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Generative AI adoption in organizations: A conceptual model of job crafting, employee productivity, creativity and work engagement

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Abstract

Generative artificial intelligence (GenAI) is rapidly reshaping organizational work, yet its behavioural consequences for employees remain unevenly understood. Existing research on productivity, creativity and engagement is fragmented and rarely examined within a single theoretical framework. Drawing on Job Demands Resources theory, Conservation of Resources theory and Self Determination Theory, this conceptual paper develops an integrative model of how organizational GenAI adoption affects employee productivity, creativity and work engagement. Job crafting is proposed as the central behavioural mechanism. The model treats GenAI as both a job resource and a job demand. It therefore recognizes a double edged pathway in which technology insecurity and passive over reliance can offset the benefits of adoption. AI literacy, ethical use clarity and organizational readiness are identified as boundary conditions that determine which pathway prevails. Four hypotheses are developed, covering the mediating role of job crafting for productivity and engagement, its moderating role for creativity, and the conditioning effect of AI literacy and ethical guidance. A time lagged, multi source survey design, supplemented by supervisor ratings and an optional field experiment, is proposed for future empirical testing. The paper offers a resource based account of human and AI collaboration. It also provides managerial guidance for organizations that want GenAI adoption to deliver sustainable gains in performance and well being rather than short lived efficiency gains that erode over time.

***Keywords*:** Generative AI, Employee Productivity, Creativity, Work Engagement, Job Crafting, Job Demands Resources Theory, Conservation of Resources Theory, Human AI Collaboration

JEL Classification: J24, M12, M54

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1. Introduction

Generative artificial intelligence (GenAI) tools such as large language model-based assistants have moved from experimental novelty to mainstream organizational infrastructure within a remarkably short span, supporting drafting, analysis, coding, and decision-making across knowledge-intensive industries (Aguinis et al. 2024; Kanbach et al. 2024). Reviews of GenAI's organizational diffusion describe both its efficiency potential and the considerable uncertainty surrounding how it should be governed and adopted (Budhwar et al. 2023; Gupta et al. 2024; Ooi et al. 2025). Controlled field evidence indicates that GenAI assistance can substantially raise the speed and quality of professional tasks (Noy & Zhang 2023), while organizational studies extend this productivity narrative into creativity and innovation, showing that AI-augmented employees can generate a wider range of ideas than unaided counterparts (Jia et al. 2024). Yet a parallel literature cautions that the same functionality can enhance technology insecurity and passive dependence, producing a "double-edged sword" that can suppress the very outcomes it is expected to enhance (Yin et al. 2024; Dong et al. 2025; Park 2024).

This ambivalence matters because GenAI is unlike earlier waves of workplace automation. Rather than displacing narrowly codifiable tasks, it intrudes directly into domains long considered uniquely human — ideation, writing, and judgment (Sedkaoui & Benaichouba 2024; Singh et al. 2024). Whether this intrusion is experienced by employees as liberating or threatening appears to depend less on the technology itself than on how organizations design its adoption, and on the resources, skills, and appraisals employees bring to the encounter (Cheng et al. 2023; Raisch & Krakowski 2021). Understanding this conditional relationship requires moving beyond a simple technology-adoption lens toward a resource-based account of how GenAI reshapes daily work.

Despite growing interest, the literature on GenAI's employee-level effects remains fragmented across productivity, creativity, and engagement streams that are rarely examined together within one theoretical architecture. This paper addresses that gap by proposing an integrative conceptual model grounded in Job Demands-Resources (JD-R) theory, Conservation of Resources (COR) theory, and Self-Determination Theory (SDT), with job crafting positioned as the behavioural mechanism connecting GenAI adoption to productivity, creativity, and engagement. The model further situates organizational adoption within the broader context of AI-enabled learning and ethical AI use, drawing on recent work on generative AI in higher education and skill formation (Grover 2024b; Grover 2024a; Vats & Khanna 2024; Grover 2024c), which suggests that employees' readiness to benefit from workplace GenAI is shaped well before organizational adoption begins. The remainder of the paper develops the theoretical background, reviews the relevant literature and derives four testable hypotheses, presents the conceptual model, proposes a methodology for future empirical validation, and discusses theoretical and managerial implications.

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2. Theoretical Background

2.1 Job Demands-Resources Theory

JD-R theory provides the primary organizing lens for this paper. The theory holds that every occupation can be characterized by job demands, which require sustained physical or psychological effort, and job resources, which are functional in achieving goals, reducing demands, or stimulating growth (Bakker et al. 2023). Job resources are theorized to fuel a motivational process leading to engagement, while excessive or poorly managed demands trigger a health-impairment process leading to strain. Recent applications of JD-R to organizational AI adoption treat AI systems as inherently dual in nature: they can function as a resource that reduces cognitive and administrative burden, or as a demand that introduces new complexity, monitoring, and uncertainty (Cheng et al. 2023; He et al. 2024). This dual categorization is central to the treatment of GenAI in the present paper as a resource-demand hybrid rather than a uniformly positive intervention.

2.2 Conservation of Resources Theory

COR theory complements JD-R by explaining how individuals respond to resource gains and losses over time. Resource loss is theorized to be disproportionately more psychologically salient than resource gain, and individuals are motivated to acquire, retain, and protect valued resources (Hobfoll et al. 2018). Applied to GenAI adoption, COR suggests that when generative tools genuinely conserve employees' cognitive and time resources — by automating drafting, summarization, or first-pass analysis — employees experience a resource gain that can be reinvested into higher-order tasks such as creative problem-solving. Conversely, when GenAI adoption is experienced as threatening, for example through fears of skill obsolescence or performance surveillance, it can trigger a resource-loss spiral that COR predicts will manifest as withdrawal, reduced engagement, or defensive, non-creative task execution (Raisch & Krakowski 2021).

2.3 Self-Determination Theory and Job Crafting

SDT holds that intrinsic motivation, engagement, and well-being flourish when the basic psychological needs for autonomy, competence, and relatedness are satisfied (Deci et al. 2017). Job crafting theory describes the proactive, bottom-up behaviours through which employees reshape the task, cognitive, or relational boundaries of their work to better align it with these needs (Wrzesniewski & Dutton 2001). Job crafting has separately been shown to sustain work engagement, task performance, and career satisfaction over time (Dubbelt et al. 2019), which positions it as a plausible mechanism through which GenAI's freed capacity is converted into durable, rather than short-lived, gains. When AI adoption is perceived as autonomy-supportive, employees are more likely to engage in the kind of task and cognitive crafting that channels freed-up capacity into meaningful, creative work (Cheng et al. 2023; Li et al. 2024). This paper

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accordingly treats job crafting as the principal mediating mechanism connecting GenAI adoption to the three focal outcomes of productivity, creativity, and engagement.

3. Literature Review and Hypothesis Development

3.1 GenAI Adoption and Employee Productivity

The most direct and best-established effect of generative AI concerns task-level productivity. Noy and Zhang's (2023) randomized field experiment remains the benchmark demonstration that AI writing assistance reduces task completion time while improving output quality, with the largest gains accruing to initially lower-performing workers — an equalizing effect with significant implications for organizational talent management. Complementary evidence shows that GenAI can reduce workplace overload and administrative burden by absorbing routine cognitive load such as drafting, summarizing, and first-pass coding (Hessari et al. 2024), while broader reviews of GenAI's business-model implications point to efficiency gains across content-heavy and analytical organizational functions (Kanbach et al. 2024; Singh et al. 2024; Sedkaoui & Benaichouba 2024). From a JD-R perspective, these findings are consistent with GenAI functioning as a job resource that frees time and attentional capacity for redirection toward higher-value tasks. These productivity gains, however, are unlikely to be automatic or self-sustaining. Consistent with COR theory's resource-investment logic, the benefit of freed capacity should depend on what employees do with it: capacity that is reinvested into deliberate, value-adding task crafting should translate into durable productivity gains, whereas capacity that is simply absorbed by passive AI reliance may not (Hobfoll et al. 2018; Raisch & Krakowski 2021). We therefore hypothesize:

H1: Organizational generative AI adoption is positively associated with employee productivity, and this relationship is mediated by employee job crafting that reallocates freed cognitive resources toward core value-adding activities.

3.2 GenAI Adoption and Employee Creativity

The relationship between GenAI and creativity is theoretically more contested than the productivity relationship. Jia and colleagues (2024) show that AI augmentation can expand employees' creative search space by surfacing unfamiliar idea combinations, effectively functioning as an associative-thinking resource. Similar mechanisms are documented in service-sector research, where AI adoption is linked to job crafting behaviour and, through it, to creative and innovative performance (Li et al. 2024; He et al. 2024; Liu et al. 2024). On the other hand, a "double-edged sword" perspective cautions that GenAI-generated suggestions can anchor employees' thinking, narrowing rather than expanding the creative solution space, and that habitual reliance on AI-generated first drafts can atrophy the generative cognitive effort that underlies genuine originality (Yin et al. 2024; Dong et al. 2025).

This tension suggests that the AI-creativity relationship is contingent on how employees engage with GenAI rather than being uniformly positive: employees who actively craft their engagement

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with AI — treating it as a co-ideation partner rather than a substitute for independent thought — should realize creativity gains, whereas habitual or passive users should not (Li et al. 2024; Cheng et al. 2023). We therefore propose:

H2: Job crafting moderates the relationship between generative AI adoption and employee creativity, such that active, crafted engagement with GenAI (for example, using it to generate counter-arguments or alternative framings rather than final answers) strengthens creative performance, while passive over-reliance weakens it.

3.3 GenAI Adoption and Work Engagement

Work engagement, characterized by vigour, dedication, and absorption, is a central outcome variable within JD-R theory and is theorized to flow from resource-rich work environments (Bakker et al. 2023). Job crafting has independently been shown to sustain engagement, task performance, and career satisfaction over multi-wave, quasi-experimental study designs (Dubbelt et al. 2019), which suggests it should extend naturally into AI-augmented roles: when GenAI reduces routine burden, employees gain the capacity to craft more meaningful, absorbing work, consistent with COR theory's resource-investment logic (Hobfoll et al. 2018).

Realizing this benefit, however, depends on adequate organizational support. Structured upskilling and reskilling investment is a documented precondition for employees to convert AI exposure into productive engagement rather than anxiety-driven avoidance (Morandini et al. 2023), and multilevel reviews of AI in organizations similarly call for attention to individual-level readiness factors that condition whether adoption is experienced as energizing or eroding (Bankins et al. 2024). A recent multilevel review of artificial intelligence and employee well-being further concludes that AI's engagement effects are strongly moderated by whether organizations frame adoption as augmentative rather than substitutive of employee judgment (Vats & Sharma 2026). Accordingly:

H3: Job crafting mediates a positive relationship between generative AI adoption and work engagement, and this indirect effect is stronger when organizations invest in structured AI upskilling, support, and an augmentative framing of adoption.

3.4 Boundary Conditions: AI Literacy, Ethics, and Organizational Readiness

A consistent theme across the reviewed literature is that GenAI's behavioural effects are not uniform but are shaped by organizational and individual boundary conditions (Budhwar et al. 2023; Gupta et al. 2024; Ooi et al. 2025). This readiness is increasingly shaped upstream, in education, which functions as the pipeline for organizational AI competence. Grover's comparative analysis of Microsoft Copilot in programming education documents how generative coding assistants are reshaping learners' problem-solving routines even before they enter the workforce (2024a), while her broader study of generative AI's role in next-generation learning environments highlights measurable gains in learner engagement and personalized skill development (2024b).

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Vats and Khanna (2024) similarly show that structured pedagogical integration of GenAI into higher education, rather than ad hoc tool exposure, is what enables these gains and aligns them with sustainable-development goals. This pipeline argument is reinforced by Seth and Grover's (2026) analysis of higher-education pedagogy for Generation Z, which finds that cohorts taught with deliberate strategies for AI integration develop stronger self-regulated learning and adaptive problem-solving habits than those exposed to AI tools without pedagogical structure — habits that plausibly transfer into more crafted, resource-oriented GenAI use once these individuals enter the workforce. Employees entering the workforce with such structured, ethically-grounded exposure are more likely to appraise organizational GenAI adoption as a resource rather than a threat.

Equally important is the ethical and sustainability frame within which GenAI is subsequently used at work. Grover's comparative analysis of ethical and unethical uses of generative AI (2024c) suggests that employees who operate under clearer ethical guidelines for AI use extract more sustainable performance benefits and report less identity threat than those navigating ambiguous or unstated norms, since ambiguity itself becomes a source of the anxiety documented in the AI-skills literature (Morandini et al. 2023). Saxena and colleagues' (2025) review of the challenges confronting sustainable artificial intelligence adds a complementary organizational-level caution: without deliberate attention to the environmental, governance, and long-term workforce costs of AI systems, adoption that appears efficient in the short run can generate hidden sustainability costs that erode its benefits over time. This suggests that boundary conditions for GenAI's positive employee effects operate simultaneously at the individual level (literacy, ethical clarity) and the organizational level (sustainable, well-governed deployment). We therefore propose a final integrative hypothesis:

H4: The positive indirect effects of generative AI adoption on productivity, creativity, and engagement (via job crafting) are stronger among employees with higher pre-existing AI literacy and clearer organizational ethical guidelines for AI use, and weaker or reversed where such literacy and guidance are absent.

4. Conceptual Model

Integrating the theoretical foundations and hypotheses developed above, GenAI adoption is modelled as the central antecedent construct, operating through two parallel appraisal pathways consistent with the challenge-hindrance stressor framework (Cheng et al. 2023; Raisch & Krakowski 2021). In the challenge pathway, GenAI adoption is appraised as a job resource, activating job crafting behaviour, which in turn drives gains in productivity (H1), creativity (H2), and work engagement (H3). In the hindrance pathway, GenAI adoption accompanied by technology insecurity or inadequate organizational support triggers a resource-loss spiral consistent with COR theory (Hobfoll et al. 2018), suppressing the same three outcomes through withdrawal or passive over-reliance. AI literacy, ethical-use clarity, and organizational readiness (H4) are positioned as boundary conditions that determine which of the two pathways

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predominates within a given organizational context. This dual-pathway structure is deliberately consistent with the "double-edged sword" characterization that recurs throughout the recent AI-organizational-behaviour literature (Yin et al. 2024; Dong et al. 2025; Park 2024), and it distinguishes the present model from earlier, unidirectionally optimistic technology-adoption frameworks. The model also makes explicit the upstream role of pre-organizational AI exposure. Consistent with evidence from educational contexts (Grover 2024b; Grover 2024a; Vats & Khanna 2024), employees' prior AI literacy — cultivated through formal education and ethically-grounded AI use (Grover 2024c) — is positioned as an individual-difference moderator of the challenge-appraisal pathway, such that employees entering the workforce with structured GenAI exposure are more likely to appraise organizational adoption as a resource rather than a threat.

4.1 Proposed Methodology for Empirical Validation

As a conceptual paper, the model developed here requires empirical testing before its practical value can be fully assessed. A time-lagged, multi-source survey design is recommended as a first step: GenAI adoption and AI literacy measured at Time 1, job crafting measured at Time 2, and productivity, creativity, and engagement outcomes measured at Time 3, ideally supplemented with supervisor-rated performance data to reduce reliance on single-source, self-reported measures. Such a design would allow the mediating role of job crafting (H1–H3) and the moderating role of AI literacy and organizational readiness (H4) to be tested using established structural equation modelling and moderated-mediation techniques, consistent with methods used in adjacent AI-adoption research (Cheng et al. 2023; Li et al. 2024; He et al. 2024). Sampling across knowledge-intensive professional-services organizations, rather than the hospitality- and service-sector contexts that dominate the current empirical base (Liu et al. 2024; He et al. 2024), would extend the model's generalizability. Where feasible, a field-experimental component modelled on Noy and Zhang's (2023) design — comparing task outcomes for employees with and without structured GenAI access and training — would strengthen causal inference around H1 in particular.

5. Conclusion, Implications, Limitations, and Future Research Directions

Generative AI is reshaping organizational work at a pace that has outstripped the field's theoretical understanding of its behavioural consequences. This paper has argued that a resource-based, dual-pathway framework — grounded in JD-R, COR, and SDT — offers a more complete account of GenAI's organizational effects than the productivity-centric narratives that currently dominate both practitioner discourse and much of the academic literature. By positioning job crafting as the central behavioural mechanism and identifying AI literacy, ethical-use clarity, and organizational readiness as key boundary conditions, the proposed model reconciles the optimistic and cautionary strands of the literature within a single, testable framework. As organizations continue to embed generative AI ever more deeply into daily work, understanding not merely whether but how and for whom these tools translate into productivity, creativity, and engagement will be essential — both for scholarship and for the design of humane, effective AI-augmented workplaces.

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5.1 Theoretical Implications

This paper contributes to organizational behaviour theory in three ways. First, it extends JD-R and COR theory into the generative AI domain by explicitly modelling GenAI as a dual-natured construct capable of functioning as either resource or demand, rather than treating "AI adoption" as a monolithic independent variable (Bankins et al. 2024; Raisch & Krakowski 2021). Second, by positioning job crafting as the central mediating mechanism across all three outcome domains, the model unifies previously disconnected literatures on AI-productivity (Noy & Zhang 2023), AI-creativity (Jia et al. 2024; Li et al. 2024), and AI-engagement (Dubbelt et al. 2019; Vats & Sharma 2026) within a single behavioural pathway. Third, the model's inclusion of pre-organizational AI literacy and ethical-use clarity as boundary conditions builds a bridge between the organizational behaviour literature and the generative-AI-in-education literature (Grover 2024b; Vats & Khanna 2024; Grover 2024c), an interdisciplinary connection that has received little explicit attention to date.

5.2 Managerial Implications

For practitioners, the model carries several actionable implications. First, because job crafting emerges as the pivotal mechanism linking GenAI adoption to positive outcomes, organizations should not treat GenAI rollout purely as a technical deployment but should actively encourage employees to reshape their own workflows around the technology. Second, given the demonstrated importance of structured skill investment as a buffer against technology insecurity (Morandini et al. 2023; Bankins et al. 2024), leaders should treat AI-literacy training as a prerequisite for, rather than a follow-up to, GenAI adoption — an argument consistent with pedagogy research showing that structured, rather than incidental, AI exposure builds more durable and self-regulated engagement with these tools (2026). Third, consistent with the ethical-use findings of Grover (2024c), organizations should pair GenAI deployment with explicit ethical-use guidelines, since ambiguity about acceptable AI use appears to be a meaningful driver of both underperformance and disengagement. Fourth, organizations should evaluate GenAI adoption against sustainability criteria rather than short-term efficiency alone: Saxena and colleagues (2025) caution that AI systems carry environmental, governance, and workforce costs that can undermine their apparent benefits if left unmanaged, making sustainable AI governance a necessary complement to the job-crafting and literacy interventions proposed here. Finally, this logic extends beyond large enterprises: for growth-stage and entrepreneurial organizations, sustainable adoption of new technologies has historically hinged on deliberate capability-building rather than tool access alone (Grover 2021), suggesting that the resource-based framework proposed here is relevant well beyond large, established firms.

5.3 Limitations and Future Research

As a conceptual paper, this work's principal limitation is the absence of primary empirical data; the hypotheses developed here require testing through the longitudinal, multi-source design

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outlined in Section 5, capable of capturing the temporal unfolding of job crafting and resource dynamics implied by COR theory (Hobfoll et al. 2018). Cross-sectional, single-source designs common in the adjacent literature (Cheng et al. 2023; He et al. 2024) risk common-method bias and cannot adequately test the moderated pathways proposed in H2 and H4. Future research should also examine industry heterogeneity, since much of the existing empirical base is concentrated in hospitality and service contexts (Liu et al. 2024; He et al. 2024) rather than knowledge-intensive professional services, where GenAI's creative and productivity implications may differ substantially. Finally, given this paper's Indian managerial and educational vantage point, future work should examine whether the proposed pathways generalize across national and cultural contexts, extending related work on technology adoption and sustainability among Indian organizations (Grover 2021).

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