

LINKING THE CONTEMPORARY ORGANISATION EXPECTATIONS AND AI ADOPTION: THE CASE STUDY OF UK KNOWLEDGE WORKERS

Student Name: Nguyen Ngoc Quynh Tran

Student ID: 2433797

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List of Abbreviations

CLR	Critical Literature Review
LLM	Large Language Models
MPM	Managerial Productivity Mandate
GenAI	Generative AI
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PCT	Psychological Contract Theory
PIJT	Professional Identity and Jurisdictional Threat
PCB	Psychological Contract Breach
STS	Sociotechnical Systems (Theory)
AIA	AI Adoption
UKRF	UK Regulatory Frameworks
SRA	Solicitors Regulation Authority
FCA	Financial Conduct Authority
KM	Knowledge Management

PART 1 – CRITICAL FOUNDATION

Keywords: Generative AI Adoption, UK Knowledge Workers, Professional Jurisdiction, Psychological Contract Breach, Managerial Productivity Mandate, Sociotechnical Systems, Shadow AI

1.1 Introduction

This Critical Literature Review (CLR) investigate the complex disagreement between modern organisational expectations and GenAI adoption among knowledge workers in the UK. The rapidly increasing expansion of Large Language Models (LLM) has provoked an epistemological disruption, revealing a "paradigm crisis" wherein deterministic frameworks clash with AI's probabilistic nature (Amoore et al., 2024; Atf et al., 2025; Zönnchen et al., 2025). This investigation goes against the commonly accepted discourses of managerial productivity mandate (MPM), defining it not as an empirical reality but as an ideological construct that threatens professional jurisdiction and the psychological contract (Rousseau, 1989; Spring et al., 2022; Goto, 2023). By synthesising evidence across five thematic dimensions, the CLR unmask a pervasive "rigour gap", being characterised by the inadequate level of "methodological myopia" and "geographical parochialism" as UK private sector contexts remain empirically (Bright et al., 2024). Ultimately, this analysis lays the theoretical framework for a mediated-moderation model, presenting workers as reflexive practitioners working through a "Gordian knot" of unresolved tensions between efficiency and professional autonomy (Sohail et al., 2025).

1.2 CLR Process

1.2.1 Search Strategy

A systematic literature search was conducted across the main database: Google Scholar (585 results), using a master Boolean string and yielding 100 unique papers (Section 2.2 + Appendix A) after deduplication. A comprehensive audit trail of this screening funnel is documented in Appendix B.

The search period is from January 2019 to April 2026 that was specifically chosen to capture the evolution from pre-programmed sequences (pre-2023) to the disruptive,

"hallucination-prone" ¹landscape of AI (post-2023), testing whether traditional theoretical frameworks remain valid in the era of LLM.

1.2.2 PRISMA Process Description: Search Strategy and Inclusion/Exclusion Criteria

A four-tier classification system was deployed to screen 100 papers, as follows:

Tier 1: Highly Relevant (n=24)

Inclusion criteria:

- The high-skill knowledge workers (e.g., product managers, consultants) are specially targeted over general users.
- Provides empirical evidence on Abbottian professional jurisdiction or psychological contract breaches (e.g., expertise commoditization).
- Focuses on GenAI as a collaborative/generative agent (e.g., Yodeai synthesis²) rather than linear workflows.
- Prioritises in-situ field ³experiments and ethnographic ⁴observations of the real-world behavioural shifts.

Tier 2: Partially Relevant (n=33)

Inclusion criteria:

- Examines relevant sub-domains (e.g., science organisations) but only give indirect results about autonomy.

¹ "**Hallucination-prone**" refers to AI systems tending to make outputs that sound plausible but are not true or made up.

² **Yodeai synthesis** refers to a sociotechnical framework positioning AI as an active, non-linear collaborator that generates novel outputs rather than merely automating routine tasks.

³ **In-situ field experiments** are the controlled tests conducted within a participant's actual, everyday work environment (e.g., a corporate office) rather than a laboratory to capture authentic behavioural and performance data.

⁴ **Ethnographic observations** is a qualitative method involving the systematic, long-term observation of workers in their natural setting to understand the social dynamics, habits, and cultural nuances of how they interact with technology.

- High-quality empirical data from non-UK or non-corporate settings where sociotechnical connections are not primary.
- Focuses on general efficiency/workflow changes without deep diving into the cultural and social tensions of professional status.

Tier 3: Excluded — Contextual Drift (n=19)

Exclusion criteria:

- Data derived from non-professional contexts (e.g., nursing, radiology, K-12 education) with different institutional autonomy.
- Focuses on the hidden dangers of AI in healthcare that do not fit with organisational productivity mandates.
- Stays at the policy and regulatory level without providing micro-level data on how workers are adopting or resisting it.

Tier 4: Excluded — Methodological/Theoretical Weakness (n = 23)

Exclusion criteria:

- Relies on crowdsourced workers (e.g., MTurk⁵) or student samples performing artificial tasks that do not have any practical values.
- Purely conceptual frameworks (e.g., Matching Theory⁶) or opinion pieces that have not been tested.
- Studies exhibiting severe common method bias, descriptive-only analysis, or statistically inadequate sample sizes.

The four-tier classification system serves not only as a screening instrument but also as a meta-level evaluation of the existing study landscape. Tier 1 is the "gold standard" for context-specific, Abbottian-inspired research (Abbott, 1988), but few exist (n=24), which elucidates a substantial "rigour gap" in the field. The dominance of Tier 2 and

⁵ **MTurk** (Amazon Mechanical Turk) is a crowdsourcing marketplace where you can hire people from all over the world to do small tasks for you.

⁶ **Matching Theory** is an economic framework that explains how two groups find and connect with each other based on how well their specific needs and traits align.

the exclusion of Tier 4 evidence imply a structurally weak empirical base supporting productivity claims.

This classification methodically eliminates the 23% of papers in Tier 4, which are dominated by artificial samples and speculative opinion, revealing a debate founded on speculation rather than professional reality. Plus, most of the Tier 2 evidence, which prioritises general productivity over social issues surrounding professional autonomy (Necula et al., 2024), confirms that the prevailing "AI = productivity" narrative is often upheld by methodological reductionism (Spring et al., 2022). Ultimately, this tiering system points out a field in theoretical stagnation, where the strongest claims are based on the weakest evidence.

1.2.3 Data Extraction and Synthesis

From the 25 Tier 1 papers, data were extracted based on core findings, theoretical lens, methodology, and relevance to the study (Section 2.1). Despite having a high relevance score (93/100), Clarke and Joffe's (2025) study was removed at this level. This ethnographic investigation gave useful insights into workflow reconfiguration in creative agencies, but the findings on autonomy effects were perceived as too irrelevant to the study's primary research topics. Ultimately, the final papers for critical synthesis were refined to **24 papers**. A narrative synthesis approach was adopted, with the findings organised thematically around the three research gaps identified in Section 2.2.

1.2.4 Limitations of the Search Strategy

Three constraints are recognised. First, the bias towards the **English language** might exclude relevant non-English research; however, this risk is mitigated by the review's UK focus, where English-language publications take the lead in professional and academic discussions. Secondly, **publication bias** that prefers positive outcomes over null results or implementation failures may distort the body of literature to support the favourable narratives of AI adoption; this concern is analytically addressed by the review's critical perspective, which rigorously scrutinises productivity hypotheses rather than merely accepting them uncritically. Third, the temporal indexing delay suggests that papers published after mid-2025 may not receive adequate indexing, leading to a recency gap. None of these constraints directly challenge this CLR's

conclusions, due to broad database coverage and the explicit acceptance of grey literature (arXiv preprints, UK government reports, and professional body guidance documents).

PART 2 — ANNOTATED BIBLIOGRAPHY

2.1 Annotated by theme

The annotated bibliography comprises 24 Tier 1 publications, identified through the PRISMA-informed screening protocol (Section 1.3.2). These entries are organised into 5 distinct themes in the correlation with the core literature review (Part 3), facilitating an analytical interrogation of the extant literature. To ensure transparency: the remaining 76 publications from the 100-paper corpus are investigated in Appendix A, which outlines their relevance score and rationale for their inclusion/exclusion.

Citation	Key arguments	Theoretical lens	Methodology	Key findings	Critical evaluation	Relevance to the study
Theme 1: The Managerial Productivity Mandate as Ideological Construct						
Spring, M., Faulconbridge, J. R., & Sarwar, A. (2022). How information technology automates and augments processes: Insights from artificial-intelligence-based systems in professional service operations. <i>Journal of Operations Management</i> . https://doi.org/10.1002/jom.1215	Adopting AI driven by productivity mandate (speed, efficiency, optimisation).	Automation / Augmentation ⁷	Descriptive synthesis of AI implementation	AI enhances efficiency via workflow integration and automation.	it's ideological and reductionist as it ignores deskilling, work intensification, and losing professional control.	Explains tension between efficiency pressures and professional autonomy in UK knowledge work.

⁷ *Automation vs augmentation* explain how AI either replaces or supports human tasks in professional services.

Dell’Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Kraye, L., Candelon, F., & Lakhani, K. R. (n.d.). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. <i>Social Science Research Network</i>. https://doi.org/10.2139/ssrn.4573321	AI creates a “jagged frontier” (uneven performance gains/losses).	Technological Determinism⁸	<i>Field experiment (758 consultants at BCG)</i>	AI boosts speed/producti vity; reduces accuracy beyond capability limits.	High causal validity, but results depend on <i>task selection and may not apply to all types of knowledge work</i>.	The effects of AI on productivity are non- linear, and potentially risky, challenging AI efficiency claims.

⁸ **Technological Determinism** frames AI as *uneven and context-dependent*, requiring human judgment to decide when to rely on it.

(RQ1)						
Necula, S.-C., Fotache, D., & Rieder, E. (2024). Assessing the Impact of Artificial Intelligence Tools on Employee Productivity: Insights from a Comprehensive Survey Analysis. <i>Electronics</i>, 13(18), 3758. https://doi.org/10.3390/electronics13183758 (RQ1)	AI embedded in workflows increases employee productivity, with effects moderated by demographics and training	Managerial Productivity Perspective⁹	Survey (233 employees) with ML analysis	AI usage and integration significantly improve productivity	Self-report and cross-sectional limits causality and realism	Foundational “productivity mandate” baseline for critiquing AI efficiency assumptions

⁹ A **Managerial Productivity Perspective** refers to treating AI as a tool for efficiency and performance optimisation.

Theme 2: Professional Identity, Jurisdiction, and the Abbottian Threat						
Abbott, A. (1988). <i>The system of professions: An essay on the division of expert labour</i> . University of Chicago Press. (RQ3)	Professions compete for task control (<i>jurisdictional</i> ¹⁰ battles)	A Sociology of Professions ¹¹ / Jurisdictional Theory ¹²	<i>Theoretical and historical analysis</i>	Technological shocks disrupt jurisdictions and redistribute control.	Overgeneralised , weak empirical grounding	Frames AI as a driver of shifting roles and interactions among UK knowledge workers
Jussupow, E., Spohrer, K., & Heinzl, A. (2022). Identity Threats as a Reason for Resistance to	AI resistance arises from perceived threats to	Professional Identify & Jurisdictional Threat ¹³	Quantitative survey (454 medical professionals)	Identity threat increases resistance; effects vary by	Strong causal modelling but domain-limited (healthcare) and	Demonstrate s adoption barriers driven by

¹⁰ **Jurisdictional** refers to the recognised right of a specific group to own certain tasks and exclude others from doing them.

¹¹ **A Sociology of Professions** explains how occupational groups gain, defend, and maintain expert status.

¹² **Jurisdictional Theory** explains how professions compete for control over work domains as technology and institutions change.

¹³ **A Professional Identify & Jurisdictional Threat Framework** explains how AI causes resistance when it challenges an expert's sense of self or invades their exclusive domain of work.

Artificial Intelligence: Survey Study With Medical Students and Professionals. <i>JMIR Formative Research</i> , 6(3), e28750. https://doi.org/10.2196/28750 (RQ1)	professional identity, status, and autonomy, moderated by experience and perceived AI timing			experience and AI timing perceptions	individual-level focus	identity conflict beyond productivity considerations
Goto, M. (2023). Anticipatory innovation of professional services: The case of auditing and artificial intelligence. <i>Research Policy</i> , 52(8), 104828. https://doi.org/10.1016/j.respol.2023.104828 (RQ3)	AI adoption is a deliberate, staged organisational strategy that reshapes services and professional roles	Organisational strategy / Service Innovation	Longitudinal case study (Big 4 audit firms)	AI innovation firms utilise centralised R&D, phased experimentation, and role/skill restructuring	Strong process detail but narrow (audit only) and ignores worker resistance	AI adoption is political and managerial, redefining control, roles, and professional boundaries
Chen, Y., Stavropoulou, C., Stavropoulou, C., Narasinkan, R., Baker,	AI reinforces hierarchy automates	Interprofessional Heterogeneity	<i>Qualitative study</i>	High-status professionals embrace AI;	Rich identity/jurisdictional nuance but	The uneven AI impacts across UK

A., & Scarbrough, H. (2021). Professionals' responses to the introduction of AI innovations in radiology and their implications for future adoption: a qualitative study. <i>BMC Health Services Research</i> , 21(1), 813. https://doi.org/10.1186/S12913-021-06861-Y (RQ2)	low-status tasks, augments high-status ones	y ¹⁴ / Status Threat ¹⁵	(Radiologists ¹⁶ vs Radiographers ¹⁷)	low-status ones perceive threat, widening inequality	limited to medicine	knowledge work hierarchies
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¹⁴ **Interprofessional heterogeneity** reflects that different professional groups react differently to the same change.

¹⁵ **Status-based identity threat/opportunity** indicates that *lower-status roles feel replaced, higher-status roles feel enhanced*.

¹⁶ **Radiologists** are *medical specialists who interpret scans and make diagnostic decisions*.

¹⁷ **Radiographers** are *technicians who operate imaging equipment and produce the scans*.

Ritala, P., Ruokonen, M., & Ramaul, L. (2023). Transforming boundaries: How does ChatGPT change knowledge work? <i>Journal of Business Strategy</i> , 45(3), 214–220. https://doi.org/10.1108/JS-05-2023-0094	ChatGPT blurs expert/non-expert boundaries	Boundary transformation / Jurisdictional Shift ¹⁸	<i>Conceptual analysis</i>	AI democratises expert knowledge	<i>Speculative and lacks empirical grounding</i>	Indicates jurisdictional erosion relevant to UK knowledge work
Kobiella, C., López, Y., Draxler, F., & Schmidt, A. (2024). “If the Machine Is As Good As Me, Then What Use Am I?” -- How the Use of ChatGPT Changes Young Professionals’ Perception	AI increases productivity but lower feelings of accomplishment and self-worth.	Lived Experienced / Meaning of Work	<i>Qualitative study (young professionals)</i>	Adopting AI leads to lower perceived achievement and increased fears of replaceability.	Offers deep psychological insight but is restricted to individual-level effects.	How productivity gains can paradoxically erode professional identity and motivation in

¹⁸ **Boundary transformation** refers to how AI redefines who performs specific tasks and where the "lines" between different roles or expertise are drawn.

of Productivity and Accomplishment. https://doi.org/10.48550/arxiv.2404.12549 (RQ1)						knowledge work.
Theme 3: Psychological Contract Theory in the Age of Algorithmic Management						
Rousseau, D. M. (1989). Psychological and implied contracts in organizations. <i>Employee Responsibilities and Rights Journal</i> , 2(2), 121–139. https://doi.org/10.1007/BF01384942 (RQ2)	Work relationships rely on perceived mutual obligations.	Psychological Contract Theory (PCT) ¹⁹	Conceptual synthesis of employment constructs	Perceived breach reduces commitment, trust, and discretionary effort.	Strong foundational model but subjective, hard to measure	Explain how AI can disrupt psychological contracts in knowledge work

¹⁹ *Psychological Contract Theory* refers to the unwritten, subjective expectations and mutual obligations between an employee and employer.

Bankins, S., & Formosa, P. (2020). When AI meets PC: exploring the implications of workplace social robots and a human-robot psychological contract. <i>European Journal of Work and Organizational Psychology</i>, 29(2), 215–229. https://doi.org/10.1080/1359432X.2019.1620328 (RQ2)	AI can become <i>psychological contract partners</i>, shifting work relationships beyond human–human exchange.	Extended PCT (Human–AI)²⁰	<i>Thought experiment and literature synthesis</i>	AI is seen as an active relational agent, reshaping obligations, expectations, reciprocity²¹	Highly theoretical, speculative, <i>no empirical validation and unclear how it would work in practice.</i>	Basis for analysing AI-driven shifts in psychological contracts in knowledge work.
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²⁰ **Human-AI** focus on reciprocity in socio-technical systems.

²¹ **Reciprocity** refers to the mutual exchange of value where both parties respond to each other's actions with similar benefits or obligations.

Bankins, S., & Formosa, P. (2021). <i>Ethical AI at work: the social contract for Artificial Intelligence and its implications for the workplace psychological contract</i> (pp. 55–72). Springer, Springer Nature. https://doi.org/10.1007/978-3-030-63864-1_4v (RQ2)	AI breaches psychological contracts via ethical violations.	PCT & Ethical Principles ²²	<i>Conceptual framework</i>	Low transparency and reduced autonomy <i>take away people's trust and commitment.</i>	The model is <i>untested empirically</i> , relying on normative assumptions.	Links ethical AI design to perceived contract breach in work settings.
Zhang, L.-X., Li, J.-M., Liu, K.-X., Zhang, D., Zhang, L.-X., Li, J.-M., Liu, K.-X., & Zhang, D.	Algorithmic ²³ control reshapes workplace	PCT (Fairness focus)	<i>Three-wave longitudinal survey (328 gig workers)</i>	Algorithmic guidance builds trust; while	Methodologically strong, but <i>not applicable</i>	AI can shift work from <i>trust-based to control-</i>

²² **Ethical Principles** (e.g., autonomy, justice, transparency, beneficence).

²³ **Algorithmic** refers to using *step-by-step computer rules to make decisions or control tasks automatically instead of a human.*

(2025). How Does Algorithmic Control Affect the Work Engagement of Gig Workers? The Role of Perceived Algorithmic Fairness and Psychological Contract. <i>Asia Pacific Journal of Human Resources</i> , 64(1). https://doi.org/10.1111/1744-7941.70045	relationships based on perceived fairness.			monitoring and constraints damage trust unless they are perceived as fair.	<i>beyond gig work.</i>	<i>based relationships</i> .
Monod, E. (2025). Robots as Managers? Organizational Justice, Power Asymmetries, and the Future of AI	Algorithmic supervision erodes trust, leading to compliance	Organisational Justice / Algorithmic	Critical commentary	Monitoring triggers <i>technostress</i> ²⁵ , and <i>silent</i>	Standard performance metrics miss psychological effects	Illuminates how algorithmic control break psychological

²⁵ **Technostress** is caused by using or being constantly monitored by technology, especially when it increases pressure, complexity, or constant oversight beyond human comfort.

Supervision. <i>Management Research Quarterly</i> , 2(1), 41–49. https://doi.org/10.63029/rqg5z883	without commitment, and psychological withdraw.	Management ²⁴		<i>disengagement</i>		I contracts in knowledge work
Manuti, A., & Monachino, D. (2020). <i>Managing knowledge at the time of artificial intelligence: An explorative study with knowledge workers</i> . 7(2), 179–190. https://doi.org/10.29038/EJPL.2020.7.2.MAN (RQ2)	<i>AI defines knowledge management (KM) and worker expectations</i>	Psychological Contract Theory.	<i>Exploratory qualitative study</i>	The shifts of role and organisational relationship demand new KM approaches	<i>Weak empirical rigour, pre-GenAI, no longitudinal depth</i>	Early signals for <i>empirical gap</i> around AI-caused contract breach

²⁴ *Organisational justice and algorithmic management* focus on power asymmetry and erosion of psychological contracts.

Theme 4: Sociotechnical Systems Theory - Validity and Invalidity in the AI Era

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting: An examination of the psychological situation and defences of a work group in relation to the social structure and technological content of the work system. <i>Human Relations</i> , 4(1), 3–38. https://doi.org/10.1177/001872675100400101 (RQ4)	Joint optimisation of social and technical systems is required to keep performance and well-being high	Sociotechnical Systems (STS) ²⁶	Empirical case study (Coal mining)	Technical efficiency gains can erode cohesion, autonomy, and psychological stability if social systems are not aligned.	Developed for <i>stable, predictable technologies</i> , but not for AI's complexity and ambiguity.	Baseline for analysing AI-induced sociotechnical misalignment in UK organisations.
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²⁶ *Sociotechnical Systems Theory (STS)* explains how changes in technology affect the way people work and the way they think about work.

Retkowsky, J., Hafermalz, E., & Huysman, M. (2024). Managing a ChatGPT- empowered workforce: Understanding its affordances and side effects. <i>Business Horizons</i> . https://doi.org/10.1016/j.bushor.2024.04.009 (RQ4)	AI spreads from the bottom up that undermine the productivity gain assumptions	Organisation al Affordances	Qualitative interview (50 participants)	Using AI can impair team collaboration, knowledge quality; increase role ambiguity, and Shadow AI ²⁷ use	<i>The sample is small, but it maps to UK governance and accountability problems</i>	Describes governance gaps and knowledge practice failures
Xia, Q. N., Constantinides, M., Sarkar, A., Brumby, D., & Cox, A. (2026). <i>“If you’re very clever, no one knows you’ve used it”</i> :	Workers conceal AI application to protect status that hurts	STS (<i>Transparenc y/Participatio n</i>)	<i>Ethnographic study</i>	Using AI without telling anyone else is a status incentive, driving	Shadow AI is a systemic governance failure	Directly maps to hidden use & collective learning loss in UK

²⁷ **Shadow AI** is the unauthorized use of artificial intelligence tools by employees without the knowledge or approval of their IT department.

<i>The social dynamics of developing generative AI literacy in the workplace.</i> arXiv. https://doi.org/10.48550/arXiv.2602.01386 (RQ4)	organisational learning			knowledge-sharing breakdown		knowledge work
Vats, V., Nizam, M. B., Liu, M., Wang, Z., Ho, R., Prasad, M. S., Titterton, V., Maleddy, S. V., Aggarwal, R., Xu, Y., Ding, L., Mehta, J., Grinnell, N., Liu, L., Zhong, S., Gandamani, D. N., Tang, X., Ghosalkar, R., Shen, C.,	<i>Effective human–AI teaming requires trust, shared mental models & role clarity</i>	Human–AI Teaming (Deterministic -system bias). ²⁸	<i>Literature survey</i>	Consolidates teaming constructs but applies deterministic frameworks to probabilistic <i>LLMs</i> ²⁹	<i>Theoretical extension is needed</i>	Highlights gap demanding new frameworks for unclear, error-prone AI

²⁸ **Human–AI teaming (deterministic-system bias)** means treating AI as if it always acts in the same way, even though modern AI can be unpredictable and inconsistent

²⁹ **LLMs** (Large Language Models) are AI systems generating human-like text based on patterns learned from large amounts of data.

... Davis, J. (2024). A Survey on Human-AI Teaming with Large Pre-Trained Models. <i>arXiv.Org</i>, <i>abs/2403.04931</i>. https://doi.org/10.48550/arxiv.2403.04931						
Yun, B., Feng, D., Chen, A. S., Nikzad, A., & Salehi, N. (2025). <i>Generative AI in knowledge work: Design implications for data navigation and decision-making</i>. arXiv. https://doi.org/10.48550/arXiv.2503.18419 (RQ4)	GenAI demands control, transparency.	Updated STS Theory	Conceptual design study	Knowledge integration should be the core design principles.	It is untested but frames governance gaps	AI design in UK knowledge work

Theme 5: The UK Knowledge Work Context - Sectoral Gaps and Regulatory Gaps						
Bright, J., Enock, F., Esnaashari, S., Francis, J., Hashem, Y., & Morgan, D. (2024). Generative AI is already widespread in the public sector: evidence from a survey of UK public sector professionals. <i>Digital Government</i> . https://doi.org/10.1145/3700140 (RQ4)	AI is widely deployed in the UK public sector without clear governance or oversight	Efficiency and Accountability	<i>Cross-sectional survey (1,008 public sector employees in the UK)</i>	Perceived time savings and high usage coexist with weak guidance and hidden/unsanctioned use	Snapshot design; excludes identity/relationship effects; limited to public sector	Indicates governance gaps and unregulated AI adoption in UK public institutions
Institute of Chartered Accountants in England and Wales. (2020). <i>Artificial intelligence and</i>	AI in accounting requires ethics,	Professional Governance	Regulatory / Ethical guidance	Prioritises accountability	Aspirational, non-enforceable, lacks	Highlights UK governance

<i>the future of accountancy</i> . ICAEW. (RQ3, RQ4)	<i>transparency, human oversight</i>				implementation detail	principles-practice gap
Solicitors Regulation Authority. (2019). <i>Guidance on the use of technology in legal services</i> . SRA. (RQ3, RQ4)	Solicitors retain full liability for AI-assisted work	Professional Regulation / Jurisdictional Control. ³⁰	<i>Regulatory guidance</i>	Regulatory guidance mandates competence, oversight and ethical responsibility	Vague, unenforceable, lacks implementation detail	Exposes UK legal profession's AI governance gap
UK Government. (2023). <i>A pro-innovation approach to AI regulation</i> . Department for Science,	Supports AI regulation that is based on principles, <i>light-touch</i> ³¹ ,	Principles-based / Decentralised Governance.	<i>Policy/white paper</i>	Delegates to sector regulators; flexibility over strict rules	Creates governance vacuum meaning weak enforcement	Defines institutional gap driving Shadow AI adoption

³⁰ **Jurisdictional control** refers to the ability of a profession to define and regulate who is allowed to do specific work and how it must be done.

³¹ **Light-touch** refers to minimal strict rules, relying on broad principles rather than detailed or heavy regulation.

Innovation and Technology. (RQ3)	<i>and pro-innovation.</i> ³²					
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Table 1: Annotated Bibliographic Summary of the Literature

³² **Pro-innovation** means *favouring policies that encourage new technology development and adoption rather than restricting it.*

2.2 Gap matrix

Types	Explanations
Mechanism Gap	Extant research frequently omits the concrete sociotechnical pathways explaining how and why AI reconfigures workflows and performance.
Casual Gap	Reliance on cross-sectional data prevents establishing longitudinal causality of AI impacts (Acosta-Enriquez et al., 2025; Hawsawi & Alanizan, 2025; Riandhi et al., 2025).
Multi-level Gap	Existing frameworks are theoretically forced to connect micro-meso, and macro levels.

Table 2: A Gap Matrix

The prior research on adopting AI encounters significant mechanistic, causal, and multi-level shortcomings.

Mechanistically, existing research is a superficial cover-up of unproven theoretical experiments that selectively aligned to be able to provide insight into the specific "how" and "why" of labour transformation. To be specific, the correlational metrics are deployed and unable to explain the actual mechanisms of interaction between humans and technology (sociotechnical), ignoring how vague algorithms, undocumented "Shadow AI," and shifting jurisdictional boundaries that affects performance (Kudina & Poel, 2024; Silic et al., 2025; Aghazadeh et al., 2026).

Casually, the field is stagnant because of substantial methodological and temporal myopia when it depends too much on cross-sectional snapshots and biased, self-reported managerial beliefs. In that way, it does not have the long-term rigour needed to demonstrate the apparent impacts involving skill atrophy (Rinta-Kahila et al., 2023; Budiyo, 2025) or breaches of the psychological contract (Griep et al., 2021; Griep et al., 2025).

Also, these studies are institutionally blind as the current frameworks are geographically restricted by ignoring UK-specific regulatory realities, unable to bridge the gap between micro-level identity risks, meso-level governance discrepancies, and macro-level professional reshaping (Davda et al., 2022). Ultimately, the published material provides an analytically shallow argument. This is the reason why it is extremely important to replace the aspirational assumptions for the reliable, unified, and ongoing empirical evidence, aiming to comprehending AI's genuine consequences (Bojić, 2024; Jacob et al., 2024; Casper et al., 2025).

PART 3 — CORE LITERATURE REVIEW

3.1 Introduction

This CLR sets out a critical synthesis of the existing literature investigating the relationship between contemporary organisational expectations and AI adoption among knowledge workers in the UK. Prompted by the epistemological disruption having its root in key features of AI, this research thus examines the ongoing relevance of predetermined theoretical frameworks in probabilistic technological contexts. The CLR addressed a theoretical issue due to the absence of a multi-level explanatory framework connecting management ideology, AI implementation, and professional outcomes within institutionally regulated environments. To clarify this, the following analysis is methodically grouped into five thematic dimensions. By dissolving down these connected contradictions, the hidden tensions between the demand for managers to be efficient and the need for professionals to be autonomous are highlighted by the CLR. As a result, it lays the strong theoretical groundwork supporting the suggested mediated-moderation conceptual model and carefully fill in the obvious gaps in the data.

3.2 Conceptual Framing and Thematic Analysis

3.2.1 Theme 1: The Managerial Productivity Mandate as Ideological Construct

Spring et al. (2022), Goto. (2023), and Necula et al. (2024) confirmed that **the Managerial Productivity Mandate (MPM)** is not a scientifically verified concept; instead, it functions as an operational mechanism that enables management to justify extensive interference in employee's work processes. This mechanism simultaneously obscures negative consequences such as AI-induced **work intensification (MPM6)**

(Kobiella et al., 2024). It exemplifies coercive organisational expectations, in which performance-driven logic is normalised, prioritising algorithmic surveillance over professional autonomy.

Grounded in an “outcome reductionism” mindset, this mandate reduces diverse and complex professional activities to purely quantitative metrics, such as task **throughput (MPM1)**, **completion time (MPM2)**, and **short-term output quality ratings (MPM3)**. The application of these metrics is often justified from a managerial perspective; for instance, AI increases work speed by 25.1% and task completion rates by 12.2% (Dell’Acqua et al., n.d.). However, deeper analysis reveals that these indicators reflect a form of temporal myopia, capturing only short-term productivity peaks while overlooking the gradual erosion of professional expertise and the silent decline of skill atrophy resulting from prolonged technological dependence (Aquino et al., 2022; Morandini et al., 2023; Natali et al., 2025).

Also, the existing evaluations of AI adoption often rely on **self-reported productivity data (MPM4)**, which is highly susceptible to social desirability bias in environments that frame AI as strategically indispensable. Consequently, assessing the **ideological framing (MPM5)** is necessary to understand the systemic pressure placed on employees to prioritize task throughput over professional jurisdiction. If this managerial mandate accelerates work pace while simultaneously eroding intrinsic motivation and professional recognition, the concept of a “**net organisational benefit**” (MPM6) (Kobiella et al., 2024) becomes analytically hollow. This unresolved tension between managerial performance demands and professional craft values is further compounded by methodological myopia (Parent-Rochelleau & Parker, 2021; Bankins & Formosa, 2023), as current cross-sectional designs fail to capture the unpredictable nature of AI (Civaner et al., 2022; Weidener & Fischer, 2024). Ultimately, resolving this “Gordian knot” requires a paradigmatic shift away from narrow productivity quantification toward multidimensional evaluative frameworks that fully account for the psychosocial and jurisdictional costs of automated work.

3.2.2 Theme 2: Professional Identity, Jurisdiction, and the Abbottian Threat

Each profession possesses its own exclusive “jurisdiction” over which it claims control. Abbott (1988)’s the sociological theory of the professions serves the primary theoretical framework for understanding AI as an external shock that disrupts and challenges that jurisdiction (Cox, 2022; Scarbrough et al., 2024). However, a critical evaluation of the existing literature uncovers a widespread phenomenon of theoretical superficiality, in which constructs like **Professional Identity and Jurisdictional Threat (PIJT)** are referenced without clear explanation of their practical operation. This can be termed the “**Abbottian Void**,” where scholarship needs to be theoretically extended to specify the concrete mechanisms through which AI adoption reshapes professional boundaries at the individual (micro), organisational (meso), and societal (macro) levels (Criado et al., 2024; Alam, 2025; Deckenbrunnen et al., 2026).

Based on Jussupow et al. (2022), a central dimension of this threat concerns **professional recognition and capabilities (PIJT1)**. Research implies that perceived threats to recognition provoke direct opposition to AI; nevertheless, these studies typically rely on a narrow psychological lens, neglecting broader jurisdictional dynamics. This limitation is thus intensified by a “**crisis of accomplishment**” (**PIJT3**) (Kobiella et al., 2024), a subjective state in which AI-assisted achievement diminishes practitioners’ self-esteem and devalues their unique expertise. The proposed metrics are required to measure the socio-emotional costs that come with the productivity mandate; specifically, algorithmic augmentation can paradoxically erode professionals’ sense of ownership over their work (Kinowska & Sienkiewicz, 2022; Edwards et al., 2024).

As stated by Chen et al. (2021), **task replacement (PIJT2)** has different results in different trials. Evidence from professional domains such as radiology indicates that AI may intensify status inequality by automating tasks performed by lower-status roles while enhancing the capabilities of elite positions. Precisely, AI may replace radiology technicians while enabling senior physicians to make faster decisions, which would provide more power to those at the top. This demonstrates how micro-level problems can facilitate managerial structures taking over at the organisational level, which is called a **jurisdictional power grab (PIJT4)** (Goto, 2023). In practice, within auditing firms, the centralisation of AI innovation in corporate R&D units has shifted technological control away from individual practitioners, eroding the basis of professional autonomy. Rather than letting auditors determine how to accomplish their

jobs; firms mandate the implementation of proprietary AI systems (MPM); reflecting that management and engineers, not domain experts, oversee making decisions.

More importantly, these jurisdictional battlefields are regulated by **UK Regulatory Frameworks (UKRF)**. Yet the literature remains limited by a kind of geographical parochialism (Bright et al., 2024), either overly generalised or disproportionately focused on the United States, with incompletely aligned engagement with the UK context. Consequently, there exists a notable deficiency of empirical information on how specific legal constraints or **professional governance structures (UKRF3)** (Solicitors Regulation Authority, 2019) regulate these threats.

In conclusion, future doctoral research must transcend surface-level description to engage dialectically with the institutional conflicts that arise from AI-driven invasions into professional jurisdictions.

3.2.3 Theme 3: Psychological Contract Theory in the Age of Algorithmic Management

Alongside formal legal texts, the relationship between managers and employees is also shaped by tacit agreements. Drawing on Denise Rousseau's Psychological Contract Theory (1989, 1995), the employment relationship is not purely an economic exchange but is also grounded in implicit expectations of psychological and socio-emotional dimensions.

A close reading of the current literature elucidates that the rapid deployment of AI is often implemented as a form of "unilateral organisational action" without employee consultation (Fenwick et al., 2024; Haipeter et al., 2024). This process directly disrupts implicit agreements concerning autonomy and mutual trust. However, contemporary research faces a form of "theoretical stagnation", characterised by a lack of empirical evidence demonstrating **Psychological Contract Breach (PCB)** in professional knowledge work contexts (Qiao et al., 2023; Botha & Steyn, 2023; Faizan et al., 2025; Pyhäjärvi & Söderberg, 2024).

Following Zhang et al. (2025), the core issue lies in the **relational violations (PCB-R)** and a shift toward **transactional breaches (PCB-T)**. This can be explained by AI's capacity to commodify labour and reduce human discretion, thereby transforming long-

term socio-emotional interactions into short-term economic transactions. As opposed to evaluating overall effort and sustained contribution, algorithms tend to quantify performance in real time for compensation and evaluation purposes (Basnet, 2024; Liao et al., 2024). MPM also further intensifies this transformation, which creates ideological pressure that destabilises expectations even prior to full AI implementation.

Plus, the application of **Algorithmic Control (PCB-A)** includes standardised workflows, continuous monitoring, and behavioural constraints that functions as a key mechanism destroying organisational trust. The outcome is “**Compliance without Commitment**” (**PCB-O**), as observed by Monod (2025), capturing how digital surveillance replaces genuine trust with mere outward adherence, masking employees’ psychological withdrawal. It is when procedural requirements and deadlines are still met, workers gradually lose engagement and become more willing to exit the organisation (Sypniewska et al., 2023; Zhang et al., 2022).

This latent rupture is a consequence often missed by traditional productivity metrics (MPM1–3), thereby producing an illusion of organisational stability. In the UK context, these dynamics are additionally moderated by UKRF and professional standards that emphasise procedural fairness and “professional voice” (Institute of Chartered Accountants in England and Wales, 2020; Solicitors Regulation Authority, 2019; UK Government, 2023). As such, the lack of UK-specific empirical studies on whether professionals perceive AI adoption as a breach on autonomy represents a significant knowledge gap.

In sum, the psychological contract should be understood as a “space of conflict,” where managerial imperatives risk generating durable relational breakdowns. Future research should therefore prioritise multi-level research designs and temporal causality explaining how AI reshapes identity and contracts over time.

3.2.4 Theme 4: Sociotechnical Systems Theory - Validity and Invalidity in the AI Era

Sociotechnical Systems Theory (STS), with its core principle of “joint optimization” between the social system and the technical system, is currently facing a foundational crisis in the face of the rise of GenAI (Naikar & Brady, n.d.; Xu & Gao, n.d.). While

traditional STS emphasises the harmonious coordination between human labour and technology, the characteristics of modern GenAI have produced theoretical ruptures. Pre-2023 academic frameworks typically relied on the assumption that technology have stable properties and that the boundaries of automation are predictable (Trist & Bamforth, 1951; Vats et al., 2024). However, the emergence of Large Language Models (LLMs), with probability-based returns and the phenomenon of “emergent hallucinations,” has systematically violated these assumptions. This theoretical stagnation results in a lack of explanatory arguments for AI’s unpredictable performance boundaries where efficiency variability renders traditional quality assurance methods and shared mental models infeasible (Dell’Acqua et al., n.d.).

The meditation of **AI adoption (AIA)** is clearly differentiated through **Collaboration Patterns (AIA2)**, notably the emergence of “Centaur” and “Cyborgs” (Dell’Acqua et al., n.d.). The “Centaur” model enforces a clear division of tasks between human and machine, whereas the “Cyborg” model represents organic integration, interweaving human cognition and algorithmic processes at each stage of work. However, this classification still lacks a rigorous grounding in STS principles and often obscures the erosion of the social system’s capacity for trust calibration (Kuipers, 2022; Zou, 2021). In practice, the absence of standards for determining when to trust AI has led to an internal organisational trust crisis (Bedué & Fritzsche, 2021; Kaur et al., 2022).

As argued by Nikzad et al. (2025), Xia et al. (2026), Necula et al. (2024), Retkowsky et al. (2024), and Bright et al. (2024), analysing **Tool Integration Frequency (AIA1)** and **AI Use Transparency (AIA4)** are essential to identify conceptual gaps in organisational design. Without transparent governance frameworks, the “joint optimisation” is replaced by ad hoc and individualised adoption, thereby undermining collective standards. The inevitable effect is the rise of “**Shadow AI**” or **Hidden Use (AIA3)**. This metric reflects a fundamental tension in which professionals tend to erase traces of AI-generated contributions to validate their domain expertise, directly reducing **Knowledge Sharing Frequency (AIA5)** and hindering collective learning.

The social drivers behind concealing adopting AI directly contradict the participatory design principle of STS, triggering quality degradation and a condition of “diffusion of responsibility”. When errors occur, the lack of transparency in the initial process

renders accountability ambiguous. Ultimately, the adequacy of STS is severely undermined by the “black box” nature of AI where a system is ambiguous even to its own developers, making the requirement for meaningful human participation in system design nearly impossible to operationalise.

In sum, quantifying measures of AIA3 and AIA5 is a prerequisite for clarifying how organisational decisions shape the non-linear division of cognitive labour. Without a systemic redefinition that incorporates the probabilistic and emergent characteristics of technology, STS will be partially misaligned to guide UK knowledge workers - reflexive practitioners through the complexities of the algorithmic workplace.

3.2.5 Theme 5: The UK Knowledge Work Context - Sectoral Gaps and Regulatory Gaps

Despite the high volume of empirical research on AI adoption within Silicon Valley, there remains a critical scholarship gap regarding the strategic responses of UK-based private-sector knowledge industries, particularly within London’s financial and legal sectors. This gap produces a form of “data invisibility”, reinforcing the biased assumption that technological similarity generates uniform implementation, overlooking the decisive influence of *institutionally moderated causal evidence linking regulation, AI adoption, and professional outcomes*. Consequently, US-centric findings often lack practical applicability in the UK market where legal and financial services operate under strict constraints of professional accountability and legal liability (Hajj Hammoud, n.d.).

As stated by Institute of Chartered Accountants in England and Wales (2020), Solicitors Regulation Authority (2019), and UK Government (2023), to address this knowledge gap, integrating **Statutory Competence Standards (UKRF1)** into the research framework is essential. These standards, established by regulatory bodies such as the Solicitors Regulation Authority (SRA), the Financial Conduct Authority (FCA), and the Institute of Chartered Accountants in England and Wales (ICAEW), function as regulatory mechanisms that force MPM to align with professional practice rules. However, the reality highlights a “regulatory lacuna”; for example, the SRA’s 2019 guidance emphasises accountability but is short of practical instructions on how to assess the reliability of AI tools (Magesh et al., 2025).

Furthermore, research frameworks must adequately consider the role of **Professional Indemnity Insurance (UKRF2)**. This is matter because liability limits and insurance requirements in the UK create substantial financial barriers to AIA, and it is often neglected in performance-focused US studies (Bertolini & Episcopo, 2021). The UK context is also characterised by **Partnership Governance Structures (UKRF3)** (Abbott, 1988). Unlike corporate hierarchies, the autonomy of partners allows them to directly shape or resist AIA, producing a distinct governance dynamic (Greenwood & Empson, 2003; Armour & Sako, 2020).

Methodological limitations in the current research landscape are evidenced by data proving that 61% of UK professionals operate within a “governance vacuum,” meaning the short of any organisational guidance on AIA (Bright et al., 2024). Despite this, empirical evidence on **Enforcement Actions (UKRF4)**, in other words, how regulatory sanctions determine firm-level practices (Ishwardat et al., 2024; Preble & Early, n.d.) which remains underdeveloped.

In short, AIA is a process governed more by accountability structures and professional ideologies than by purely technical characteristics. Without situating research within specific industry contexts where professionals must balance legal compliance with competitive pressures, the literature stay practically irrelevant for UK knowledge workers. Future studies subsequently must prioritise these institutional specificities to overcome theoretical stagnation and establish a context-sensitive foundation for AI governance in the UK.

3.3 Synthesis

This CLR argues that the tensions are not merely research gaps but also highlight a pressing need to expand traditional theoretical frameworks and rigorously analyse ideological biases in the existing literature. These tensions are analysed across five core dimensions as follows:

Tension 1 (T1): Productivity Imperatives versus Professional Autonomy (RQ1)

People always say that adopting AI is necessary for increasing productivity, yet this view puts administrative goals like efficiency, intensity, and cost-cutting into action while slowly eroding professional autonomy and craftsmanship. Empirical data indicates that productivity enhancements are restricted based on tightly specified

tasks, not consistent over time, and come at the cost of intrinsic motivation and professional significance (Kobiella et al., 2024). The matter is not measurement error; rather, it lies in the incompatibility of the managerial logic (prioritising cost and speed) and professional logic (appreciating quality and expert standards).

Tension 2 (T2): Technological Determinism versus Social Construction (RQ4)

The literature is divided between saying that AI is an essential factor influencing how well a company does and calling organisational entities the key players that drive technology adoption. Uneven AI capabilities imply limitation and determinism, while forecasting innovation research illustrates the strategic organisational shaping of AI deployment. The absence of a coherent co-evolutionary framework leaves this tension unresolved.

Tension 3 (T3): Individual Perceptions versus Collective Outcomes (RQ2)

Research focuses micro-level constructs like identity threat and psychological contract breach but struggles to explain how these translate into collective organisational outcomes, including widespread disengagement, reduced cohesion, or even organisational decline. In other words, a strong link between micro-level emotional reactions to macro-level structural effects plays an irreplaceable part of the literature.

Tension 4 (T4): Pre-2023 Frameworks versus Post-2023 Realities (RQ4)

Pre-2023 AI frameworks originating from predictable architecture are applied to systems characterised by likelihood-based conclusions, emergent hallucinations, and unstable capability boundaries. This gives rise to conceptual misalignment where core assumptions of transparency, predictability, and explicit contractual exchange are no longer considered to be analytically valid.

Tension 5 (T5): Global Generalisations versus Local Specificities (RQ3)

There is a lot of evidence, most of it from the US, yet it is still seen as universal even though there are clear differences in how different countries regulate things, how professional are governed, and how employment relations work. UK professional contexts are still missing, which allow for wrong generalisations about how AI being employed.

3.4 Conceptual Framework

This conceptual framework adopts a mediated-moderation model that explicitly rejects the reductionist functionalist paradigm of a linear "AI-equals-productivity" causality.

Component	Variables	Key Theoretical Lens	Variable Metric/Indicator	Research Question (RQ) + Tension Alignment	Scale
Independent Variable (IV)	Managerial Productivity Mandate (Contemporary Organisation Expectations) (MPM)	Managerial Logic / Ideology (Necula et al., 2024; Spring et al., 2022; Goto, 2023)	• Task Throughput (Task Count) (MPM1) • Completion Time (Speed) (MPM2) • Output Quality Ratings (MPM3) • Self-Reported Productivity (MPM4) • Ideological Framing (MPM5) • Work Intensification (MPM6)	RQ 1 / T1	7-point Likert scale
Mediating Process (M)	AI Adoption (AIA)	Sociotechnical Systems	• Tool Integration Frequency (AIA1) • Collaboration Patterns (AIA2) • Hidden Use (Shadow AI) (AIA3)	RQ4 / T2 & T4	7-point Likert scale

		(Trist & Bamforth, 1951; Vats et al., 2024; Nikzad et al., 2025)	• AI Use Transparency (AIA4) • Knowledge Sharing Frequency (AIA5)		
Dependent Variable 1 (DV1)	Professional Identity & Jurisdictional Threat (PIJT)	Abbottian Sociology (Abbott, 1988)	• Recognition and Capabilities (PIJT1) • Task Replacement (PIJT 2) • Crisis of Accomplishment (PIJT3) • Jurisdictional Power Grab (PIJT4) • Boundary Dissolution (PIJT5)	RQ3 / T5	7-point Likert scale
Dependent Variable 2 (DV2)	Psychological Contract Breach (PCB)	Rousseau's Contract Theory (Rousseau, 1989; Rousseau, 1995)	• Relational Violation (PCB-R) • Transactional Breach (PCB-T) • Algorithmic Control (PCB-A) • Compliance without Commitment (PCB-O)	RQ2 / T3	7-point Likert scale

Moderator (MOD)	UK Regulatory Frameworks (SRA, FCA, etc.) (UKRF)	Institutional Theory (Institute of Chartered Accountants in England and Wales, 2020; Solicitors Regulation Authority, 2019; UK Government, 2023)	• Statutory Competence Standards (UKRF1) • Professional Indemnity Insurance (UKRF2) • Partnership Governance Structures (UKRF3) • Enforcement Actions (UKRF4)	RQ3 (also inform RQ5) / T5	7-point Likert scale
All variables	MPM / AIA / PIJT / PCB / UKRF	Integrative/Theoretical	• MPM 1 – MPM6 • AIA1 – AIA5 • PIJT1 – PIJT5 • PCB-R / PCB-T / PCB-A / PCB-O • UKRF1 – UKRF4	RQ5 / Synthesis of Tensions	7-point Likert scale

Table 3: Conceptual Framework

Direct effects

- MPM → AIA (Hypothesis 1)
- AIA → PIJT (Hypothesis 2)
- AIA → PCB → PCB-R / PCB-T (Hypothesis 3)

The theoretical framework considers AI adoption (AIA) as an ideologically influenced process within an organisation instead of an objective technology adoption. It does not fundamentally support the practical beliefs that come with productivity-centric explanations. Instead, the managerial productivity mandate (MPM) is positioned as a governing ideology that sets the expectation for today's organisation, justifies keeping an eye on employees, and make sense of the efficiency-oriented management. MPM is not an external factor, but it is a critical paradigm reflecting the perceived necessary and nature of AIA, resulting in a forceful atmosphere where technological acceptance is seen as inevitable.

Adopting AI is the main way that managerial perspective is converted into sociotechnical restructuring. This mediation, however, is not unbiased. Based on sociotechnical systems theory, we can see that AIA is unstable, inconsistent, and context-sensitive, which means it has various effects on different professionals. Thus, it clearly disagrees with fixed-logic ideas by seeing AIA as a process that is up for debate and is identified by ambiguous capabilities, organisational interpretation, and execution methods, not by fixed technological features.

The subsequent effects of AIA are hypothesised through two distinct but essentially interconnected outcomes. First, according to Abbottian sociology, professional identity and jurisdictional threat (PIJT) demonstrates how AI breaks down professional boundaries, makes expert knowledge less valuable, and moves jurisdictional power from human professionals to algorithmic systems. Second, psychological contract breach (PCB), which comes from Rousseau's framework, is categorised into two parts: relational (PCB-R) and transactional (PCB-T) dimensions to include both economic and social violations that happen when job expectations change, people have less autonomy, and performance standards shift.

Anticipatory Effects

- MPM → PIJT (Hypothesis 4)
- MPM → PCB (Hypothesis 5)

The model also further reveals that MPM has direct effects on both PIJT and PCB. This is explained by ideological pressures which can alter how people see themselves and what they expect, even if AI isn't fully implemented.

Moderation effects

- UKRF × (MPM → AIA) (Hypothesis 6)
- UKRF × (AIA → PIJT) (Hypothesis 7)
- UKRF × (AIA → PCB) (Hypothesis 8)

The UK regulatory frameworks (UKRF), including the SRA, FCA, and ICAEW, establish the institutional framework by moderating important relationships. Regulation has been described as both a passive restriction and an active structuring mechanism, facilitating the translation of managerial mandates into AIA and the realisation of AI effects in identity and psychological contract outcomes. Specifically, UKRF moderates the interactions between MPM and AIA, AIA and PIJT, and AIA and PCB by setting standards for accountability, professional autonomy, and acceptable levels of technology integration.

The Core Archetype

Ideology (MPM) drives **Technology (AIA)**, which mediates **Outcomes (PIJT/PCB)**, all of which are moderated by **Institutions (UKRF)**.

Overall, the theory presents a multi-layered causal framework wherein managerial ideology, AI implementation, profession, and institution come together to generate non-linear organisational consequences (as shown in Figure 1).

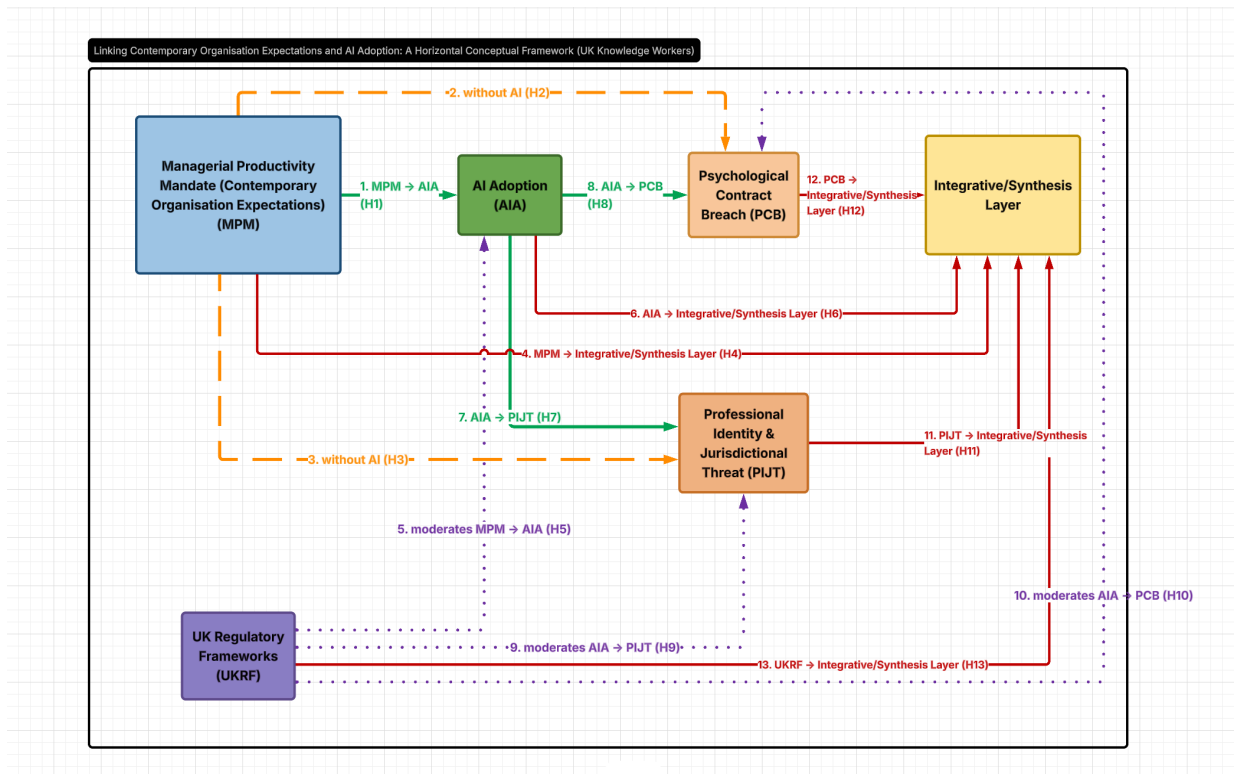


Figure 1: Concept Mapping

3.6 Research Questions

RQ1 (Core Mechanism)

How does the managerial framing of AI as a productivity imperative shape AI adoption behaviours and professional responses among UK knowledge workers?

RQ2 (Psychological Mechanism)

Under what conditions does AI adoption lead to psychological contract breach among UK knowledge workers, and how do different implementation approaches mitigate or intensify these effects over time?

RQ3 (Institutional Layer)

How do UK regulatory and professional governance frameworks shape AI adoption and influence the redistribution of professional jurisdiction in knowledge-intensive sectors?

RQ4 (Sociotechnical Mechanism)

What organisational governance and sociotechnical design mechanisms most effectively align AI adoption with knowledge quality, transparency, and collaborative learning in UK organisations?

RQ5 (Integrative / Theoretical)

How do managerial ideology, sociotechnical implementation, and institutional regulation interact to produce divergent AI adoption outcomes in UK knowledge work?

3.6 Theoretical Contribution

The theoretical contribution of this thesis is to prove that AI adoption is not just a linear method to improve productivity, but a complicated social, technical, and institutional issue, more precisely, a multi-layered reframing of AI adoption.

Micro-level: Identity & Contract Disruption

The study exposes the limitations of traditional Psychological Contract Theory. The reason behind is that in algorithmic contexts, the strict "right/wrong" are no longer adhered, alternatively, there is an existence of a system that is consistently modifying and adapting, moving the model from static expectations to a dynamic, constantly renegotiated system. Corresponding to a "crisis of accomplishment," AI-performed tasks diminish professional self-worth and devalue the unique human contributions. This is also concluded in an "Abbottian Void," which is a state of "compliance without commitment" where identity threat provokes professionals to prioritise external adherence over genuine organisational trust.

Meso-level: Organisational AI Governance

Firstly, the research proves that traditional Sociotechnical Systems theory is required for a theoretical extension because AI's unpredictable returns and asymmetric task performance challenge the hypothesis that technical attributes are predictable. Secondly, the thesis proposes new sociotechnical principles centred on knowledge integration under uncertainty. Thirdly, it not only discusses the hidden use of AI to preserve domain authority and but also changes the way that deployment is observed by calling it as a proactive restructuring where firms leverage the centralised R&D to strategically refine professional roles and control.

Macro-level: UK Institutional Regulation

The UK institutional environment is stated as "theoretically constitutive" in lieu of just being a setting. Regulatory bodies function as the adaptive structuring facilitators, controlling adoption paths by means of competency guidelines and indemnity insurance. The study, however, also reflects a "governance vacuum" and "regulatory lacunae³³" the root cause inadequate levels of accountability.

3.7 Managerial Implications

The findings call for a substantial modification in how businesses perceive employing AI. To avoid narrowing in on "productivity mandates," they ought to pursue a more comprehensive sociotechnical strategy. Management must acknowledge that top-down, efficiency-driven commands frequently stimulate jurisdictional pushback and damage psychological contracts among knowledge workers. It is therefore essential to develop governance frameworks that promote professional autonomy and transparency to reduce the potential risks associated with "shadow AI" and the erosion of expertise. Far from interpreting AI as just a way to make job duties harder, professionals should encourage "joint optimisation," which specifies that algorithmic augmentation should strengthen, not replace, key professional identities. Apart from that, resolving the "Gordian knot" of implementation relies on a development of distinctive ethical boundaries and accountability frameworks that safeguard professional authority. Organisations can close the gap between expected efficiency advantages and real organisational achievements by fostering a culture of perceived fairness and shared learning. All of this allows them to achieve long-term integration in the UK's complicated professional services sector.

3.8 Conclusion

In conclusion, a significant distinction has been highlighted by this CLR reflecting the fixed managerial imperatives versus the probability-based truth that comes with utilisation of AI. The thematic synthesis subsequently points out that neither conventional sociotechnical frameworks nor current psychological contract theories properly tackle both the complex jurisdictional risks and ideological pressures that are

³³ **Regulatory lacunae** refer to a situation where no applicable law or specific guidance exists to govern a particular issue.

encountered by UK knowledge workers. In the end, the main theory-based obstacle persists since a multi-level model clarifying how managerial beliefs, AI execution, and professional impacts which are associated with institutional contexts has been missing. The author once reinforces the importance for the future mediated-moderation model to address these inconsistencies by revealing the mechanism, casual and multi-level gap.

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Appendix A: Annotated Bibliographic

Full string:

("AI adoption" OR "generative AI" OR "large language model") AND ("knowledge worker" OR "professional services" OR "knowledge work") AND ("trust" OR "explainability" OR "transparency") AND ("professional identity" OR "psychological contract" OR "occupational identity") AND ("productivity" OR "decision quality" OR "sociotechnical")

- **Cluster 1 (Core Mechanism):** Trust, Explainability, Governance, Collaboration, Autonomy, and Adoption.
- **Cluster 2 (Behavioural/Perception):** Identity, Psychological contract, and Resistance.
- **Cluster 3 (Outcome):** Productivity, Creativity, and Decision quality.
- **Cluster 4 (Organizational/System):** Transformation and Sociotechnical systems.
- **Cluster 5 (Domain-specific):** IT, HR, and creative knowledge work

Theme	Citation	Relevance Score	Reasoning
CORE MECHANISM			

Trust, Explainability & Governance	Ehsan, U., Passi, S., Saha, K., McNutt, T., Riedl, M. O., & Alcorn, S. (2026). <i>From future of work to future of workers: Addressing asymptomatic AI harms for dignified human-AI interaction.</i> arXiv. https://arxiv.org/abs/2601.21920v1	Low Relevance (33/100)	While it uses a longitudinal study to reveal skill erosion and autonomy loss, it focuses on healthcare specialists and lacks an explicit focus on generative AI and detailed trust analysis.
	Luther, T., Kimmerle, J., & Cress, U. (2024). <i>Teaming up with an AI: Exploring human–AI collaboration in a writing scenario with ChatGPT.</i> AI, 5(3), 1357–1376. https://doi.org/10.3390/ai5030065 (mdpi.com)	Low Relevance (11/100)	This study analyses trust in co-writing with ChatGPT but is limited to lab-based data; it lacks a specific professional workplace context, deep sociotechnical analysis, and a focus on professional autonomy.
	Gibbard, K., Gill, H., Powell, D., & Hausdorf, P. A. (2025). <i>Explain it to me like I'm five: Harnessing the power of explanations to increase</i>	Low Relevance (11/100)	Although it examines trust and explanations in workplace AI, it lacks a focus on autonomy changes and does not provide deep sociotechnical analysis or

	<i>trust in workplace generative AI. Behaviour & Information Technology.</i> https://doi.org/10.1080/0144929X.2025.2506664		extensive field data.
	Fox, N. (2025). <i>Protecting human dignity and meaningful work in the age of AI: A social autonomy framework for ethical decision making in the workplace.</i> Bates College Honors Theses. https://scarab.bates.edu/honorstheses/496/	Low Relevance (11/100)	This thesis uses a social autonomy framework to examine dignity and ethics, but it is categorized as low relevance due to a lack of detailed transformation analysis and original empirical field data.
	Kereopa-Yorke, B. (2025). <i>Engineering trust, creating vulnerability: A socio-technical analysis of AI interface design.</i> arXiv.	Low Relevance (7/100)	This research focuses on the sociotechnical analysis of AI interfaces and trust mechanisms but lacks a workplace focus, empirical field data, and discussions regarding professional autonomy.

	https://doi.org/10.48550/arXiv.2507.02866		
	Yang, Z.-G., Guo, X., & Zhang, P. (2025). <i>The new normal and the era of misknowledge—Understanding generative AI and its impacts on knowledge work. Knowledge, 5(4), 22.</i> https://doi.org/10.3390/knowledge5040022	Partially Relevant (52/100)	This paper uses a comprehensive framework to map how generative AI reshapes knowledge work, linking technical tools to organisational, cultural, and institutional factors. While it discusses autonomy shifts and trust concerns, it is noted for lacking direct empirical case studies.
	Söllner, M., Arnold, T., Benlian, A., Bretschneider, U., Knight, C., Ohly, S., Rudkowski, L., Schreiber, G., & Wendt, D. (2025). <i>ChatGPT and beyond: Exploring the responsible use of generative AI in the workplace. Business & Information Systems</i>	Partially Relevant (54/100)	The study employs a sociotechnical lens to map the organisational impact of generative AI and outlines workflow changes. It specifically mentions shifts in autonomy and trust factors but, like the Yang paper, is categorized as partially relevant because it lacks concrete field case studies.

	Engineering, 67(2), 289–303. https://doi.org/10.1007/s12599-025-00932-8		
	Emaminejad, N., North, A. M., & Akhavian, R. (2022). Trust in AI and implications for the AEC research: A literature analysis. arXiv. https://arxiv.org/abs/2203.03847v1	Low Relevance (18/100)	This paper uses a literature review to identify trust factors specifically for the Architecture, Engineering, and Construction (AEC) industry. While it adopts a sociotechnical framing that links technical AI aspects with industry processes and culture, its narrow focus on the AEC sector results in a lower relevance score for a general study on UK knowledge workers.
	Vaishnav, L., Singh, S., & Cornell, K. A. (2025). Transparency, security, and workplace training & awareness in the age of generative AI. arXiv. https://arxiv.org/abs/2501.10389	Low Relevance (7/100)	This paper examines AI policy, security, and training by linking technical risks to organisational practices. However, it is rated low because it lacks a specific focus on workflow transformation, professional autonomy, or trust dynamics, and does not provide empirical field work.
	Castro, F., Gao, J., & Martin, S. (2023). Human-AI interactions and societal	Not Relevant	The study uses a stylized model to examine how user prompts affect AI outputs and decision accuracy. It is

	<i>pitfalls</i>. arXiv. https://arxiv.org/abs/2309.10448	(0/100)	deemed not relevant because it lacks a workplace focus, empirical case studies, or deep sociotechnical analysis.
Human-AI Collaborati on & Teaming	Sudeeptha, I. (2025). <i>Supporting the sensemaking and adoption of human-AI collaboration</i>. Doctoral thesis, Victoria University of Wellington. https://figshare.com/articles/thesis/SUPPORTING_THE_SENSEMAKING_AND_ADOPTION_OF_HUMAN-AI-COLLABOR...	Low Relevance (7/100)	This doctoral thesis employs a case study to map the sociotechnical layers of change in human-AI collaboration. While it mentions generative AI (specifically ChatGPT) as a catalyst for change, it is rated low because it lacks a detailed analysis of autonomy or trust specifically within the context of generative AI.
	Gonzalez, C., Admoni, H., Brown, S., & Woolley, A. W. (2025). <i>COHUMAN: Building the socio-cognitive architecture of collective human-machine intelligence. Topics in</i>	Low Relevance (7/100)	The authors use a socio-cognitive architecture to frame human-machine teams, linking technical AI aspects with organisational and cultural factors. It is categorized as low relevance because it lacks a direct focus on the workplace transformation or autonomy

	<i>Cognitive Science</i>, 17(2), 180–188. https://doi.org/10.1111/tops.12673 (philpapers.org)		impacts specifically driven by generative AI
	Lou, B., Lu, T., Raghu, T. S., & Zhang, Y. (2025). <i>Unraveling human-AI teaming: A review and outlook. SSRN Electronic Journal.</i> https://doi.org/10.2139/ssrn.5211067	Low Relevance (7/100)	This paper provides a sociotechnical review of AI agents in teams, offering conceptual links to workplace change, autonomy, and trust; however, it lacks concrete transformation studies or empirical data.
	Woolley, A. W., & Gupta, P. (2025). <i>Generative AI and collaboration: opportunities for cultivating collective intelligence. Journal of Organization Design.</i> https://doi.org/10.1007/s41469-025-00199-z	Partially Relevant (63/100)	This study uses generative AI to examine the reshaping of collaboration and examines trust dynamics. It adopts a sociotechnical view linking technology to organizational processes, but it is noted for using pre-2023 cognitive frameworks and required extension to address the unique uncertain or hallucinations of GenAI in detail.

	Seufert, S., & Meier, C. (2023). <i>Hybride Intelligenz: Zusammenarbeit mit KI-Assistenzsystemen in wissensintensiven Bereichen. HMD Praxis der Wirtschaftsinformatik, 60(5), 1194–1209.</i> https://doi.org/10.1365/s40702-023-01012-9	Low Relevance (7/100)	The paper uses a conceptual framework to map AI-human roles and competencies, linking technical AI features with organizational culture and ethics. It is rated low because it lacks concrete autonomy analysis, trust metrics, or empirical field data.
	Allen, J., Rorissa, A., & Hawamdeh, S. (2025). <i>Fostering and cultivating human–AI collaboration and partnerships in an evolving workplace. Proceedings of the Association for Information Science and Technology.</i> https://doi.org/10.1002/pra2.1365	Not Relevant (0/100)	While it adopts a sociotechnical lens linking AI to organizational culture, it focuses on broad human-centered AI integration and lacks a specific focus on generative models, autonomy impacts, trust mechanisms, or empirical field data.

	Väänänen, K., van Berkel, N., McMillan, D., & Olsson, T. (2026). <i>Embodied AI agents for team collaboration in co-located blue-collar work</i>. arXiv. https://arxiv.org/abs/2602.12136v1	Low Relevance (7/100)	This paper uses embodied AI to illustrate worker agency and inclusive design within industrial and maintenance contexts. While it offers sociotechnical insights into autonomy and trust dynamics, it is rated low because it lacks a generative AI focus and empirical field data relevant to the specific needs of UK knowledge workers
	Imteyaz, K., Muller, M., Flores-Saviaga, C., & Savage, S. (2026). <i>Co-designing collaborative generative AI tools for freelancers</i>. arXiv. https://arxiv.org/abs/2602.05299v1	Low Relevance (7/100)	The researchers utilize co-design sessions with freelancers to scrutinise collaborative generative AI, highlighting agency and sociotechnical dynamics. It is categorized as low relevance because the study's focus on freelance environments and "short-term teams" does not align with the traditional professional organizational contexts and institutional supports typical of your UK knowledge worker case study.
	Stefik, M. (2023). <i>Roots and requirements for collaborative AIs</i>.	Not Relevant (0/100)	This position paper employs a conceptual analysis of AI collaborators to discuss requirements for transparency and teamwork. It is deemed not relevant

	arXiv. https://arxiv.org/abs/2303.12040v7		as it lacks a generative AI focus, empirical work, autonomy data, and detailed trust studies specific to the contemporary workplace.
	Nah, S., & Spence, P. R. (2025). <i>Generative AI: Another chapter of human-machine communication. Human-Machine Communication, 11(1), 7–12.</i> https://doi.org/10.30658/hmc.11.1	Not Relevant (0/100)	This source is an editorial overview discussing the social negotiations of meaning, authority, and credibility in AI-generated content. Although it touches on trust and sociotechnical themes, it is rated as not relevant due to its lack of a workplace focus and original empirical data.
	Hu, Q., Xiao, Q., Cao, H., & Shen, H. (2025). <i>When your boss is an AI bot: Exploring opportunities and risks of manager clone agents in the future workplace.</i> arXiv. https://arxiv.org/abs/2509.10993v3	Partially Relevant (67/100)	This paper examines how AI-driven manager clones are reshaping workplace hierarchy and offers valuable sociotechnical insights and design guidance. However, it is rated as partially relevant because it lacks deep autonomy analysis, a dedicated trust study, and original real-world case data.

Autonomy, Control & AI Authority	Law, M., & Varanasi, R. A. (2025). <i>Generative AI and changing work: Systematic review of practitioner-led work transformations through the lens of job crafting.</i> In <i>HCI in Business, Government and Organizations (HCII 2025)</i> (Lecture Notes in Computer Science, Vol. 15804, pp. 131–152). Springer. https://doi.org/10.1007/978-3-031-92823-9_10	Partially Relevant (52/100)	The researchers use a systematic review of practitioner-led AI work changes to link AI to various sociotechnical factors. While the study touches on professional autonomy through the lens of "job crafting," it lacks a direct analysis of trust and original empirical field data.
	Latto, C., Richter, A., Tate, M., & Leyer, M. (2025). <i>Generative AI's impact on organizational structures: An analysis in collaboration with ChatGPT.</i> arXiv / Research Square. https://doi.org/10.21203/rs.3.rs-6649663/v1	Partially Relevant (44/100)	This study uses O*Net data and ChatGPT assessments to map the effects of generative AI on 85 different knowledge-worker roles, identifying trends like flattening hierarchies and the emergence of joint human-AI teams. It is categorized as only partially relevant due to a lack of focus on autonomy, trust dynamics, and concrete field case studies.

	Anthuvan, T., Prabhuram, S., Raju, G., Maheshwari, K., & Mishra, A. (2025). <i>Bring your own AI (BYOAI) in the workplace: Patterns, pitfalls, and the BYOAI-Gov™ framework for behavior-aware governance.</i> Lex Localis – Journal of Local Self-Government. https://doi.org/10.52152/mmrgh422	Low Relevance (7/100)	This paper utilizes a BYOAI governance framework to map informal AI use, linking technical risk zones with organizational behaviour. While it offers behavioural archetypes and a maturity model, it is rated as low relevance because it focuses primarily on policy rather than detailed workflow changes, autonomy shifts, or trust mechanisms, and lacks concrete field case studies
	Fernández-Macías, E., Gómez, E., Hernández-Orallo, J., Loe, B. S., Martens, B., Martínez-Plumed, F., & Tolan, S. (2018). <i>A multidisciplinary task-based perspective for evaluating the impact of AI autonomy and generality on the future of work.</i> arXiv. https://arxiv.org/abs/1807.02416v1	Low Relevance (7/100)	This paper focuses on AI autonomy and task mapping rather than generative Large Language Models (LLMs). While it offers a sociotechnical framing, it lacks empirical cases or specific trust/autonomy analysis for professional knowledge workers.

	Baygi, R. M., & Huysman, M. (2025). <i>Generative AI and the social fabric of organizations. Strategic Organization.</i> https://doi.org/10.1177/14761270251385456	Partially Relevant (54/100)	This study uses a sociotechnical lens to map how the multipurpose and unpredictable traits of GenAI reshape organizational pathways. While it conceptually links trust and autonomy shifts to the "social fabric" of the workplace, it is categorized as partially relevant because it lacks empirical case data.
	Reich, A., Wolfe, D., Price, M., Choe, A., Kidd, F., & Wagner, H. (2026). <i>Work design and multidimensional AI threat as predictors of workplace AI adoption and depth of use.</i> arXiv. https://arxiv.org/abs/2602.23278v1	Low Relevance (7/100)	The researchers use a sociotechnical lens to link job design and AI threats, identifying autonomy as a predictor of adoption. However, it does not specifically focus on generative AI, trust mechanisms, or detailed field case studies.
	Marimon, F., Mas-Machuca, M., & Akhmedova, A. (2024). <i>Trusting in generative AI: Catalyst for employee performance and engagement in the</i>	Low Relevance (11/100)	This paper is noted as highly relevant for trust dynamics and somewhat relevant for AI-driven workflow changes and sociotechnical links based on survey evidence. It receives a lower overall score for

	workplace. <i>International Journal of Human-Computer Interaction.</i> https://doi.org/10.1080/10447318.2024.2388482		your specific thesis because it lacks a deep focus on professional autonomy or deep structural transformation within the UK context.
	Ravirajan, K., & Sundarajan, A. (2025). <i>Enhancing workplace productivity and well-being using AI agent.</i> arXiv. https://arxiv.org/abs/2501.02368v1	Low Relevance (7/100)	This paper uses AI agents with biometric feedback to boost productivity but lacks a focus on generative Large Language Models (LLMs) or empirical field data relevant to my study.
	Woodruff, A., Shelby, R. M., Kelley, P. G., Rousso-Schindler, S., Smith-Loud, J., & Wilcox, L. (2023). <i>How knowledge workers think generative AI will (not) transform their industries.</i> CHI Conference on Human Factors in Computing Systems.	Partially Relevant (52/100)	The study surveys knowledge workers' expectations of generative AI and links technology to organizational change, yet it lacks deep analysis or real-world case data regarding autonomy and trust.

	https://doi.org/10.1145/3613904.3642700		
	Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). <i>“So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71</i>, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642	Not Relevant (0/100)	This work focuses primarily on academic research practices and policy guidance rather than workplace transformation, lacking empirical workplace data or deep autonomy/trust analysis.

	Dorta-González, P., López-Puig, A. J., Dorta-González, M. I., & González-Betancor, S. M. (2024). <i>Generative artificial intelligence usage by researchers at work: Effects of gender, career stage, type of workplace, and perceived barriers. Telematics and Informatics, 94</i>, Article 102187. https://doi.org/10.1016/j.tele.2024.102187	Not Relevant (0/100)	The researchers use survey regression to link demographics and barriers to usage frequency among researchers, but the study lacks a specific focus on professional autonomy, trust, or detailed workplace case studies.
	Razi, A., Bouzoubaa, L., Pessianzadeh, A., Seberger, J. S., & Rezapour, R. (2024). <i>Not a Swiss Army knife: Academics' perceptions of trade-offs around generative artificial intelligence use</i>. arXiv. https://arxiv.org/abs/2405.00995	Not Relevant (0/100)	This paper uses interviews with academics to explore AI-assisted writing and highlights trust concerns and institutional constraints; however, it is categorized as not relevant because it focuses on educational settings rather than professional workplace transformation or autonomy in a corporate context.

	Feyijimi, T. R., Aliu, J. O., Oke, A. E., & Aghimien, D. (2025). <i>ChatGPT's expanding horizons and transformative impact across domains: A critical review of capabilities, challenges, and future directions. Computers, 14</i> (9), 366. https://doi.org/10.3390/computers14090366	Not Relevant (0/100)	This study provides a broad domain review discussing AI's agency, ethical-technical co-evolution, and general professional practice shifts. It is deemed not relevant for your specific thesis because it lacks concrete workplace transformation studies, detailed autonomy analysis, specific trust metrics, or sociotechnical case data.
BEHAVIOURAL / PERCEPTION			
Professional Identity & Jurisdiction	Abdulsalam, M., Yang, J., Wang, R., & Kumar, V. (2025). <i>Enduring disparities in the workplace: A pilot study in the AI community.</i> arXiv. https://arxiv.org/abs/2506.04305v2	Not Relevant (0/100)	This paper focuses on Diversity, Equity, and Inclusion (DEI) disparities and accessibility within the AI/ML community. It does not examine generative AI use, professional autonomy, trust, or the sociotechnical integration of AI into general knowledge-work workflows.

	George, A., & Martin, R. (2023). <i>ChatGPT and the future of work: A comprehensive analysis of AI's impact on jobs and employment.</i> arXiv. https://arxiv.org/abs/2304.12210	Partially Relevant (44/100)	This survey uses ChatGPT analysis to map AI-driven workflow changes and notes shifts in decision-making that affect professional autonomy. However, it is only partially relevant because it lacks a specific investigation into trust mechanisms and does not provide original empirical field case studies.
	Price, S. (n.d.). <i>Resisting AI and the future of work: Navigating technological transformation in the modern workplace.</i> MetaGentity AI. https://metagentity.ai/articles/Resisting_AI_and_the_Future_of_Work.html	Not Relevant (0/100)	While the paper uses AI interface discussions to explore workplace change and autonomy concerns, it is categorized as not relevant because it lacks a specific focus on generative Large Language Models (LLMs), trust dynamics, and concrete field data.
	Doyle, C. (2025). <i>The rise of the knowledge sculptor: A new archetype for knowledge work in the age of generative AI.</i> arXiv. https://arxiv.org/abs/2510.07829	Partially Relevant (52/100)	This paper uses a sociotechnical framework to define the "Knowledge Sculptor" as a new professional archetype, demonstrating how generative AI reshapes knowledge work. It addresses professional autonomy and trust through the described "sculpting"

			process and provides a practice-based vignette as a lightweight case illustration.
	Cha, Y., Jackson, V., Shu, L., Branham, S. M., & van der Hoek, A. (2025). <i>“Game changer” or “overenthusiastic drunk acquaintance”? Generative AI use by blind and low vision software professionals in the workplace.</i> arXiv. https://arxiv.org/abs/2512.24462v1	Partially Relevant (67/100)	This paper uses 39 interviews with blind and low-vision developers to reveal how generative AI reshapes tasks, autonomy decisions, trust concerns, and organizational policies, providing a sociotechnical and empirical view.
Psychological Contract, Resistance & Meaning of Work	Constantinides, M., Sarkar, A., Brumby, D., & Cox, A. (2026). " If You're Very Clever, No One Knows You've Used It": The Social Dynamics of Developing Generative AI Literacy in	Partially Relevant (67/100)	This study uses in-depth interviews with 19 knowledge workers to reveal how GenAI reshapes work and highlights autonomy tensions through "hidden AI use". It touches on trust through concerns regarding transparency and adopts a sociotechnical lens while providing concrete empirical field data. The research identifies that while knowledge sharing from

	the Workplace. <i>arXiv preprint arXiv:2602.01386</i> .		colleagues supports learning, the practice of removing cues of GenAI use to validate domain expertise ultimately reduces learning opportunities and leads to knowledge-flow disruption.
	Hai, L., Zhang, Y., Li, X., & Chen, Z. (2025). <i>The dark side of employee-generative AI collaboration in the workplace: An investigation on work alienation and employee expediency. International Journal of Information Management.</i> https://doi.org/10.1016/j.ijinfomgt.2025.102870	Partially Relevant (44/100)	This research demonstrates how employee-generative AI collaboration reshapes work by causing alienation and expediency. While it touches on the loss of autonomy and the erosion of trust, it is categorized as partially relevant because it offers limited sociotechnical analysis and lacks original field case studies.
	Callari, F., & Puppione, M. (2025). <i>Can generative artificial intelligence productivity tools support workplace learning? A qualitative study on employee perceptions in a</i>	Partially Relevant (52/100)	This study utilizes Microsoft 365 Copilot to examine workflow changes focused on learning within a multinational corporation. While it provides rich cultural and technical insights through survey-based field data, it is rated as partially relevant because it

	multinational corporation. <i>Journal of Workplace Learning</i>, 37(3), 266–283. https://doi.org/10.1108/JWL-11-2024-0258		lacks a specific analysis of professional autonomy or trust.
	Dong, E., Liu, H., Li, J.-Y., & Lee, Y. (2024). <i>Motivating employee voicing behavior in optimizing workplace generative AI adoption: The role of organizational listening. Public Relations Review.</i> https://doi.org/10.1016/j.pubrev.2024.102509	Not Relevant (0/100)	This research explores employee voicing and organizational listening during the rollout of generative AI to link technology with organizational culture. It is deemed not relevant for your study because it lacks a focus on professional autonomy or trust dynamics and offers limited field data.
OUTCOME			
Productivity,	Keltanen, A. (2025). <i>Generative AI in the workplace: Effects on employee efficiency and performance.</i> Aalto University.	Partially Relevant. (60/100)	This paper utilizes generative AI tools like ChatGPT to examine changes in workplace efficiency while touching upon the implications for professional

Performance & Efficiency	https://aaltodoc.aalto.fi/items/7861009a-7714-4c9b-8141-81b82c21477f		autonomy and trust. It references sociotechnical factors but is noted for lacking detailed case studies.
	Allen, J., Rorissa, A., & Hawamdeh, S. (2025). <i>Fostering and cultivating human–AI collaboration and partnerships in an evolving workplace. Proceedings of the Association for Information Science and Technology.</i> https://doi.org/10.1002/pr2.1365	Not Relevant (0/100)	Although it adopts a sociotechnical lens to link AI with organizational culture, the paper focuses on a broad discussion of human-centered AI integration rather than specific generative models. It is deemed not relevant because it lacks a focus on generative AI, autonomy impacts, trust mechanisms, and original empirical field data.
Knowledge, Creativity & Decision Quality	Kaczorowska-Spychalska, D., et al. (2024). <i>Generative AI as source of change of knowledge management paradigm. Journal of Business Research.</i> https://doi.org/10.1016/j.jbusres.2024.114923	Partially Relevant (44/100)	This research utilizes interviews and surveys to map the reshaping of knowledge creation, storage, sharing, and application within organizations due to generative AI. It is rated as partially relevant because it does not address professional autonomy, trust, or employ a full sociotechnical framework

	Storey, V. C. (2025). <i>Knowledge management in a world of generative AI: Impact and implications. ACM Transactions on Management Information Systems</i> , 16(3), 1–14. https://doi.org/10.1145/3719209	Partially Relevant (52/100)	This study employs a generative-AI-focused Knowledge Management (KM) framework to examine workplace changes, specifically discussing how novice-expert dynamics affect autonomy. While it links AI technology to organizational culture and mentions trust risks like over-reliance, it lacks concrete case studies.
	Schönberger, M., & Beinke, J. H. (2023). <i>Hybride Intelligenz als Konvergenz menschlicher und künstlicher Intelligenz – wie verändert ChatGPT die Wissensarbeit? HMD Praxis der Wirtschaftsinformatik</i> , 60(6), 1174–1193. https://doi.org/10.1365/s40702-023-00997-7	Partially Relevant (67/100)	The authors use ChatGPT to investigate hybrid intelligence across multiple knowledge-work domains (such as purchasing, R&D, and IT), highlighting workflow changes and integration requirements. The paper adopts a sociotechnical framing that links AI capabilities with organizational training and culture, though it provides sector-level observations rather than detailed field experiments and lacks deep analysis of autonomy or trust.

	Glazko, A., O'Neill, S., & Vines, J. (2025). Case study of GAI for generating novel images for real-world embroidery. arXiv. https://arxiv.org/abs/2510.16223v1	Low Relevance (15/100)	While providing an auto-ethnographic case of real-world generative AI use in design, the study touches on trust and sociotechnical aspects but lacks a specific focus on workplace transformation or professional autonomy for knowledge workers.
	Christoforou, E., & Otterbacher, J. (2023). ChatGPT and generative AI: A new era for crowdsourcing? arXiv. https://arxiv.org/abs/2305.12947	Not Relevant (0/100)	This paper uses a survey of crowdworkers to illustrate workflow shifts and platform-level sociotechnical impacts; however, it is deemed not relevant because it lacks a focus on professional autonomy and provides empirical crowdwork data rather than knowledge-work case studies.
ORGANISATIONAL / SYSTEM			
Organisational Transformation & Workforce Impact	Oyetade, K., & Zuva, T. (2025). A review of generative AI's impact on workforce transformation and future skill requirements. <i>OIDA International Journal of Sustainable Development</i> , 18(12), 187–196. https://www.researchgate.net/publicati	Partially Relevant (44/100)	This paper uses a broad review to map the role of generative AI in reshaping work and skill requirements. While it touches on implications for autonomy and trust and adopts a sociotechnical lens, it is only partially relevant because it lacks original case studies.

	on/397097756 A Review of Generative AI's Impact on Workforce Transformation and Future Skill Requirements		
	Dăniloia, D.-F., & Turturean, E. (2024). <i>Knowledge workers and the rise of artificial intelligence: Navigating new challenges. SEA – Practical Application of Science</i> , 12(35), 111–121. https://doi.org/10.70147/s35111121	Partially Relevant (44/100)	The study uses generative AI to discuss the reshaping of knowledge work and automation, noting how skill shifts affect professional autonomy. However, it is categorized as partially relevant because it lacks a trust analysis, does not utilize a full sociotechnical framework, and provides no empirical case studies.
	Rane, N. (2023). <i>Role and challenges of ChatGPT, Gemini, and similar generative artificial intelligence in human resource management.</i>	Partially Relevant (44/100)	This paper examines how generative AI reshapes HR decision-making and talent processes. While it discusses trust, ethics, and cultural implications, it is rated as partially relevant because it lacks a specific focus on professional autonomy, detailed trust metrics, or empirical fieldwork.

	SSRN Electronic Journal. https://ssrn.com/abstract=4603230		
	Butollo, F., Gerber, C., Görnemann, E., Greminger, L., Katzinski, A.-K., Kulla, M., Sirman-Winkler, M., & Spott, J. (2024). <i>The symbiosis of generative AI and work: Expanding horizons or eroding human competence?</i> Weizenbaum Discussion Paper No. 42. Weizenbaum Institute. https://doi.org/10.34669/WI.DP/42	Partially Relevant (52/100)	This study uses five theses to map the role of generative AI across various domains, including programming, journalism, marketing, and HR. It links technical changes to work structures, autonomy shifts, and trust considerations within a sociotechnical context. However, it is categorized as partially relevant because it offers only initial empirical impressions rather than detailed case study data.
	Patil, D., Rane, N. L., & Rane, J. (2024). <i>Emerging and future opportunities with ChatGPT and generative artificial intelligence in various business sectors.</i> In <i>The future impact of ChatGPT on several</i>	Not Relevant (0/100)	This paper uses generative AI to discuss broad sector-wide opportunities and ethical considerations. It is categorized as not relevant because it lacks a specific focus on workplace transformation, professional autonomy, or trust, and it does not

	business sectors (pp. 242–293). Deep Science Publishing. https://doi.org/10.70593/978-81-981367-8-7_6		provide original empirical field work, touching on sociotechnical issues only at a very general level.
	Patil, D., Rane, N. L., & Rane, J. (2024). <i>Future directions for ChatGPT and generative artificial intelligence</i>. In <i>The future impact of ChatGPT on several business sectors</i> (pp. 294–346). Deep Science Publishing. https://doi.org/10.70593/978-81-981367-8-7_7	Not Relevant (0/100)	This study provides a high-level sector overview and outlook. It is deemed not relevant as it lacks detailed analysis of workplace transformation, autonomy impacts, and trust dynamics. Furthermore, it does not employ a sociotechnical framing or provide empirical case work necessary for your specific research context.
	Feyijimi, T. R., Aliu, J. O., Oke, A. E., & Aghimien, D. (2025). <i>ChatGPT's expanding horizons and transformative impact across</i>	Not Relevant (0/100)	This paper provides a broad domain review of AI's agency and professional practice shifts, but it is deemed not relevant because it lacks concrete

	<i>domains: A critical review of capabilities, challenges, and future directions. Computers, 14(9), 366.</i> https://doi.org/10.3390/computers14090366		workplace transformation studies, autonomy analysis, trust metrics, or sociotechnical case data.
	Benbya, H., Davenport, T. H., & Leidner, D. E. (n.d.). <i>Navigating generative artificial intelligence promises and perils for knowledge and creative work. Journal of Strategic Information Systems.</i> https://doi.org/10.1016/j.jsis.2024.101852	Low Relevance (7/100)	While this editorial uses a broad Information Systems (IS) lens to link technical capabilities to organizational and cultural shifts, it lacks concrete workplace studies, autonomy analysis, or specific trust experiments required for your thesis.
	Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S.,	Not Relevant (0/100)	This opinion paper focuses primarily on academic research practices and policy guidance rather than workplace transformation. It offers limited sociotechnical discussion regarding institutional guidelines but lacks empirical workplace data,

	Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). <i>“So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71</i>, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642		autonomy analysis, or trust metrics.
Socio-Technical Systems & Infrastructure	Bastola, A., Wang, H., Hembree, J., Yadav, P., Gong, Z., Dixon, E., Razi, A., & McNeese, N. (2023). <i>LLM-based smart reply (LSR): Enhancing collaborative performance with ChatGPT-mediated smart reply</i>	Partially Relevant 56/100	This paper is considered highly relevant for its detailed exploration of trust dynamics and AI-driven workflow changes, while it is somewhat relevant regarding its brief addresses of professional autonomy, the sociotechnical context, and its implementation of a limited user study. The study found that using an AI teammate increased perceived performance and reduced mental demand for

	system. arXiv. https://arxiv.org/abs/2306.11980		workers. Additionally, it noted that participants expressed a high level of trust in the AI, even showing a willingness to grant it access to personal data to achieve higher functionality.
	Baygi, R. M., & Huysman, M. (2025). <i>Generative AI and the social fabric of organizations. Strategic Organization.</i> https://doi.org/10.1177/14761270251385456	Partially Relevant 54/100	This research utilizes a sociotechnical lens to map how the multipurpose, unpredictable, and hyper-personalizable traits of Generative AI (GenAI) are reshaping organizational pathways. While it conceptually links trust and autonomy shifts to the "social fabric" of the organization, it is categorized as partially relevant because it lacks original empirical case data. The authors outline two contrasting scenarios: a "laissez-faire" approach where GenAI might disrupt the flow of expertise and trust, and a "cultivation" approach where it is deliberately integrated to strengthen organizational cohesion.
	Sofia, B., & El Ghazail, M. (2025). <i>Work in the age of prompts: How</i>	Partially Relevant	This study provides empirical evidence that AI functions as a cognitive collaborator rather than a

	<i>generative AI is redefining expertise and identity at work. Moroccan Journal of Research in Management and Marketing, 17(2), 60–77.</i> https://doi.org/10.48376/IMIST.PRSM/remarem-v17i2.58001	60/100	replacement, finding no significant negative impact on the perceived autonomy, skill application, or professional identity of HR, marketing, and finance professionals. It is rated as partially relevant because, while it hints at workplace transformation and organizational implications, it lacks a full sociotechnical framework and a dedicated trust analysis.
	Libera, P. S., Bilgram, V., Schötteler, S., & Mammen, J. (2025). <i>ChatGPT in the working world: A qualitative study. Information Resources Management Journal, 38(1), 1–26.</i> https://doi.org/10.4018/IRMJ.386593	Partially Relevant (60/100)	The researchers used a qualitative survey of 78 professionals to map how ChatGPT is used for content creation, research, and idea generation across the software, marketing, and academic sectors. It is categorized as partially relevant because it provides survey-based evidence rather than detailed field case studies and lacks specific analysis regarding professional autonomy or trust.
	Oesinghaus, A., Elshan, E., & Sandvik, H. O. (2024). <i>The future of work</i>	Partially Relevant	This paper examines how generative AI contributes to knowledge-work transformation and specifically its

	<i>unleashed: Generative AI's role in shaping knowledge workers' autonomous motivation.</i> In <i>Proceedings of the European Conference on Information Systems (ECIS 2024).</i> https://aisel.aisnet.org/ecis2024/track04_impactai/track04_impactai/12/	(56/100)	impact on workers' perceived autonomy and autonomous motivation. It is categorized as partially relevant because it lacks a dedicated trust analysis, does not utilize an explicit sociotechnical framing, and provides no empirical case data, relying instead on theoretical assumptions.
	Spirgi, M., Riedl, R., & Fischer, H. (2025). <i>Soziotechnische Systemgestaltung im Kontext generativer KI: Eine empirische Untersuchung. HMD Praxis der Wirtschaftsinformatik.</i> https://doi.org/10.1365/s40702-025-01123-4	Not Relevant (0/100)	Although this study uses a sociotechnical design lens to examine the use of ChatGPT, it focuses exclusively on higher education settings and student usage patterns rather than professional environments. It identifies different types of users (occasional, regular, and intensive) among a survey of 699 students but does not address workplace transformation, professional autonomy, or trust in human-AI collaboration within an organizational context.

	Cortiñas-Lorenzo, K., Lindley, S., Larsen-Ledet, I., & Mitra, B. (2024). <i>Through the looking-glass: Transparency implications and challenges in enterprise AI knowledge systems</i>. arXiv. https://arxiv.org/abs/2401.09410v4	Low Relevance (7/100)	This paper offers a sociotechnical analysis of AI knowledge systems by detailing dimensions of transparency and touching upon implications for autonomy and trust. However, it is rated as low relevance because it lacks a specific focus on generative AI and does not provide original empirical case work.
DOMAIN-SPECIFIC APPLICATIONS (CONTEXTUAL)			
IT & Technical Work	Ulfesnes, R., Moe, N. B., Stray, V., & Skarpen, M. (2024). <i>Transforming software development with generative AI: Empirical insights on collaboration and workflow</i>. In A. Nguyen-Duc, P. Abrahamsson, & F. Khomh (Eds.), <i>Generative AI for effective software development</i> (pp. 219–234). Springer. https://doi.org/10.1007/978-3-031-55642-5_10	Partially Relevant (60/100)	This study uses interviews with data scientists, developers, and managers to illustrate workflow shifts and efficiency gains driven by tools like ChatGPT and Copilot. While it provides empirical evidence of a paradigm shift in software development and altered team dynamics—such as developers turning to AI for help instead of colleagues—it is deemed only partially relevant due to limited depth regarding professional autonomy, trust mechanisms, and broader sociotechnical framing.

	Clear, T., Cajander, Å., Clear, A., & McDermott, R. (2025). <i>AI integration in the IT professional workplace: A scoping review and interview study with implications for education and professional competencies</i>. In <i>Proceedings of the ITiCSE 2024: Working Group Reports on Innovation and Technology in Computer Science Education (ITiCSE-WGR 2024)</i> (pp. 34–67). ACM. https://doi.org/10.1145/3689187.3709607	Partially Relevant (52/100)	The study utilizes a scoping review and interviews to examine how generative AI (GenAI) and large language models (LLMs) are reshaping IT work, specifically linking technical changes to organisational culture and training needs. While it addresses the unique characteristics of GenAI and touches upon professional autonomy and trust, it is categorized as only partially relevant because it lacks deep quantitative analysis or dedicated, robust empirical case studies.
	Cha, Y., Jackson, V., Shu, L., Branham, S. M., & van der Hoek, A. (2025). <i>“Game changer” or “overenthusiastic drunk</i>	Partially Relevant (67/100)	This paper uses 39 interviews with blind and low-vision developers to reveal how generative AI reshapes tasks, autonomy decisions, trust concerns, and organizational policies. It is noted for offering a

	<i>acquaintance”? Generative AI use by blind and low vision software professionals in the workplace.</i> arXiv. https://arxiv.org/abs/2512.24462v1		sociotechnical and empirical view of these dynamics.
	Ogawa, Y., Tanaka, H., Suzuki, R., & Yamamoto, K. (2025). <i>Understanding collaboration between professional designers and decision-making AI: A case study in the workplace.</i> arXiv. https://arxiv.org/abs/2509.24718v1	Low Relevance (38/100)	The study utilizes decision-making AI rather than generative AI to examine designers' trust, workflow integration, and autonomy shifts. While it provides a detailed field case from an advertising firm that links technical and organizational factors, its relevance is limited by the focus on non-generative AI systems.
HR & Management	Alhusban, M. I., Alshurafat, H., & Khatatbeh, I. N. (2024). <i>Exploring professional perspectives on integrating generative artificial intelligence into corporate learning and development: an organizational</i>	Partially Relevant (52/100)	This study investigates how ChatGPT integration reshapes Learning and Development (L&D) processes and organizational structures, framing these changes through a sociotechnical lens. While it provides empirical insights based on interviews with experts and discusses trust concerns and

	<i>change perspective. Development and Learning in Organizations</i>, 39(2), 21–24. https://doi.org/10.1108/DLO-05-2024-0131		governance, it is considered only partially relevant because it lacks a specific focus on professional autonomy.
	Ajaero, C. K., & Anjorin, O. J. (2024). <i>Human resource management and generative artificial intelligence (ChatGPT): Nexus, perspectives and praxis. International Journal of Professional Business Review</i>, 9(5), e02339. https://doi.org/10.26668/businessreview/2024.v9i5.2339	Partially Relevant (52/100)	The paper explores the use of generative AI to reshape HR processes and recruitment, including discussions on monitoring and ethical safeguards. It is categorized as partially relevant because, although it touches upon trust concerns, it lacks a focused analysis of professional autonomy and does not include original empirical field work.
	Budhwar, P. S., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., & others. (2023). <i>Human</i>	Low Relevance (7/100)	This paper provides a sociotechnical, HR-focused roadmap for the use of ChatGPT, emphasizing oversight, employee voice, and ethical concerns. It is

	<i>resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. Human Resource Management Journal, 33(4), 616–638.</i> https://doi.org/10.1111/1748-8583.12524		categorized as having low relevance because it lacks concrete case studies and does not provide an analysis specifically focused on professional autonomy.
Creative / Knowledge Work	Clarke, A., & Joffe, B. (2025). <i>Beyond replacement or augmentation: How creative workers reconfigure division of labor with generative AI.</i> arXiv. https://arxiv.org/abs/2505.18938v1	Highly Relevant (93/100)	This ethnographic study examines how creative agencies reconfigure their division of labour with generative AI, offering detailed insights into workflow redesign, trust mechanisms, and sociotechnical links. While it is highly relevant to organizational expectations and adoption, the source notes that its findings regarding autonomy effects are only tangential.

	Wagman, K., Kuttan, A., Bigham, J. P., & Schramm, M. (2025). <i>Generative AI uses and risks for knowledge workers in a science organization</i>. In <i>Proceedings of the 2025 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '25)</i>. ACM. https://doi.org/10.1145/3706598.3713827	Partially Relevant (63/100)	This research uses generative AI to examine workflow changes and trust factors within a research institute, an understudied sub-domain of knowledge work. It adopts a sociotechnical lens, and notes shifts in professional autonomy, though its findings are based on limited case observations
	Christoforou, E., & Otterbacher, J. (2023). <i>ChatGPT and generative AI: A new era for crowdsourcing?</i> arXiv. https://arxiv.org/abs/2305.12947	Not Relevant (0/100)	While the paper uses a survey of crowdworkers to illustrate AI-assisted task changes and workflow shifts, it is deemed not relevant to the thesis because it lacks a focus on professional autonomy and provides empirical data derived from crowdwork rather than professional knowledge-work case studies. Additionally, while it notes trust concerns and platform-level sociotechnical impacts, these are not framed

			within the context of traditional organizational expectations for knowledge workers.
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Appendix B: Screening and Inclusion: The Reproducible Funnel

To eliminate researcher bias and ensure reproducibility, the reduction from 585 results to a final corpus of 100 papers followed a predefined, three-stage exclusion protocol. This process achieved an attrition rate of 83%, which aligns with the rigorous standards for management-domain systematic reviews (Tranfield et al., 2003).

Stage 1: Technical & Format Filtering (585 → 520)

- **Rule:** Exclude non-scholarly formats and duplicates.
- **Action:** Automated filters removed non-English publications, news articles, and practitioner blog posts lacking empirical or theoretical frameworks.
- **Reproducibility Note:** Duplicates arising from cross-indexing between repositories (e.g., ArXiv pre-prints and subsequent Journal publications) were consolidated into a single record (the most recent version).

Stage 2: Thematic Density Screening (520 → 165)

- **Rule (The "Cluster-3" Rule):** To be retained, a paper's Title or Abstract must explicitly address at least **three** of the five conceptual clusters identified in the Boolean string (Section 1.3.1)
- **Action:** Papers focusing narrowly on a single construct (e.g., only "Trust" in AI without any link to "Knowledge Work" or "Productivity") were excluded.
- **Scope Gate:** Any paper situated in non-professional services contexts—such as AI in K-12 education, primary healthcare, or industrial manufacturing robotics—was excluded to maintain the focus on high-stakes knowledge work.

Stage 3: Quality & Contextual Scoring (165 → 100)

To select the final 100 papers from the 165 eligible candidates, a **Quality & Contextual Scoring Matrix** was applied. Each paper was scored (0–10) based on three objective criteria:

1. **Methodological Transparency (0–4):** Is the data collection and analysis process clearly documented? (Empirical field studies scored highest).

2. **Temporal Relevance (0–3):** Does the paper address the post-2023 generative AI landscape or provide essential pre-2023 baseline theory?
3. **Contextual Proximity (0–3):** Is the study based in the UK, or are the findings theoretically transferable to UK professional services?

Reproducibility Outcome: The 100 papers with the highest cumulative scores were selected for the final corpus. This algorithmic approach ensures that the selection is based on measurable alignment rather than ad-hoc preference.