Rogers (2003)	H8a	Expert rating scale
Gender (SRQ8)	J7		Gender & Technology Adoption Literature	Venkatesh & Morris (2000), Venkatesh et al. (2003),	H8b	Binary/spectrum

				Raman et al. (2024)		
CONTROL VARIABLES						
Age (Q4)			Generational differences in technology adoption			
Organisational Tenure (Q3)			Acculturation and organisational commitment effects			
Occupational Role (Q1)			Different adoption requirements by role			
Industry Sector (Q2)			Sector-specific AI adoption norms			
Organisation Size (Q5)			Resource availability and adoption pace			
Prior Technology Adoption Experience (J4)			Past technology success			
UK Regional Context (J8)			Regional digital infrastructure variation			

3.2. Integrated Conceptual Framework

The framework operates through eight theoretically grounded pathways — from organisational expectations and readiness (Pathways 1–2), through leadership, training, and psychological mediators (Pathways 3–6), to meaningful work and boundary conditions (Pathways 7–8) — with key relationships and effect directions, critical interaction effects, temporal dynamics across implementation stages, and alternative outcome scenarios summarised in **Appendix A**.

PRIMARY

- **PATHWAY 1: Organisational Expectations**

H1a: Organisational Expectations → AI Adoption (Direct)

H1b: Constrained by Organisational Readiness (Resource Dependency)

H1c: Expectation-Reality Gap → Employee Well-being (Negative)

- **PATHWAY 2: Organisational Readiness**

H2a: Organisational Readiness → AI Adoption (Direct)

H2b: *MEDIATED* by Performance Expectancy

H2c: *MODERATED* by Organisational AI Readiness (Culture)

- **PATHWAY 3: Leadership**

H3a: Leadership Support → AI Adoption (Direct)

H3b: *MEDIATED* by Trust in AI

H3c: *MODERATED* by Emotional Intelligence

SECONDARY

- **PATHWAY 4: Training**

H4a: Training Provision → Technology Acceptance

MEDIATED by Organisational Support

H4b: *MODERATED* by Learning Ability

- **PATHWAY 5: Stress Appraisal**

H5a: Organisational Expectations → Innovative Behaviour

MEDIATED by Stress Appraisal (Challenge vs. Hindrance)

H5b: High expectations + Hindering appraisal = REDUCED Innovation

H5c: *MODERATED* by Organisational Readiness (amplifies effects)

- **PATHWAY 6: Job Security**

H6a: AI Adoption → Employee Well-being

MEDIATED by Job Insecurity

H6b: *MODERATED* by Corporate Social Responsibility

(Strong CSR buffers negative effects)

TERTIARY

- **PATHWAY 7: Meaningful Work**

H7a: Organisational Support → Work Engagement

MEDIATED by Meaningful Work

H7b: Willingness-Use Gap reflects Meaningful Work Concerns

H7c: Knowledge workers conceal AI use when expectations conflict with identity

- **PATHWAY 8: Boundary Conditions**

H8a: Occupational Exposure moderates adoption patterns

H8b: Gender moderates innovation attribute prioritization

4. Research Methodology

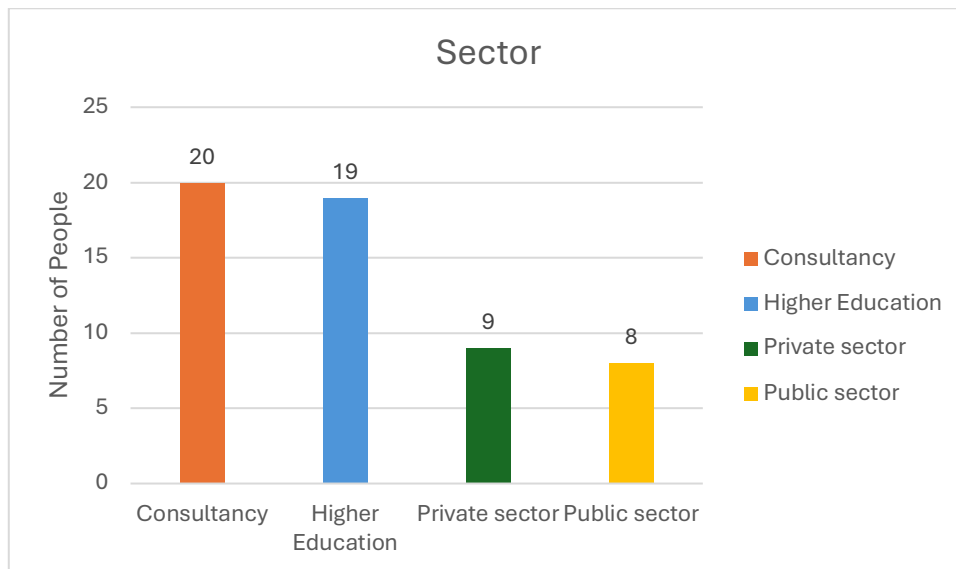
4.1 Research Design Rationale

This pilot study employs a mixed-methods convergent design in which quantitative survey data (N=56) are integrated with qualitative interview synthesis (N=3) within an empirically grounded conceptual framework. This design facilitates the parallel assessment of the feasibility of measurement instrument and the relevant theoretical validation, which is particularly suitable for investigating complex socio-technical phenomena where organisational contexts inherently shape individual adoption trajectories.

4.2 Quantitative Component

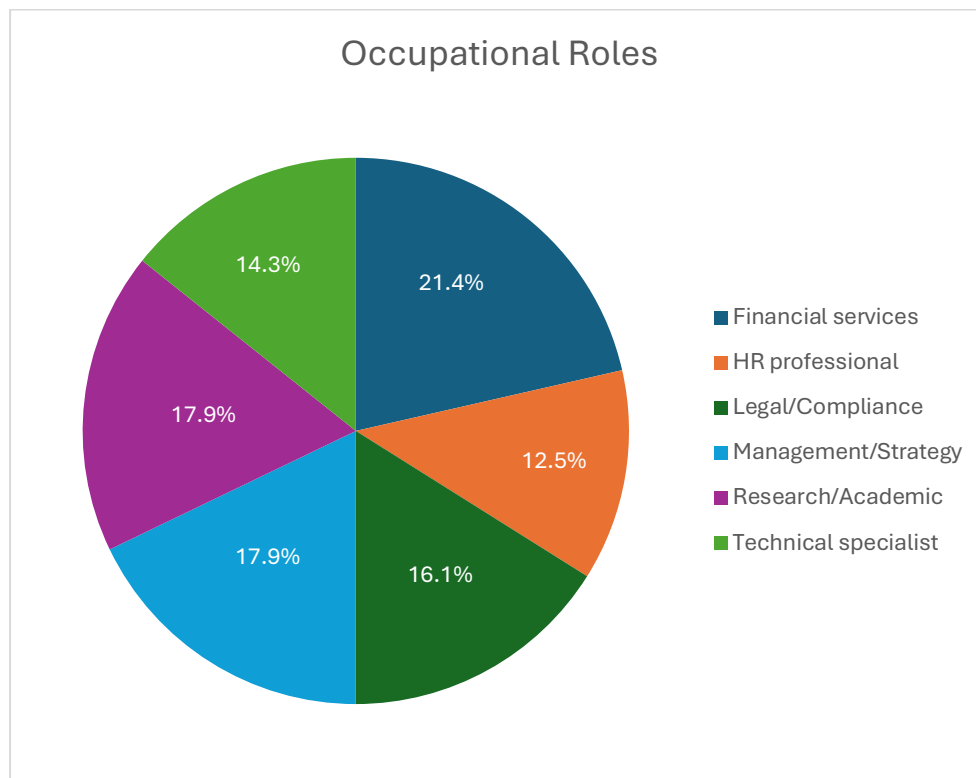
The online survey operationalises 26 variables (see Table 1) derived from an integrative framework (TAM, UTAUT, DOI, TOE, and Job Characteristics Theory). The instrument is structured into ten substantive sections—ranging from organisational expectations and readiness (5 dimensions) to leadership support and psychological mediators (job insecurity, stress appraisal). To ensure construct validity, item development was directly mapped onto these theoretical constructs. The sample comprises UK knowledge workers across the public sector (14.3%), higher education (33.9%), private sector (16.1%), and consultancy (35.7%) in Figure 1.

Figure 1: Distribution of Respondents by Professional Sector (N=56)



Occupational roles encompassed HR professionals (n=7), legal/compliance specialists (n=9), research/academics (n=10), financial services professionals (n=12), management/strategy roles (n=10), and technical specialists (n=8), as illustrated in Figure 2.

Figure 2: Distribution of Participants by Occupational Role (N=56)



As illustrated in Figure 3 and 4, **millennials are the primary drivers of the workforce, effectively replacing legacy Gen X hierarchies**, with an age distribution that leans towards the 30-49 age ranges ($M=38.05$ years, $SD=4.86$), 48.2% female representation, and minimal non-binary representation (8.9%). The cohort combines longitudinal expertise with digital fluency and a significant non-binary representation that signals a dynamic community, redefining the welcoming professionalism beyond the traditional binary and age-based institutional frameworks.

The data was collected in Q2 2026 via a secure platform shared in the Facebook community "Viet Referrals". This digital hub provided access to a geographically distributed professional cohort, thus guaranteeing international diversity. The study had a 100% completion rate among engaged respondents and adhered to institutional ethics by using informed consent and strict confidentiality.

Figure 3: Distribution of Participants by Age Range (N=56)

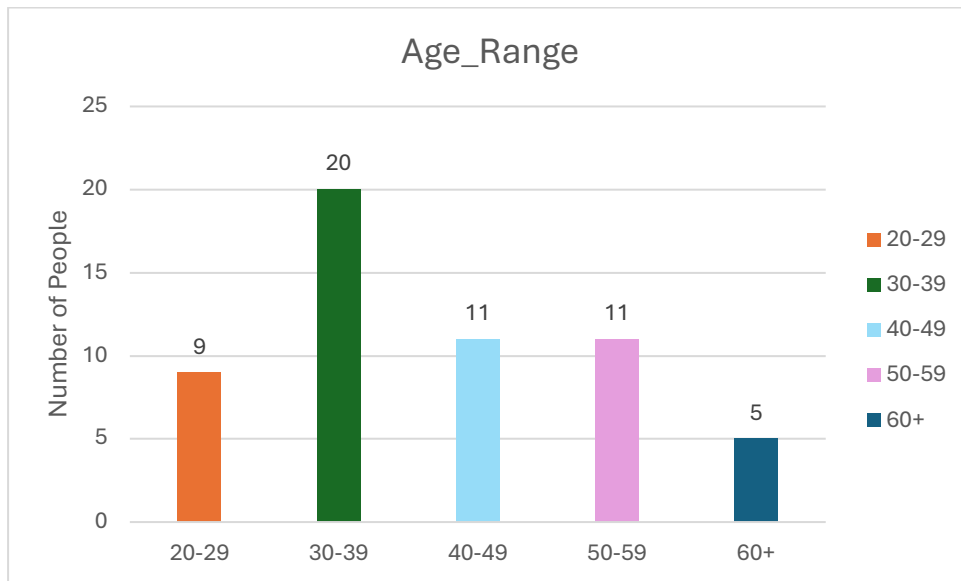
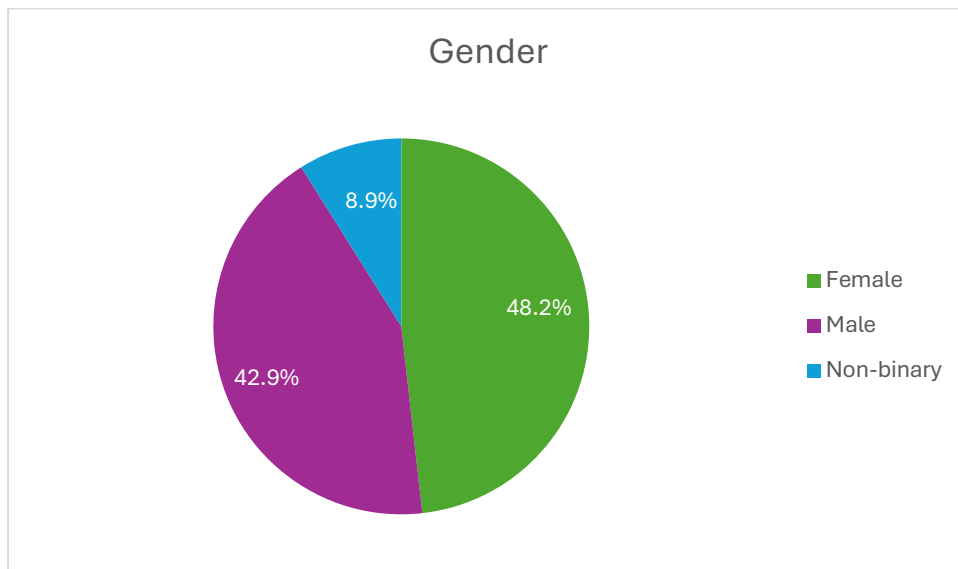


Figure 4: Distribution of Participants by Gender Identity (N=56)



4.3 Qualitative Component and Integration

Semi-structured interviews (N=3) addressed domains such as organisational expectations, support system adequacy, and professional identity implications. The participants were a legal consultant (Mohammed), a research scientist (Huy), and a financial analyst (Linh), prioritising *theoretical diversity over statistical*

representativeness. Data was analysed using thematic synthesis and mapping emergent patterns including the “productivity trap” and “meaningful work erosion” onto framework constructs. Integration occurred through systematic comparison of quantitative patterns with qualitative insights to clarify underlying causal mechanisms.

4.4 Ethical Considerations and Limitations

The analysis was careful to avoid pathologising² resistance, instead recognising concerns around AI's impact for professional identity. While the limitations include a small pilot sample size (N=56) and a cross-sectional design that prevents causal inference, they establish a robust foundation for future research.

4.5 Findings and Analysis

4.5.1 The Expectation-Readiness Gap

Pilot data reveal a critical finding that *organisational expectations significantly exceed organisational readiness capacity*. Mean expectations (M=3.59) substantially exceed mean readiness (M=2.34), yielding a robust gap of 1.25 scale points. A paired-samples t-test confirms this disparity is highly significant, $t(55) = 19.16$, p-value $(5.22 \times 10^{-26}) < .001$, with the trend persisting across all surveyed sectors, supporting the hypothesis that expectations are constrained by readiness.

Figure 5: Comparative Analysis of Mean Organisational Readiness Metrics (N=56)



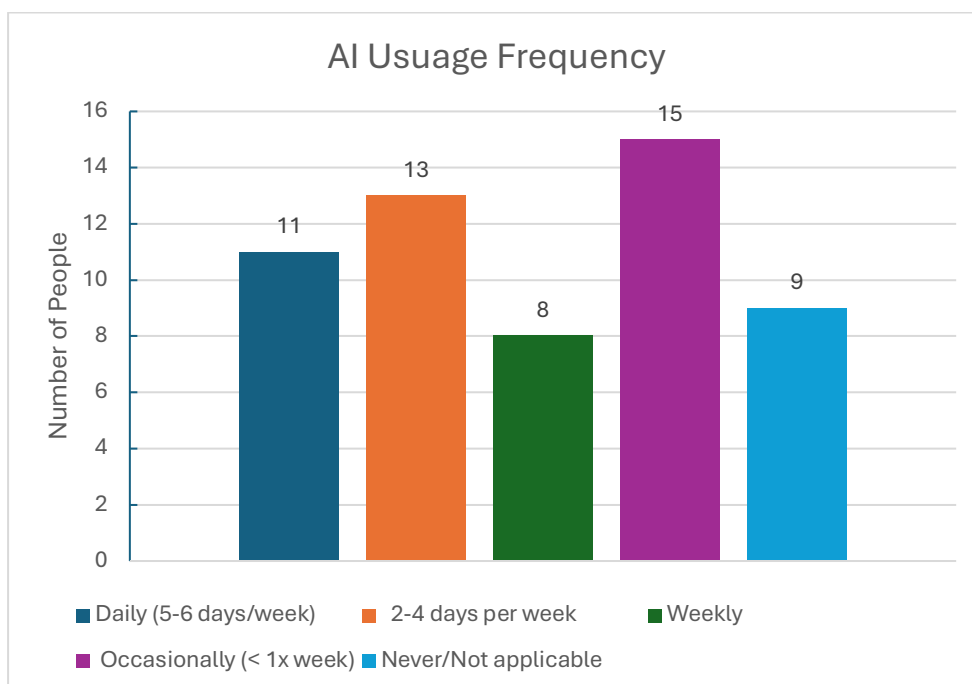
² **Pathologising** means treating a normal response as a problem or disorder.

Specifically, organisational readiness demonstrates substantial unevenness. Its variable metrics consist of the technical infrastructure (M=2.4) and cultural and psychological readiness (M=2.30) illuminate a pervasive state of implementation failure. While leadership vision (M=2.6) is marginally stronger, its position below the neutral midpoint (M=3) indicates that *strategic clarity remains insufficient to guide workers through complex transitions*. This pattern also strengthens the assertion that *technological readiness often exceeds cultural and psychological readiness* (as shown in Figure 5).

4.5.2 Adoption Behaviour and Concealment

Based on Figure 6, AI adoption demonstrates moderate prevalence, with 19.6% of respondents reporting daily use. However, adoption quality exhibits concerning patterns that 21.4% use AI for routine tasks exclusively (F3b), and 37.5% report intentionally concealing AI use from colleagues or management (F3d). *The high rate of concealment directly indicates the insufficient psychological safety and unclear governance frameworks.*

Figure 6: Distribution of Participants by Usage Frequency (N=56)



4.5.3 Employee Well-being Outcomes

Employee well-being composite ($M=2.43$) displays considerable strain, largely due to a breakdown in work-life balance ($M=1.98$). Career anxiety ($M=2.8$) is the most notable negative feeling, yet its below-neutral mean implies that *the immediate collapse of personal-professional boundaries acts as a more serious threat than the prospective fear of job displacement*. Thus, low work engagement ($M=2.5$) seems to be a physiological response to the intensification of the contemporary workload, rather than a future-oriented concern.

4.5.6 Critical Relationships: Mediation and Moderation

The Impact of Job Insecurity and Stress Appraisal

As demonstrated by Figure 7, AIA is positively associated with job insecurity, contrary to the simple models that predict only positive adoption effects. Job insecurity mediates the relationship between AIA and reduced well-being. Furthermore, adoption correlates negatively with well-being when threat appraisal is dominant but remains unrelated when challenge appraisal is present.

Protective Factors

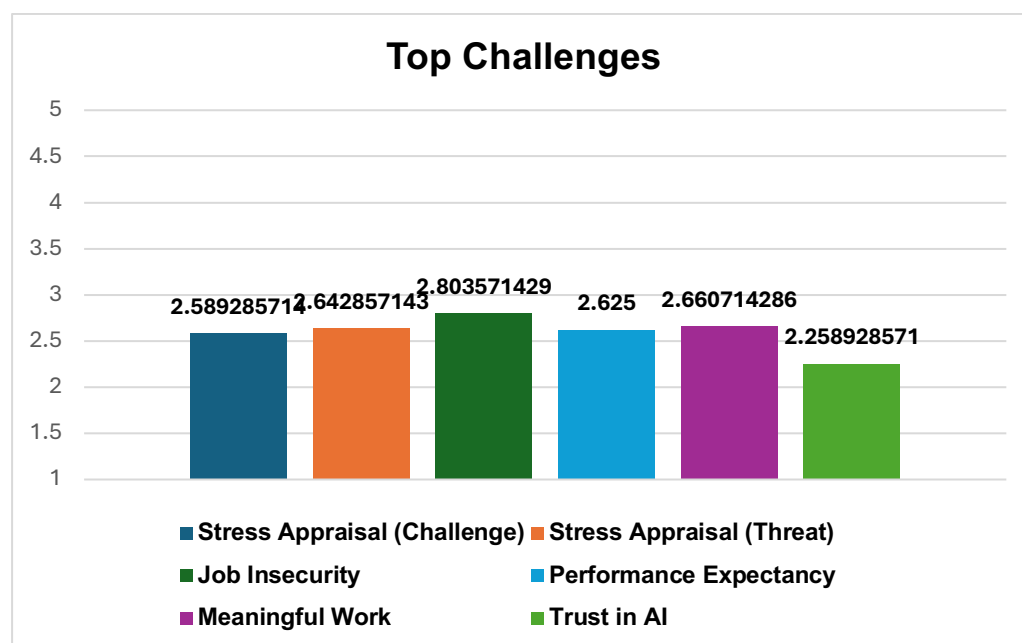
The analysis indicates that **Organisational Support ($M=2.2$)** remains low, suggesting its role as a 'buffer' against stress is currently underutilised. While leadership support influences AI adoption, this is likely constrained by insufficient **training provision ($M=2.3$)**. Furthermore, individual **Emotional Intelligence (EI) ($M=2.9$)** represents a moderate psychological baseline, rather than directly improving management, higher EI may instead help employees navigate transitions, acting as a vital asset for maintaining supportive workplace dynamics.

The Role of Meaningful Work

Meaningful work ($M=2.66$) is a vital mediator for overall well-being and satisfaction. Crucially, findings reveal that AIA often reduces perceived work meaningfulness, indicating that technological transformation may potentially erode the main reason

people find their work meaningful and valuable which is encountered by knowledge workers in their specific daily roles and responsibilities.

Figure 7: Distribution of Participants by Top Challenges (N=56)



4.5.7 Sector-Specific Patterns

Sector analysis reveals that the private sector demonstrates the highest adoption ($M=2.08$) but the lowest well-being ($M=2.42$) and highest job insecurity. Conversely, the public sector shows lower adoption but slightly higher well-being ($M=2.43$), suggesting that the flexibility in adoption is helpful for well-being. Consultancy had the highest meaningful work perception ($M=2.69$), indicating that high levels of professional autonomy and adoption flexibility allow workers to integrate AI as a supportive tool without eroding their core professional identity or expertise.

5. Discussions and Conclusions

5.1 Principal findings and gaps

This pilot study provides empirical evidence of a persistent misalignment between organisational expectations and readiness for AI adoption, resulting in tension, concealment, and reduced employee well-being. A substantial expectation–readiness gap, consistent across sectors and occupational groups, indicates structural imbalance requiring organisational recalibration. Findings further show that AI

adoption–work experience relationships are more complex than assumed in traditional technology acceptance models. Higher levels of AI use are associated with reduced perceived work meaningfulness and increased job insecurity, suggesting that adoption does not inherently improve job quality and may coincide with its deterioration.

These effects are not driven by the technology itself but by organisational context and employee interpretation. When AI is framed as an opportunity, outcomes can be constructive; when framed as a threat, it increases anxiety and reduces work meaning. Overall, the findings reject linear assumptions linking technology acceptance to positive outcomes, highlighting the decisive role of organisational readiness and psychological appraisal.

In practice, a clear gap persists between academic recommendations and organisational implementation. Despite literature emphasising culture, leadership, and governance, these remain among the weakest areas in practice. Low psychological safety, weak data governance, and unclear accountability reflect missing organisational foundations. Organisations often prioritise deployment over enabling conditions, increasing failure risk despite technical capability. Employee concealment of AI use further signals low psychological safety and misalignment between policy and practice, creating non-transparent environments that heighten isolation and stress, contrary to organisational learning theory.

5.2 Methodological contributions and limitations

The pilot confirms feasibility of a framework-driven mixed-methods design in UK knowledge workers. The survey reliably operationalises 26 variables, and interviews generate rich insights into AIA processes, with methodological convergence supporting validity. However, the study is limited by a small cross-sectional sample, preventing causal inference. Quantitative analysis was mainly conducted in Excel using descriptive statistics and partial correlations, with limited SPSS use, leaving some of the relationships underexplored. Full-scale research requires larger samples, longitudinal design, full SPSS-based analysis, and advanced modelling techniques.

5.3 Implications for future research

This pilot establishes critical reconceptualisation of AIA as organisational transformation basically separate from the ordinary technology deployment. Successful adoption, in turn, is associated with cultural change, leadership development, governance establishment, and psychological support system creation. Full-scale research must investigate (1) whether organisations can together achieve high expectations AND adequate readiness, (2) mechanisms through which meaningful work preservation moderates adoption-well-being relationships, (3) how institutional contexts (legal profession, research, civil service) differently shape adoption pathways, and (4) whether strategic career positioning represents rational adaptation or organisational failure indicator.

5.4 Conclusions

AI adoption among UK knowledge workers is fundamentally an organisational transformation challenge not just a mere technological execution. This study reveals a remarkable shortcoming in terms of expectation–readiness gap, that contributes to the diminished well-being, AI concealment widespreading, and the erosion of meaningful work. These are the outcomes of institutional choices on culture, governance and leadership.

Theoretically, the proposed socio-technical framework transcends linear models like TAM and UTAUT by integrating psychological mediators and governance structures. Practically, organisations must prioritise cultural transformation and ethical governance over performance mandates to avoid the "productivity trap".

Future research should continue to examine these pathways in longitudinal designs. At the end of the day, sustainable human–AI collaboration is not a technological inevitability, but a matter of intentional organisational choices and responsible governance.

PART 2: REFLECTIVE ACCOUNT

Topic Selection and Justification

The decision to investigate “Linking Contemporary Organisation Expectations and AI Adoption: The Case Study of UK Knowledge Workers” was due to the realisation of a critical gap within the body of academic literature and organisational practice. In my early reading, I found many academic papers exploring the determinants of AI technology readiness and adoption, but surprisingly few papers focused on the experience of knowledge workers and how workers interpret organisational expectations about AI change.

Through informal conversations with professional contacts across UK organisations, I observed consistent pattern that organisations communicating ambitious AI adoption aspirations, but frontline workers expressing substantial uncertainty and concern about these expectations. This disconnect seemed theoretically interesting and practically important.

The decision to specifically focus on UK knowledge workers reflected several considerations. First, knowledge work represents increasingly important economic sector in UK. Second, UK context reflects interesting characteristics, involving mature regulatory environment, diverse sectoral landscape, and distinctive employment law protections. Third, knowledge workers indicate particular theoretical interest as individuals with considerable existing expertise and occupational authority, they stand for a distinctive adoption challenge.

Research Purpose and Expected Impact

This research matters both practically and theoretically. In practice, for AIA to be successful in UK organisations, knowledge workers must be able to engage meaningfully with AI tools. Organisations are unable to realise their AI investments and workers experience stress and career concerns when knowledge workers engage in defensive behaviours or workarounds.

The study addresses a concrete practical question: How can UK organisations communicate expectations around AIA in ways that generate authentic worker commitment, in place of superficial compliance or resistance?

The research theoretically extends the understanding of technology adoption and organisational change. Most of the adoption literature has focused either on technology characteristics or organisational factors. This research highlights organisational expectations as an explicit mediating construct.

The project's anticipated impact spans academic, professional, and institutional domains. By examining organisational expectations as a primary determinant of technology adoption, this work will contribute significant theoretical insights to existing literature. For practitioners, it provides evidence-based guidance specifically tailored for change management professionals navigating digital transitions. Finally, the findings will inform organisational policy by directly shaping AI governance frameworks and change management protocols.

Novel Contribution

The value of clear communication is acknowledged in change management literature but there are relatively few studies that empirically assess how particular features of expectations forecast adoption readiness. This thesis explicitly considers organisational expectations as a variable.

Besides, this research centres knowledge worker perspective, explicitly, their interpretations, concerns and sense-making processes, from this, acknowledging them as active meaning-makers.

Plus, this study is specifically focused on the UK context, with its specific regulatory, sectoral and cultural characteristics, which increases practical applicability for UK organisations.

Ultimately, the quantitative readiness assessment and qualitative exploration of experience offer both breadth and depth.

Implementation Challenges and Resolution

Initially, it was difficult to recruit knowledge workers due to AI uncertainty in the organisation. The resolution focused on highlighting the necessity of confidentiality and reporting only in general; as well, recruitment should be done through professional networks to avoid the organisational gatekeepers; and greater reliance on snowball sampling.

Notably, the construct was found to be vague in the beginning. The resolution was iterative refinement, comprehending that expectations are at multiple levels and that individuals integrate multiple signals into the overall expectation interpretation .

Because the pilot study aimed to be exploratory, while remaining methodologically rigorous. The solution was to retain the rigour of the exploratory framework and to be transparent about limitations.

Concrete Immediate Applications

For HR and Change Management Professionals

Findings provide the evidence-based recommendations to inform communication strategies for AIA which can be used by organisations to communicate clearly about the role-specific expectations for AIA, commit to training provision and employ structured change management.

For Organisational Leaders

The results imply that expectation credibility plays a huge mediating role in adoption performance. Leaders can audit their AIA communications for credibility gaps and discover that transparency about real uncertainty wins over false certainty.

For Educators

Research has found high levels of interest among knowledge workers in developing AI literacy but a lack of organisational support.

For Policymakers

Research into worker anxiety about transparency, fairness and skill requirements can inform policy design.

Learning Journey

Mixed-methods research helped me understand the strengths and limitations of different methodological approaches. Quantitative surveys identify patterns in the data, while qualitative interviews provide a rich understanding of the mechanisms. Both together give a more complete picture than either alone.

Furthermore, I also acknowledge that conducting research involves ethical complexities beyond theoretical guidelines. Researchers should be prepared to manage situations in which interviewees disclose anxiety during the course of an interview. The extent to which researchers should be honest about research boundaries.

I personally think that a closer look at the literature and data confirms that organisational change is far more multifaceted than was originally thought. Simple clarifications become less plausible on closer inspection. The responses of the workers are not emotional or resistant but display a clear grasp of real uncertainty and a rational calculation of personal risk.

Qualitative interviews provide greater awareness of the nature of knowledge work. Hearing from professionals themselves about their feelings for finding themselves “less valuable” makes this insight much more tangible and vivid. Such emotional experiences cannot be captured through data or statistics alone, as quantitative measures fail to reflect lived human experience.

Next step for Research

Following the current cohort forward through actual AI applications would tell us if expectations had changed and whether predicted adoption patterns had actually occurred.

Plus, I believe that generalisation would be tested by replicating study in SME context, public sector organisations and non-English contexts.

A deeper investigation of specific psychological and social processes should be carried out to answer how do workers build trust in organisational leadership? what is the role of peer dynamics in adoption decisions?

Last but not least, future research should explore what good AIA is and how organisations should balance the wellbeing of workers with the pressure of competition.

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APPENDIX

Appendix A: Extended Framework Specifications — Key Effects, Boundary Conditions, and Temporal Dynamics

SUMMARY

KEY RELATIONSHIPS & EFFECT DIRECTIONS

- **Direct Positive Effects:** Readiness, Leadership, Support, Training
- **Curvilinear/Complex Effects:** Organisational Expectations (inverted-U relationship)
- **Indirect Positive Effects:** Through mediators (Performance Expectancy, Trust)
- **Indirect Negative Effects:** Through Job Insecurity, Stress Appraisal (Hindrances)
- **Buffering Effects:** CSR reduces negative AI adoption consequences

CRITICAL INTERACTION EFFECTS

Optimal Conditions for Positive AI Adoption

High Org. Readiness + High Leadership Support + High Emotional Intelligence = Maximum AI adoption with minimal resistance

Problematic Conditions

High Org. Expectations + Low Org. Readiness = Low Adoption + High Frustration + Worker cynicism³

Protective Conditions

AI Adoption + Strong CSR + Organisational Support = Minimal negative impacts on Employee Well-being despite Job Insecurity

Concealment Behaviours

³ Worker cynicism refers to a persistent distrustful, negative stance toward organisational motives.

High Org. Expectations + Organisational Culture Misalignment + Low Psychological Safety = Workers engage in AI concealment (hidden, covert AI use to manage expectations)

TEMPORAL DYNAMICS (Implementation Stages)

PRE-IMPLEMENTATION (Expectation Formation)

- Organisational expectations set
- Worker anxiety and anticipation high
- Stress appraisal forming (challenge vs. hindrance)

DURING IMPLEMENTATION (Learning & Adaptation)

- Training effectiveness determines early adoption
- Leadership support critical for maintaining commitment
- Initial stress appraisal may shift based on experience

POST-IMPLEMENTATION (Sustained Adoption)

- Meaningful work and trust crucial for sustained engagement
- Job insecurity perceptions may increase over time
- CSR initiatives determine long-term well-being outcomes

ALTERNATIVE OUTCOME SCENARIOS

Scenario 1: SUCCESSFUL INTEGRATION

High readiness + Clear expectations + Strong support + High CSR
→ High adoption, maintained well-being, innovation enhancement

Scenario 2: CHALLENGING ADJUSTMENT

Adequate readiness + Realistic expectations + Moderate support
→ Moderate-to-high adoption, temporary well-being dip, eventual adaptation

Scenario 3: IMPLEMENTATION FAILURE

Low readiness + Unrealistic expectations + Weak support + No CSR

→ Low adoption, significant well-being reduction, job insecurity, concealment behaviours

Scenario 4: SELECTIVE ADOPTION

Variable readiness + High occupational exposure + Worker discretion

→ High adoption in high-exposure roles, resistance in low-exposure roles

Appendix B: Online Survey Questionnaire

ONLINE SURVEY QUESTIONNAIRE

Linking Contemporary Organisational Expectations and AI Adoption: The Case Study of UK Knowledge Workers

PARTICIPANT INFORMATION & CONSENT FORM

Study Title: Linking Contemporary Organisational Expectations and AI Adoption: The Case Study of UK Knowledge Workers

Researcher: [Your Name]

Institution: [Your Institution]

Contact: [Email/Phone]

PURPOSE OF THE RESEARCH:

This study explores how organizational expectations regarding AI adoption influence knowledge workers' readiness, engagement, and performance outcomes in UK organizations. Your responses will help us understand the factors that facilitate or hinder successful AI implementation.

CONFIDENTIALITY & DATA PROTECTION:

- All responses are completely anonymous and confidential
- Data will be securely stored and encrypted
- Your responses will be used for research purposes only
- You can withdraw at any time without penalty
- Data will be retained for 3 years post-publication in accordance with GDPR

ESTIMATED TIME: 15-20 minutes

By clicking "Next" below, you consent to participate in this research and confirm that you:

- ☐ Have read and understood the information above
- ☐ Voluntarily agree to participate
- ☐ Understand your responses are confidential
- ☐ Are aged 18 or over
- ☐ Are currently employed as a knowledge worker in the UK

RESPONDENT INFORMATION & DEMOGRAPHICS

Q1. What is your occupational role?

- ☐ HR professional
- ☐ Legal/Compliance professional
- ☐ Research/Academic
- ☐ Financial services
- ☐ Management/Strategy
- ☐ Technical specialist
- ☐ Other (please specify)

Q2. Organisational sector:

- ☐ Public sector (Central/Local Government)
- ☐ Higher Education
- ☐ Private sector (Corporate)
- ☐ Consultancy
- ☐ Other

Q3. Years in current role: ____

Q4. Age range:

- ☐ 20-29

☐ 30-39

☐ 40-49

☐ 50-59

☐ 60+

J7. Gender:

☐ Male

☐ Female

☐ Non-binary

☐ Prefer not to say

Q5. Approximately how many employees does your organisation have?

☐ 1-50 (Micro)

☐ 51-250 (Small)

☐ 251-1,000 (Medium)

☐ 1,001-5,000 (Large)

☐ 5,000+ (Enterprise)

Q6. Is your organisation currently implementing or using AI technologies?

☐ Yes, actively implementing

☐ Yes, already implemented

☐ Yes, in pilot/testing phase

☐ No, but planning to

☐ No, and no plans currently

☐ Unsure

SECTION A: ORGANISATIONAL EXPECTATIONS (H1a-c)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

A1. Senior leadership expects AI adoption to reduce operational costs within 12 months

- A2. My organisation expects AI tools to increase productivity by at least 20%
- A3. Leadership expects AI implementation to enhance decision-making quality
- A4. The organisation expects rapid adoption across most knowledge work roles
- A5. Senior leaders believe AI will drive significant innovation in our sector
- A6. There is pressure to demonstrate AI adoption success within the current fiscal year

SECTION B: ORGANISATIONAL READINESS (H2a-c)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

- B1. [Technology] Our IT infrastructure is adequate for AI tool integration
- B2. [Technology] Data governance and quality management systems are in place
- B3. [Culture] Our organisational culture encourages experimentation and innovation
- B4. [Culture] There is psychological safety to admit mistakes during AI implementation
- B5. [Leadership] Senior leaders articulate a clear vision for AI's role in our work
- B6. [Leadership] Leaders actively remove barriers to AI adoption
- B7. [Skills] Staff possess foundational AI literacy
- B8. [Skills] Comprehensive training programmes are available for AI tools
- B9. [Structure] Clear policies exist regarding responsible AI use
- B10. [Structure] Accountability frameworks for AI-generated decisions are evident

SECTION C: LEADERSHIP SUPPORT (H3a-c)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

- C1. My direct manager actively supports my AI tool experimentation
- C2. Leadership provides both emotional and instrumental support for change
- C3. Leaders communicate transparently about AI implementation challenges
- C4. My manager solicits my input on AI adoption decisions
- C5. Leaders model appropriate use of AI tools in their own work
- C6. Communication about AI adoption is frequent and bidirectional

SECTION D: TRAINING PROVISION (H4a-b)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

- D1. Pre-implementation training was provided before AI tool deployment
- D2. Training addressed both technical skills and ethical use
- D3. On-the-job support is available during implementation
- D4. Training depth matches actual job requirements
- D5. Trainers are credible and possess strong AI knowledge
- D6. Continuous learning opportunities exist post-implementation

SECTION E: ORGANISATIONAL SUPPORT (H7a-c)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

- E1. Technical support is responsive and competent
- E2. There are established communities of practice for peer support
- E3. The organisation provides mental health support during technological change
- E4. Job redesign has enhanced autonomy and meaning in my work
- E5. Resources are adequate for successful AI implementation
- E6. Feedback systems enable continuous improvement

SECTION F: AI ADOPTION (H1a-c, H2a-c, H3a-c)

F1. How frequently do you use AI tools in your work?

- a) Daily (5-6 days/week)
- b) 2-4 days per week
- c) Weekly
- d) Occasionally (< 1x week)
- e) Never/Not applicable

F2. How many different AI applications do you use regularly? (0 / 1 / 2-3 / 4+)

F3. Rate your agreement (1=Strongly Disagree → 5=Strongly Agree):

- F3a. I use AI tools for strategic/high-stakes tasks
- F3b. I use AI tools for routine information processing
- F3c. I have discontinued use of AI tools
- F3d. I intentionally conceal my AI use from colleagues/management

SECTION G: PSYCHOLOGICAL MEDIATORS (H5a-H5c, H6a, H6b, H2b, H7a, H3b)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

- G1. [Stress Appraisal - Challenge] Learning AI systems represents an exciting opportunity
- G2. [Stress Appraisal - Threat] I am anxious about job displacement due to AI
- G3. [Job Insecurity] AI threatens my current job security
- G4. [Job Insecurity] My skills may become obsolete
- G5. [Performance Expectancy] AI tools will improve my work performance
- G6. [Meaningful Work] My work has clear purpose and significance
- G7. [Trust in AI] I trust AI systems to provide reliable outputs
- G8. [Trust in AI] AI decision-making processes are transparent

SECTION H: WELL-BEING OUTCOMES (H6a, H6b)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

- H1. [Job Satisfaction] Overall, I am satisfied with my current role
- H2. [Engagement] I am engaged and absorbed in my work
- H3. [Burnout] I feel emotionally exhausted by work demands
- H4. [Anxiety] I experience work-related anxiety
- H5. [Organisational Commitment] I intend to remain with this organisation
- H6. [Work-Life Balance] I maintain healthy work-life balance
- H7. [Career Anxiety] I am concerned about my career prospects

SECTION I. INNOVATIVE BEHAVIOUR (H1c, H5a-c)

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

- I1. I actively seek opportunities to apply AI tools to improve my work
- I2. I contribute ideas for how AI could benefit our team/organisation
- I3. I am willing to experiment with new AI applications

I4. I encourage colleagues to adopt and use AI tools

SECTION J: MODERATING & BOUNDARY VARIABLES

J1. How would you rate your emotional intelligence?

(1=Low → 5=High)

J2. How adaptable are you to technological change?

(1=Not adaptable → 5=Highly adaptable)

J3. [Occupational Exposure] How exposed is your role to AI?

(1=Minimal exposure → 5=Extensive exposure)

J4. Prior technology adoption experience?

(1=Minimal → 5=Extensive)

Corporate Social Responsibility

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

J5a. Responsible AI practices are clearly established in my organisation

J5b. I trust that my organisation will protect data security with AI systems

J5c. I understand how ethical guidelines apply to AI use in my organisation

Organisational AI Readiness

Rate your agreement (1=Strongly Disagree → 5=Strongly Agree)

J6a. My organisation treats AI innovation as a top strategic priority

J6b. My organisation follows a clear long-term digital roadmap

OPEN-ENDED REFLECTIVE QUESTION

J9. What is your primary concern regarding AI adoption in your organisation?

[Text box - max 200 words]

THANK YOU

Thank you for completing this survey. Your responses are invaluable to our research on AI adoption in UK organizations.

Your feedback will directly contribute to:

- ✓ Understanding organizational expectations around AI
- ✓ Identifying key success factors for AI implementation
- ✓ Developing practical recommendations for organizations
- ✓ Shaping future digital transformation strategies

If you have any questions about this research or your rights as a participant, please contact:

[Researcher Name]

[Email]

[Phone]

[Institution]

CONFIDENTIALITY REMINDER: All your responses are anonymous and will be kept strictly confidential in accordance with GDPR and institutional data protection policies.

Survey ID: [Auto-generated for tracking purposes]

Submission Date: [Auto-populated]