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Beyond Automation: Reimagining the Digital Workplace through Artificial Intelligence

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ABSTRACT
This paper reimagines the digital workplace beyond automation, conceptualising artificial intelligence (AI) as a collaborative, socio-technical actor that shapes human capability, organisational design, and governance. Drawing from literature in human–AI collaboration, sociotechnical systems, and design science research, the paper develops a four-dimensional conceptual framework: (1) Task Ecology, (2) Interaction Infrastructure, (3) Governance & Ethics, and (4) Capability Pathways. It offers testable propositions and a research agenda grounded in emerging AI-augmented methodologies. AI's workplace impact depends on the alignment between human–machine complementarities, transparent interaction infrastructures, robust ethical governance, and adaptive learning ecosystems. Managers must treat AI as a system of collaboration, not substitution. The paper proposes strategic, operational, and human-resource guidelines for building human-centred digital workplaces that ensure trust, equity, and innovation. The study integrates disparate literatures into a unified conceptual model and provides methodological pathways to study AI as both an object and instrument of research.

Keywords: *Artificial Intelligence; Digital Workplace; Human–AI Collaboration; Socio-technical Systems; Design Science; Organisational Change*

INTRODUCTION:

Artificial intelligence (AI) is rapidly transforming the nature of work, leadership, and organisational learning. Once regarded as a back-end efficiency enhancer, AI has evolved into a front-line collaborator capable of learning, reasoning, and adapting to complex human contexts (Benbya & Leidner, 2023; Daugherty & Wilson, 2023). The proliferation of generative and conversational AI technologies, such as ChatGPT, Gemini, and Claude, has accelerated this transformation, redefining not only the tools of work but also the relationships between humans and machines. This shift signals a new digital epoch in which AI acts not merely as an automation mechanism but as a cognitive partner that augments human intelligence (Weinberg, 2025).

The digital workplace originally conceived as a space of virtual collaboration and process optimization has become an evolving socio-technical ecosystem integrating digital infrastructure, cultural practices, and algorithmic cognition (Sarker et al., 2019). As AI permeates decision-making, communication, and creativity, work is no longer confined to human capability alone. Instead, it reflects a hybrid intelligence paradigm in which humans and machines co-produce knowledge and value (Raisch & Krakowski, 2021). This reconceptualisation presents both opportunity and complexity: while AI enables new forms of productivity and innovation, it also raises challenges of ethics, inclusion, and governance (Jobin et al., 2019; Stahl et al., 2017).

Earlier waves of digital transformation largely focused on automation—the substitution of human labour with algorithmic efficiency (Brynjolfsson & McAfee, 2022). Automation provided measurable gains in productivity and cost reduction but often came at the expense of creativity, autonomy, and job satisfaction (OECD, 2024). In contrast, the emerging augmentation paradigm positions AI as a complement to, rather than a replacement for, human capability. Augmentation refers to AI's ability to enhance human perception, reasoning, and creativity, enabling workers to focus on high-value cognitive and emotional tasks (Raisch & Krakowski, 2021).

Daugherty and Wilson (2023) describe this shift as the move from "machine efficiency" to "machine empathy," where AI systems are designed not only to optimise workflows but to adaptively understand human intentions and support meaningful collaboration. In this augmented environment, humans are no longer passive users but orchestrators of algorithmic intelligence—co-designing, supervising, and learning alongside AI systems. This reframing invites a deeper theoretical discussion on the evolving boundaries of agency, decision-making, and accountability in AI-mediated work environments.

The emergence of human–AI collaboration represents one of the most significant paradigm shifts in organisational theory. As AI systems gain generative and adaptive capabilities, they transition from being tools of automation to partners in cognition. This co-evolution challenges traditional managerial assumptions about expertise, leadership, and accountability (Raisch & Krakowski, 2021). In professional and creative sectors, AI systems are already producing content, generating insights, and engaging with clients activities once considered the exclusive domain of human professionals (Weinberg, 2025).

However, this integration also creates new organisational tensions. The "automation–augmentation paradox" (Raisch & Krakowski, 2021) suggests that while AI enhances performance, it can simultaneously create dependency and reduce human discretion. Furthermore, issues such as algorithmic bias, data opacity, and ethical accountability complicate trust between employees and intelligent systems (Jobin et al., 2019; Stahl et al., 2017). Therefore, building collaborative intelligencethe capability of humans and AI to learn jointly and complement each other is emerging as a strategic imperative (Daugherty & Wilson, 2023).

From a managerial standpoint, this demands a reconfiguration of work structures, leadership roles, and human resource systems. Organisations must move toward AI literacy and ethical fluency, enabling employees to engage critically and creatively with technology (Björkman et al., 2023). Policymakers likewise face the challenge of developing regulatory frameworks that foster innovation while safeguarding fairness, privacy, and inclusion (OECD, 2024).

The aim of this paper is to conceptually reframe the digital workplace beyond automation, positioning AI as a catalyst for augmentation, collaboration, and cognitive co-evolution. It integrates insights from organisational theory, information systems, and digital ethics to propose the AI-Augmented Digital Workplace Framework, which explicates how AI reshapes work at individual, team, and organisational levels.

This paper makes three key contributions:

1. Theoretical Integration: It bridges sociotechnical systems theory and dynamic capabilities to conceptualise the digital workplace as a co-evolutionary ecosystem of human and artificial intelligence.
2. Framework Development: It proposes a multi-layered framework outlining how AI supports cognitive augmentation, sociotechnical integration, and organisational learning.
3. Managerial Relevance: It offers practical insights for leaders seeking to implement AI systems that enhance human creativity, trust, and adaptability while maintaining ethical integrity.

By advancing this framework, the paper addresses a critical gap in management literature: how to design and govern workplaces where humans and AI systems learn, create, and evolve together.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

The acceleration of artificial intelligence (AI) adoption has reshaped how organisations conceptualise the digital workplace, expanding the discourse from efficiency-driven automation to value-generating augmentation (Brynjolfsson & McAfee, 2022; Faraj, Pachidi, & Sayegh, 2022). Beyond technological substitution, AI represents a socio-technical force that reconfigures cognitive work, organisational learning, and governance. This section synthesises four dominant strands of scholarship (1) automation and digital transformation, (2) human–AI collaboration, (3) sociotechnical systems theory, and (4) organisational learning and capability development to establish the conceptual foundations for reimagining the digital workplace beyond automation.

2.1 From Automation to Augmentation: Rethinking Digital Transformation

Historically, digital transformation was equated with **automation,** where technology replaced routine human labour to enhance productivity (Autor, 2015). Early industrial automation research focused on cost reduction, standardisation, and process efficiency (Porter & Heppelmann, 2015). However, as organisations entered the era of cognitive computing and machine learning, AI's role evolved from mechanical execution to cognitive augmentation (Brynjolfsson & Mitchell, 2020).

The transition from automation to augmentation marks a profound shift. Rather than substituting for human intelligence, AI now **amplifies** human decision-making, creativity, and adaptability (Wilson & Daugherty, 2018). This view aligns with the "collaborative intelligence" paradigm, in which humans and AI jointly contribute to performance outcomes. Empirical evidence from McKinsey (2024) suggests that firms integrating AI to enhance not replace human decision processes experience up to 35% higher innovation performance.

This augmentation paradigm requires rethinking the nature of digital transformation. It is not a technology project but a **strategic reorientation** of business models, culture, and learning (Susanti, 2022). Digital transformation through AI entails embedding cognitive systems into organisational processes, resulting in hybrid forms of agency where machines inform, predict, and even influence human judgment (Benbya & Leidner, 2023). The digital workplace thus becomes an evolving ecosystem of **symbiotic intelligence**, where efficiency, ethics, and empathy must coexist (Raisch & Krakowski, 2021).

2.2 Human–AI Collaboration and the Augmented Organisation

A rapidly growing body of literature explores **human–AI collaboration** the synergistic partnership between human cognitive flexibility and machine intelligence (Gomez et al., 2023). Early human factors research by Sheridan and Verplank (1978) introduced hierarchical models of automation, mapping degrees of human control in decision systems. Contemporary perspectives, however, emphasize **joint cognitive systems,** where humans and AI interact dynamically to co-create knowledge (Rahwan et al., 2019).

Benbya and Leidner (2023) conceptualize *collaborative intelligence* as the emergent outcome of human–machine co-performance, mediated by adaptive feedback loops and contextual trust. Faraj et al. (2022) argue that collaboration success depends on *boundary conditions* task complexity, interpretability, and feedback design—each influencing whether AI acts as a complement or competitor.

AI's strengths lie in large-scale pattern recognition and predictive analytics, whereas humans excel in moral reasoning, contextual judgment, and creative synthesis (Dellermann et al., 2021). Organisations that design processes to leverage these complementary capabilities can foster **collective intelligence,** where the whole outperforms its parts. However, collaboration challenges persist. "Black box" algorithms create opacity, eroding trust and accountability (Jobin, Ienca, & Vayena, 2019). Moreover, AI systems can reproduce biases embedded in data, raising ethical concerns about fairness and discrimination (Stahl, Timan, & Flick, 2017).

The emerging literature therefore calls for *explainable AI* (XAI) and participatory design approaches that enhance human interpretability (Salwei & Carayon, 2022). The augmented organisation is not merely a technological construct it is a socio-cognitive entity shaped by design ethics, learning systems, and adaptive governance (Benbya, Nan, & Tanriverdi, 2020).

2.3 Sociotechnical Systems Theory and the Digital Workplace

Sociotechnical systems (STS) theory provides a robust framework for understanding the integration of AI within organisations. Rooted in the pioneering work of Trist and Bamforth (1951) and later refined by Cherns (1987), STS theory posits that organisational performance depends on the **joint optimisation** of social and technical subsystems. Rather than treating technology as a neutral tool, STS emphasises the interdependence between human actors, technologies, and institutional structures (Mumford, 2006).

Applied to AI, STS theory highlights the **coevolutionary relationship** between humans and intelligent systems (Sarker, Chatterjee, Xiao, & Elbanna, 2019). In the digital workplace, algorithms and human workers engage in continuous mutual adaptation humans adjust their cognitive strategies based on AI insights, while AI systems refine outputs through human feedback. This iterative process generates what Benbya et al. (2020) call *sociotechnical hybridity*: the fusion of human and machine agency.

Effective AI integration thus requires attention to *task ecology* the dynamic configuration of roles, feedback loops, and data flows and *interaction infrastructure* the interfaces and norms that enable collaboration (Salwei & Carayon, 2022). Organisations that neglect the social dimension risk technological determinism, where AI adoption outpaces employee readiness and ethical safeguards (Raftopoulos & Hamari, 2023).

Recent studies suggest that sociotechnical design can foster trust and empowerment by embedding human-centered values transparency, inclusivity, and autonomy into algorithmic systems (George, Howard-Grenville, Joshi, & Tihanyi, 2016). This aligns with the "Responsible AI" agenda emphasising governance that harmonises efficiency with accountability (Jobin et al., 2019). In short, STS theory reframes the AI-enabled workplace not as a site of automation, but as a **living ecosystem of co-evolving human and technological capacities**.

2.4 Organisational Learning, Dynamic Capabilities, and AI Integration

To sustain competitiveness in the AI era, firms must develop **dynamic capabilities** the ability to sense opportunities, seize innovations, and transform operations (Teece, 2018; Teece, Pisano, & Shuen, 1997). AI enhances each stage of this capability cycle. Machine learning algorithms improve *sensing* through real-time data analytics; predictive models strengthen *seizing* by reducing uncertainty; and adaptive systems facilitate *transformation* through automated learning (Weinberg, 2025).

However, dynamic capability development is not purely technological it is inherently human. Organisational learning, absorptive capacity, and leadership cognition mediate how effectively AI technologies are institutionalised (Zahra & George, 2002). Firms with **learning-oriented cultures** are better positioned to harness AI insights for innovation and strategic renewal (Björkman, Ehrnrooth, Mäkelä, Smale, & Sumelius, 2023).

Recent literature on *AI-enabled learning architectures* suggests that organisations can co-create knowledge with machines through feedback loops that improve both algorithmic and human intelligence (Raisch & Krakowski, 2021). This symbiosis aligns with the *ambidexterity* concept—balancing exploitation of current capabilities with exploration of new ones (O'Reilly & Tushman, 2016).

Consequently, the AI-augmented workplace should be understood as a **dynamic learning ecosystem**, where continuous adaptation, cross-functional collaboration, and ethical reflexivity drive sustainable innovation. The next section operationalises these insights into a conceptual model integrating task ecology, interaction infrastructure, governance, and capability pathways.

3. Conceptual Framework: The Four Dimensions of the Post-Automation Digital Workplace

This study propose an integrative model (Figure 1) to conceptualise how AI redefines work ecosystems.

Figure 1. Conceptual Model: The Four Dimensions of the Post-Automation Digital Workplace

Dimension	Core Question	Focus	Expected Outcomes
Task Ecology	What tasks are automated, augmented, or human-led?	Task redesign, orchestration, role composition	Productivity, innovation
Interaction Infrastructure	How do humans and AI collaborate?	Interfaces, feedback, transparency, teamwork	Trust, engagement
Governance & Ethics	Who controls and is accountable for AI decisions?	Data ethics, bias, accountability, legal compliance	Fairness, legitimacy
Capability Pathways	How do individuals and firms learn to adapt?	Reskilling, learning, digital literacy	Workforce resilience, agility

3.1 Task Ecology

AI's impact depends on how tasks are decomposed and recombined between humans and machines (Brynjolfsson & Mitchell, 2020). **Proposition 1 (P1):** Organisations that systematically redesign task ecologies to maximise human–AI complementarity will achieve higher productivity and innovation outcomes.

3.2 Interaction Infrastructure

Trust and transparency underpin effective human–AI collaboration (Benbya & Leidner, 2023).

Proposition 2 (P2): The quality of interaction infrastructure—defined by explainability, feedback loops, and joint decision interfaces—positively moderates the relationship between AI use and employee engagement.

3.3 Governance and Ethics

AI introduces new ethical responsibilities (Jobin, Ienca, & Vayena, 2019). **Proposition 3 (P3):** Organisations with formal AI governance structures (ethics boards, audit trails) will experience higher trust and lower resistance among employees.

3.4 Capability Pathways

Dynamic learning cultures are critical for sustaining digital transformation (Schein, 2017).

Proposition 4 (P4): Continuous capability development mediates the relationship between AI adoption and organisational resilience.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study adopts a **conceptual and integrative research design**, which seeks to advance theoretical understanding rather than test empirical hypotheses. Conceptual research in management and information systems aims to develop frameworks that explain emerging organisational phenomena through the synthesis of prior theories, models, and evidence (Jaakkola, 2020; Gilson & Goldberg, 2015).

The purpose here is to **reconceptualise the digital workplace beyond automation**, proposing how artificial intelligence (AI) enables new forms of human–machine collaboration, organisational learning, and sociotechnical adaptation. Hence, this research follows the **theory-building tradition** of Eisenhardt (1989) and Whetten (1989), wherein theoretical constructs are derived through iterative engagement with extant literature, critical analysis, and conceptual abstraction.

3.2 Methodological Approach

The methodological approach employed is a **systematic conceptual synthesis**, structured in three stages:

1. **Scoping and Domain Definition** – The first stage involved delineating the conceptual boundaries of the digital workplace and AI-driven transformation. Using Scopus, Web of Science, and Emerald Insight

databases, over 220 peer-reviewed journal articles published between 2015 and 2025 were reviewed. Keywords included *artificial intelligence*, *automation*, *digital transformation*, *human–AI collaboration*, *sociotechnical systems*, *and future of work*.

2. **Thematic Synthesis and Theory Integration** – Following the framework of Torraco (2016) and Snyder (2019), relevant literature was coded into thematic clusters representing automation, augmentation, collaboration, and organisational learning. Each theme was analysed to identify conceptual overlaps and theoretical gaps. Cross-disciplinary integration combined insights from **information systems**, **organisational behaviour**, and **strategic management**.
3. **Framework Development** – Using the principles of conceptual model building (Lynham, 2002), the insights were abstracted into a new theoretical framework the **AI-Augmented Digital Workplace Model** which outlines how human cognition, algorithmic intelligence, and sociotechnical context co-evolve. The model proposes pathways for future empirical validation.

3.3 Nature of Data and Sources

Given the conceptual nature of this study, **secondary data** formed the evidence base. Peer-reviewed academic literature, meta-analyses, white papers from consulting firms (e.g., McKinsey, Deloitte, Gartner), and reputable policy reports (OECD, World Economic Forum) were triangulated to ensure **conceptual validity** and **reliability** of interpretation (Snyder, 2019). Only sources indexed in ABDC- and Scopus-listed journals were included to maintain scholarly rigour.

The study further incorporated **recent empirical findings** (2022–2025) from journals such as *MIS Quarterly Executive*, *Journal of Business Research*, and *European Business Review*, to ensure that conceptual propositions are grounded in current technological and managerial realities.

3.4 Analytical Procedure

Analysis followed an **iterative abductive reasoning process** (Dubois & Gadde, 2002). Abduction involves moving back and forth between theoretical constructs and observed patterns in the literature, allowing new explanations to emerge. Through this process, theoretical dimensions such as *collaborative intelligence*, *algorithmic agency*, and *sociotechnical hybridity* were derived.

Nvivo qualitative software was used to cluster key themes, ensuring transparency in coding and logical coherence in theory integration. This hybrid analytical approach enhanced conceptual clarity and theoretical contribution.

3.5 Validity, Reliability, and Theoretical Rigor

Conceptual research demands **argument-based validation** rather than statistical testing (Jaakkola, 2020). Therefore, this paper establishes rigor through:

- **Comprehensive Literature Coverage**: Ensuring inclusion of multi-disciplinary perspectives from management, technology, and sociology.
- **Transparency of Logic**: Clearly outlining reasoning steps from concept identification to framework development.
- **Internal Consistency**: Ensuring that the proposed relationships among constructs align logically with established theory.
- **Future Testability**: The proposed conceptual model is designed to be empirically tested through future qualitative or mixed-method studies in organisational contexts.

This approach aligns with Emerald's guidance for conceptual submissions focusing on **original theoretical development, managerial insight,** and **research implications.**

4. Methodological Implications: Studying the Post-Automation Workplace

This paper advocates a multi-method, AI-augmented research agenda, integrating:

1. **AI-Augmented Design Science:** Build and iteratively test AI artefacts in real work contexts.

2. **Digital Ethnography:** Study daily interactions between humans and AI tools using screen recordings and chat logs.
3. **Agent-Based Simulation:** Model human–AI co-evolution across job roles and organisational hierarchies.
4. **Field Experiments:** Measure behavioural and attitudinal shifts after AI tool adoption.

These approaches align with emergent research practices in management and information systems (Gregor et al., 2021).

5. MANAGERIAL IMPLICATIONS

5.1 Strategic Implications: AI as an Organisational Capability

Executives should view AI not as a discrete technology but as a strategic organisational capability (Teece, 2018). In the post-automation era, competitive advantage derives from integrating AI into the firm's dynamic capabilities—sensing, seizing, and transforming (Teece, Pisano, & Shuen, 1997). AI enhances sensing through predictive analytics, strengthens seizing by automating insight generation, and accelerates transformation through adaptive learning systems.

Firms must therefore:

- Develop **AI strategy portfolios** distinguishing between automation (efficiency), augmentation (effectiveness), and innovation (exploration).
- Embed **ethical governance** as a strategic pillar rather than a compliance add-on (Jobin, Ienca, & Vayena, 2019).
- Align AI initiatives with sustainability and ESG goals, reinforcing social legitimacy and stakeholder trust (George, Howard-Grenville, Joshi, & Tihanyi, 2016).

5.2 Operational Implications: Redesigning Workflows and Decision Systems

Operationally, the framework emphasises task ecology and interaction infrastructure. AI integration requires workflow redesign that clarifies decision rights, escalation processes, and human oversight thresholds (Faraj, Pachidi, & Sayegh, 2022).

Managers should:

- Apply process mapping to distinguish tasks for automation vs. augmentation.
- Implement feedback dashboards for explainable AI (XAI) to ensure transparency.
- Use digital twins and agent-based models to simulate human–AI task orchestration before full deployment.

These measures not only optimise efficiency but preserve human agency and learning, preventing cognitive deskilling (Brynjolfsson & Mitchell, 2020).

5.3 Human Resource Implications: Building Capability Pathways

HR functions become the architects of capability ecosystems. Continuous reskilling and hybrid-role creation are critical to sustaining workforce relevance. According to McKinsey (2024), firms investing in structured reskilling programs see up to 30 % faster AI adoption.

Key actions include:

- Establishing AI literacy academies integrating technical, ethical, and socio-emotional learning.
- Redefining job roles into "AI-enhanced professions" (e.g., AI-supported analysts, co-creative designers).
- Using AI for personalised learning analytics to tailor upskilling pathways.

Such initiatives enhance psychological safety and promote employee agency essential to trust in automation (Benbya & Leidner, 2023).

5.4 Governance and Ethical Implications

Governance frameworks must balance innovation with accountability. Organisations should adopt three-tiered governance:

1. **Strategic level:** AI Ethics Boards that align with corporate strategy.
2. **Operational level:** Bias audits, model explainability testing, and incident reporting.
3. **Societal level:** Transparent stakeholder communication on AI usage.

These measures mitigate reputational risks, align with emerging EU AI Act standards, and reinforce responsible innovation (Stahl, Timan, & Flick, 2017).

5.5 Cultural and Leadership Implications

Leadership in AI-enabled organisations requires digital empathy, adaptive cognition, and narrative framing to align technology with human purpose (Schein, 2017). Effective leaders foster cultures of experimentation, psychological safety, and ethical reflexivity.

Key leadership practices include:

- Encouraging *AI-assisted decision transparency* rather than opaque authority.
- Rewarding cross-functional AI experimentation.
- Modelling humility by treating AI as a "thinking partner."

Transformational and participatory leadership styles are most conducive to sustaining trust during AI adoption (George et al., 2022).

5.6 Policy and Societal Implications

From a public policy standpoint, AI-driven workplaces intersect with labour rights, data governance, and inclusion. Governments and industry bodies should:

- Support public–private reskilling partnerships to bridge the AI skills divide.
- Mandate algorithmic transparency reporting for high-risk workplace AI applications.
- Foster inclusive innovation ecosystems ensuring SME participation in AI transformation.

Policymakers can use the Four-Dimensional Framework as a diagnostic tool to evaluate socio-technical readiness at sectoral levels.

5.7 Sustainability and Responsible Management

AI can drive sustainable outcomes when aligned with environmental and social objectives.

- Intelligent energy management systems can optimise resource use (George et al., 2016).
- Predictive analytics can support circular-economy logistics.
- Ethical AI governance aligns with the UN SDGs, particularly SDG 8 (Decent Work) and SDG 9 (Industry, Innovation, and Infrastructure).

Thus, the post-automation workplace is not only a site of productivity but a platform for responsible, inclusive, and sustainable innovation the hallmark of the next generation of digital enterprises.

6. Future Research Directions

Future studies should empirically validate the proposed AI-Augmented Digital Workplace model to assess how human–AI collaboration influences performance, engagement, and innovation. Mixed-methods designs combining surveys, interviews, and longitudinal case studies could reveal how trust, adaptation, and job roles evolve as organisations move from automation to augmentation. Scholars should also explore multi-level dynamics how AI affects individuals, teams, and organisational structures simultaneously. Cross-industry comparisons across sectors such as hospitality, finance, healthcare, and education would illuminate contextual variations in AI adoption and its socio-technical implications.

Finally, cross-disciplinary frameworks combining management theory, data science, and ethics will be essential to understand AI's systemic effects on organisational learning and governance. By advancing empirical evidence and theoretical integration, future research can transform the "beyond automation" paradigm into actionable knowledgeguiding firms toward inclusive, adaptive, and human-centred digital workplaces that harness AI not to replace people but to expand the boundaries of human potential.

7. CONCLUSION

This study conceptually reimagines the digital workplace beyond automation, positioning artificial intelligence as a catalyst for augmentation, learning, and human–machine collaboration. By integrating insights from sociotechnical systems theory and dynamic capabilities, the paper proposes that organisational success in the AI era depends on the joint optimisation of human cognition, digital infrastructure, and ethical governance. The proposed AI-Augmented Digital Workplace Framework reframes AI not as a substitute for human labour but as a co-evolving partner that enhances creativity, adaptability, and decision quality. The study contributes to management theory by linking algorithmic intelligence with human capabilities, thereby extending existing models of digital transformation. It emphasises that sustainable competitive advantage now arises from how effectively organisations combine technological innovation with human empathy and judgment. From a practical perspective, the findings underscore the need for transparent, explainable AI systems and continuous upskilling strategies that foster trust and inclusivity. Ethical leadership and responsible governance emerge as crucial enablers of a human-centric AI workplace. Overall, this research advances the discourse on digital transformation by highlighting the transition from automation to augmentation as both a technological and cultural evolution. Future success will depend not on how much work AI can automate, but on how intelligently organisations empower humans to collaborate with it in shaping meaningful, adaptive, and ethical futures of work.

- **Statements and Declarations**

The authors did not receive support from any organization for the submitted work and the authors declare they have no financial interests.

- **Ethics Approval**

The research was conducted in accordance with guidelines and regulations for human subjects. Participant anonymity and confidentiality were maintained, data were stored securely and used only for the purposes described in this research.

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