Generative AI in the Workplace: A Systematic Review of Productivity Effects, Employment Perceptions, and Job Insecurity

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ABSTRACT

The growing adoption of generative artificial intelligence (AI) in workplace settings has generated significant interest in its implications for productivity, employee perceptions, and job security. This systematic literature review synthesises findings from 40 empirical and conceptual studies published between 2020 and 2025 across organisational and professional contexts to evaluate the multifaceted impact of generative AI on organisational and workforce outcomes. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, a structured search was conducted across Google Scholar and Dimensions.ai, yielding 3,252 database records, with 8 additional hand-searched studies, of which 40 met the inclusion criteria. The review identifies consistent evidence of productivity improvements driven by task automation, decision support, and knowledge augmentation. However, these gains are accompanied by mixed employee perceptions, with increased efficiency and job satisfaction coexisting alongside concerns about skill obsolescence and role displacement. Job insecurity emerges as a critical mediating factor influencing employee attitudes and behavioral responses, including upskilling intentions and resistance to technological change. Importantly, the review reveals a significant research gap in the comparative understanding of generative AI's impact across developed and developing economies, where differences in technological infrastructure, labor market dynamics, and skill distributions may lead to uneven outcomes. The findings highlight that the effects of generative AI are heterogeneous and context-dependent, shaped by job roles, skill levels, and institutional environments. By integrating fragmented literature into a cohesive framework, this study contributes to the emerging discourse on AI-driven workplace transformation and offers implications for managers and policymakers to ensure more balanced, inclusive, and context-sensitive AI adoption strategies.

Keywords: generative artificial intelligence, workplace productivity, job insecurity, employee perception, large language models, workforce transformation, systematic review.

INTRODUCTION

The emergence of generative artificial intelligence (AI) — encompassing large language models (LLMs) such as GPT-4, Google Gemini, and tools including GitHub Copilot and Microsoft Copilot — represents one of the most consequential technological shifts in the contemporary workplace. Unlike earlier automation waves that primarily displaced routine manual tasks, generative AI demonstrates the capacity to perform complex cognitive, creative, and communicative functions previously considered the exclusive domain of skilled workers (Eloundou et al., 2024; Raisch & Krakowski, 2021). Following the public release of ChatGPT in November 2022, the technology reached 100 million users within two months — a rate of diffusion exceeding any prior consumer technology — and by 2024, nearly 40% of U.S. working adults reported using generative AI tools in some professional capacity (Bick et al., 2024; Dwivedi et al., 2023). This rapid diffusion has generated urgent questions about its implications for organizational productivity, workforce dynamics, and employment security.

Early empirical evidence documents substantial productivity gains: Noy and Zhang (2023) found a 40% reduction in task completion time among knowledge workers using ChatGPT; Brynjolfsson et al. (2025), in a peer-reviewed field experiment published in the Quarterly Journal of Economics, documented a 15% increase in customer service agent output; and Peng et al. (2023), in a controlled experiment (preprint, arXiv), reported a 55.8% improvement in coding task speed for GitHub Copilot users. However, these gains coexist with growing employee anxiety. Eloundou et al. (2024) estimated that approximately 80% of the U.S. workforce could have at least 10% of their job tasks exposed to LLMs, while BCG's (2025) global workforce survey found that 46% of employees at AI-advanced firms reported heightened job insecurity. This paradox — simultaneous gains in efficiency and rises in displacement concern — defines the central tension this review seeks to examine.

Despite growing scholarly attention, the literature on generative AI in the workplace remains fragmented and geographically imbalanced. The overwhelming majority of empirical studies have been conducted in developed economy contexts, with limited systematic evidence from South Asia, Sub-Saharan Africa, or Latin America (Aderibigbe et al., 2023; Sarfo et al., 2024). Given that developing economies account for most of the global workforce and face substantially different institutional conditions and labor market structures, this geographic bias risks producing governance frameworks poorly calibrated to the realities of most working people worldwide.

This systematic review addresses these gaps by synthesizing 40 peer-reviewed studies published between 2020 and 2025, following the PRISMA framework (Page et al., 2021). The review is guided by the following research questions:

RQ1. What is the empirical evidence on the effect of generative AI adoption on workplace productivity?

RQ2. How do employees perceive generative AI in the workplace, and what factors shape those perceptions?

RQ3. How does generative AI adoption relate to job insecurity, and does this differ across developed and developing economies?

The paper proceeds as follows: Section 2 presents the theoretical framework; Section 3 details the PRISMA methodology; Section 4 reports findings; Section 5 discusses implications; Sections 6 and 7 address limitations and research gaps; and Section 8 concludes.

THEORETICAL FRAMEWORK

This review draws on three complementary theoretical frameworks: the Task-Technology Fit (TTF) model, the Job Demands-Resources (JD-R) model, and the Automation-Augmentation Paradox. Together they provide a multi-level analytical architecture spanning task, individual, and organizational dimensions of the generative AI-workplace relationship.

Task-Technology Fit (TTF) Model

The Task-Technology Fit model (Goodhue & Thompson, 1995) posits that technology positively impacts performance only when its functionality aligns with the demands of the tasks it supports. In the generative AI context, TTF predicts that productivity gains will be greatest for tasks characterized by high language intensity, knowledge synthesis, and information processing— precisely the categories most amenable to LLM capabilities (Dell'Acqua et al., 2023; Noy & Zhang, 2023). Tasks requiring embodied skill, real-time physical judgment, or deep tacit knowledge show lower fit and weaker productivity effects. This framework explains why productivity gains are heterogeneous across occupations rather than uniform.

Job Demands-Resources (JD-R) Model

The Job Demands-Resources model (Bakker & Demerouti, 2007; Demerouti et al., 2001) distinguishes between job demands — aspects requiring sustained effort and associated with psychological costs — and job resources — aspects that help achieve goals and stimulate personal growth. Generative AI operates as both simultaneously: as a resource, it reduces cognitive load and enables higher-order work; as a demand, it introduces upskilling pressure, role uncertainty, and surveillance anxieties (Liang et al., 2024; Patel et al., 2024). This dual role explains the paradoxical co-presence of increased satisfaction and heightened insecurity documented across multiple studies, directly informing RQ2 and RQ3.

The Automation-Augmentation Paradox

Raisch and Krakowski (2021), in a conceptual framework published in the Academy of Management Review, articulate the tension between automation logic — replacing human cognitive effort with machine processing — and augmentation logic — enhancing human capabilities through human-machine collaboration. Organizations emphasizing automation may realize short-term efficiency gains at the cost of employee engagement and long-term adaptive capacity, while those emphasizing augmentation tend to generate more sustainable and equitably distributed productivity improvements. This paradox provides normative grounding for the managerial implications discussed in Section 5 and is particularly relevant to RQ3, where developing economy organizational contexts may face structural pressures toward automation logic that amplify displacement risk.

METHODOLOGY

Review Design

This study adopts the PRISMA framework (Page et al., 2021) to ensure a transparent and reproducible review process. Given the heterogeneity of study designs and outcome measures across the included literature, a narrative synthesis approach was adopted rather than a formal meta-analysis.

Search Strategy

A systematic search was conducted across Google Scholar and Dimensions.ai, covering publications from January 2020 to December 2025. Scopus and Web of Science were initially identified as target databases but were inaccessible due to subscription constraints, which is acknowledged as a limitation in Section 6. Hand-searching of reference lists from retrieved papers yielded an additional eight studies. Six search strings were applied across both databases, as presented in Table 1.

Database	Search	Search String
Google Scholar	A	"generative AI" "workplace productivity"
Google Scholar	B	"generative AI" "job insecurity" OR "employee perception"
Google Scholar	C	"generative artificial intelligence" "workforce" "job displacement" OR "skill obsolescence"
Dimensions.ai	A	"generative AI" AND "workplace" AND "productivity"
Dimensions.ai	B	"generative AI" OR "ChatGPT" OR "large language model" AND "employee perception" OR "job insecurity" AND "workplace"
Dimensions.ai	C	"generative artificial intelligence" AND "employment" OR "workforce" AND "productivity" OR "displacement"

Table 1 - Search Strings Used Across Databases

Inclusion and Exclusion Criteria

Studies were included if they: (I1) specifically addressed generative AI, LLMs, ChatGPT, GPT-3/4, or Copilot; (I2) were set in a workplace or employment context; (I3) reported on productivity, employee perception, job insecurity, displacement, or skill change; (I4) were published between 2020 and 2025; (I5) were in English; and (I6) were empirical studies, systematic reviews, or conceptual frameworks accessible in full text. Studies were excluded if they focused solely on traditional automation without a generative AI component (E1), were exclusively set in non-workplace settings (E2), reported only technical benchmarks (E3), or were opinion pieces without scholarly contribution (E4).

Study Selection and PRISMA Flow

The search yielded 3,252 records from database searches: 1,940 from Google Scholar and 1,312 from Dimensions.ai. An additional 8 records were identified through hand-searching. After deduplication, 2,892 unique records remained. Title screening removed 1,164 irrelevant records. Abstract screening of the remaining 1,728 records excluded a further 1,693. Three hand-searched records were removed following a full-text review. The final corpus comprised 40 studies. The PRISMA flow is presented in Figure 1.

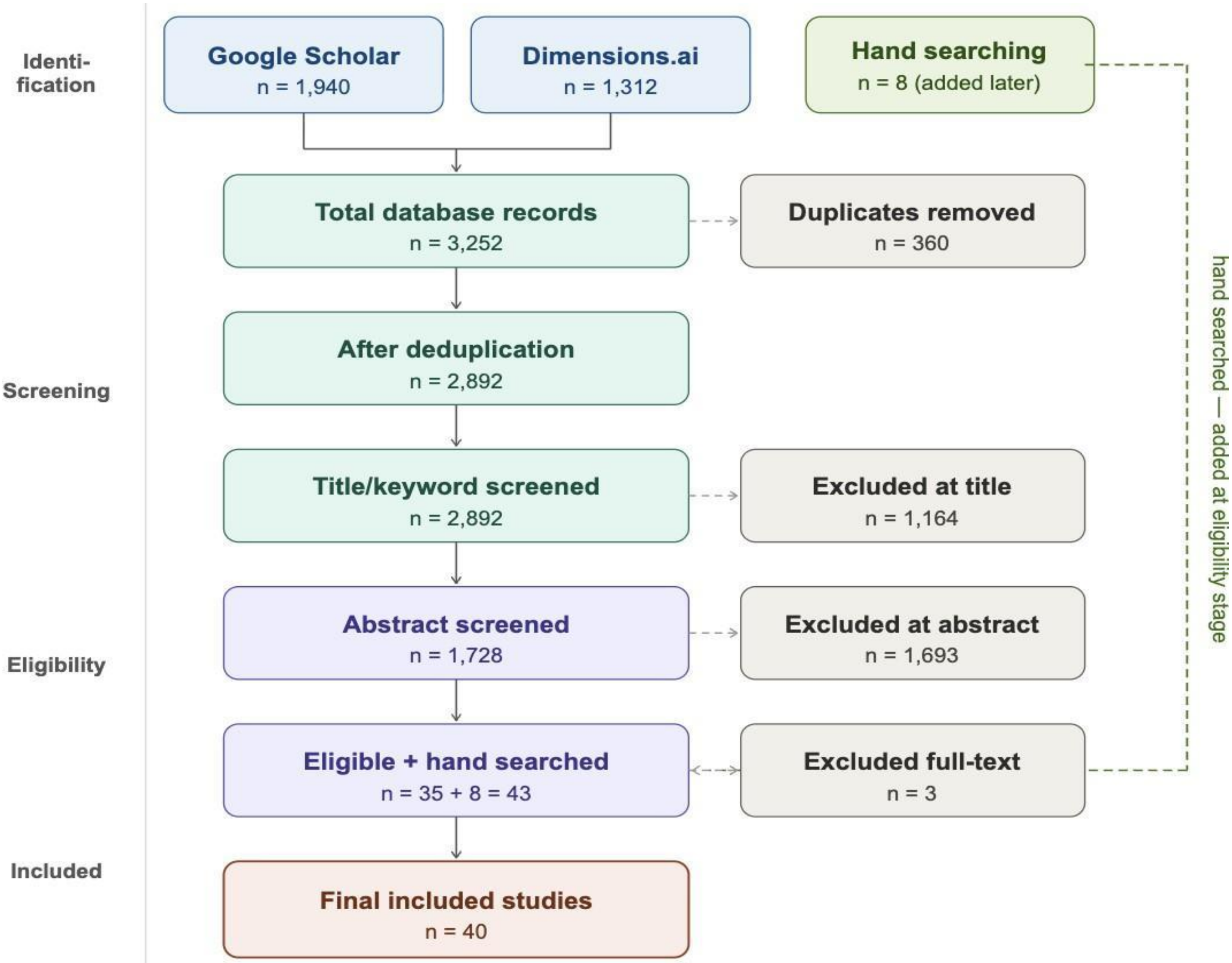

Figure 1 - PRISMA Flow Diagram of Study Selection

Data Extraction and Quality Assessment

Data were extracted from each included study using a standardized template recording: author(s), year, country or region, study design, evidence type (peer-reviewed empirical study, working paper, conceptual framework, or secondary synthesis), AI tool investigated, sector, key outcomes, and principal findings. This classification of evidence type was applied consistently throughout the synthesis to ensure that empirical findings, theoretical contributions, and grey literature were weighted appropriately and not treated as equivalent sources of evidence. Study quality was assessed using a three-tier framework appropriate to each design type. Experimental and quasi-experimental studies were evaluated against internal validity criteria including randomization, control conditions, blinding, and attrition. Survey-based and observational studies were assessed for sample representativeness, measurement validity, response rate adequacy, and potential common method bias. Qualitative, conceptual, and secondary synthesis studies were assessed against criteria of analytical rigor, theoretical grounding, reflexivity, and transferability of findings. Where conflicting evidence was identified across studies — for example, studies documenting productivity gains alongside studies reporting negligible or conditional effects — the synthesis gave greater evidentiary weight to peer-reviewed experimental and quasi-experimental studies over working papers, conceptual contributions, and secondary syntheses. Conflicts were explicitly noted in the findings text rather than resolved artificially, and the methodological and contextual differences likely to explain divergent findings were discussed. This approach to evidence weighting follows best practice guidance for narrative synthesis in systematic reviews (Page et al., 2021).

FINDINGS

This section synthesizes evidence from the 40 included studies, organized around the three research questions. Table 2 provides a summary of the key included studies.

Authors	Year	Study Type	Key Focus & Finding
Noy & Zhang	2023	RCT	ChatGPT reduced task time 40%; quality improved 18%
Brynjolfsson et al.	2025	Field Experiment	15% productivity gain in customer service; skill-leveling effect
Dell'Acqua et al.	2023	Field Experiment	GPT-4 improved performance within frontier; degraded beyond it
Peng et al.	2023	Controlled Experiment	GitHub Copilot users coded 55.8% faster
Eloundou et al.	2024	Exposure Analysis	80% of US workers have 10%+ task exposure to LLMs
Liang et al.	2024	Empirical Survey	Employee-AI collaboration has double-edged effects
Zhao & Wu	2024	Empirical Survey	AI substitution risk linked to psychological distress
Remund & Bernays	2024	Empirical	Emotional preferences drive AI use decisions
Samokhina	2024	Qualitative	Automation anxiety vs. optimism among data scientists
Sarfo et al.	2024	Systematic Review	AI perceptions in Ghana and Nigeria — trust deficits
Aderibigbe et al.	2023	Systematic Review	Four structural barriers to AI in developing countries
Gabas	2025	Country Analysis	AI concentrates gains among large firms in Brazil
Autor	2022	Theoretical	AI drives labor market polarization
Raisch & Krakowski	2021	Conceptual	Automation vs. augmentation logic shapes AI outcomes

Table 2 - Summary of Key Included Studies

Productivity Effects of Generative AI (RQ1)

Evidence of Productivity Gains

Empirical evidence consistently documents substantial productivity improvements from generative AI across knowledge-intensive occupations. Noy and Zhang (2023), in a randomized controlled trial — a peer-reviewed empirical study published in Science — with 453 professionals, found that ChatGPT reduced task completion time by 40% and improved output quality by 18%, with the largest gains concentrated among initially lower-performing workers — a skill-leveling effect replicated by Brynjolfsson et al. (2025), who documented a 15% average increase in customer service agent output across 5,179 workers. In software development, Peng et al. (2023) found GitHub Copilot users completed tasks 55.8% faster. Dell'Acqua et al. (2023), in a preregistered field experiment (Harvard Business School working paper), added a critical qualification: GPT-4 improved BCG consultant performance by 40% in quality and 25% in speed for tasks within the AI's capability frontier, but degraded performance by 19 percentage points on tasks beyond it — establishing that productivity effects are conditional on task-technology fit. Al Naqbi et al. (2024), in a comprehensive literature review, synthesized these findings into three core mechanisms: task automation, decision support, and knowledge augmentation. In terms of sectoral and geographic distribution, the strongest productivity evidence comes from software development (Peng et al., 2023 — United States, controlled experiment), professional consulting (Dell'Acqua et al., 2023 — United States, field experiment), and customer service (Brynjolfsson et al., 2025 — United States, field experiment). Evidence from manufacturing, healthcare administration, retail, and public sector organizations — particularly in developing economies — remains sparse, limiting the generalizability of productivity conclusions beyond knowledge-intensive, developed economy contexts.

Heterogeneity of Effects

Productivity gains are unevenly distributed across occupations, individuals, and organizational contexts. Eloundou et al. (2024) estimated that while 80% of U.S. workers have some LLM task exposure, only 19% face high exposure across more than half their tasks. Zhang et al. (2024) found that individual openness and job complexity moderated AI's effect on innovation behavior, while Popescu (2024) noted that algorithmically managed AI deployments improved measurable output but reduced worker autonomy — illustrating that implementation design shapes realized outcomes as much as the technology itself. Raisch and Krakowski (2021) argue that organizations adopting an augmentation logic realize more sustainable and broadly distributed productivity gains than those prioritizing substitution.

Employee Perceptions of Generative AI (RQ2)

Positive Perceptions

Several studies document genuine enthusiasm and high perceived utility among knowledge workers. Liang et al. (2024) found that employee-AI collaboration reduced cognitive load and improved task confidence. Adiasto (2024) found that workers who proactively engaged with AI as a complementary resource reported higher career self-efficacy and sustainable employability perceptions. Li et al. (2024) documented high perceived utility among UX professionals for creative tasks, while Oghene (2024) found a significant positive association between AI adoption and job satisfaction where organizations provided adequate training and psychological safety.

Negative Perceptions and Resistance

Negative perceptions cluster around three themes: professional identity threat, AI reliability concerns, and organizational trust deficits. Remund and Bernays (2024) found workers frequently avoided AI for tasks constitutive of their professional identity regardless of productivity arguments. Patel et al. (2024) identified a paradoxical relationship between heavy AI use and workplace loneliness, particularly among remote workers. Lnenicka and Machova (2024) found that poor change management generated substantially more negative perceptions than transparent, participatory implementation. Sarfo et al. (2024), in a systematic review synthesizing evidence from Ghana and Nigeria, found that perceptions were shaped by historical experiences of exclusion and concerns about algorithmic bias, demonstrating that employee perceptions are embedded in broader institutional and historical contexts.

Job Insecurity, Employment Effects, and the Developing Economy Divide (RQ3)

Job Insecurity as a Mediating Variable

Job insecurity emerges as a critical mediating variable in the generative AI-workplace relationship. Zhao and Wu (2024) found that perceived AI substitution risk was positively associated with psychological distress and reduced organizational commitment, with digital self-efficacy moderating this relationship — indicating that upskilling programs have mental health implications alongside productivity benefits. Samokhina (2024) identified coexisting frames of technological optimism and automation anxiety within the same professional communities, while Strom (2024) found that anticipatory insecurity — driven by perceived future threat — is itself causing measurable organizational harm through disengagement and elevated turnover intention.

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Labor Market Restructuring

The reviewed literature documents significant labor market restructuring. Eloundou et al. (2024) established that LLM exposure is highest for high-wage, high-education occupations — inverting the historical pattern of automation that primarily displaced low-skill workers. Autor (2022) predicted AI-driven labor market polarization, with growing demand at the high-skill and low-skill ends and greatest displacement pressure on middle-skill administrative roles. Ersanlı et al. (2024) found that AI reskilling programs are expanding but unevenly distributed, and Tenakwah and Amankwaa (2024) found that collective resistance was most likely when AI deployment was experienced as disempowering and opaque.

The Generative AI Divide

The most underexplored finding concerns the differential impact of generative AI across developed and developing economies. Aderibigbe et al. (2023), in a systematic review of AI implementation in developing countries, identified four structural barriers in developing countries: inadequate digital infrastructure, shortage of skilled AI talent, weak regulatory frameworks, and limited organizational change management capacity. Gabas (2025), in an empirical country-level analysis of Brazil, found that AI benefits are concentrated among large firms and high-skill workers, widening wage inequality. Sarfo et al. (2024) documented substantially lower AI trust in Ghana and Nigeria relative to Western samples. Albaroudi et al. (2024) found that governance frameworks in Saudi Arabia lag behind adoption rates. Collectively, these findings establish the generative AI divide — a structural asymmetry between developed and developing economies in the capacity to harness AI productivity gains while managing associated employment disruptions.

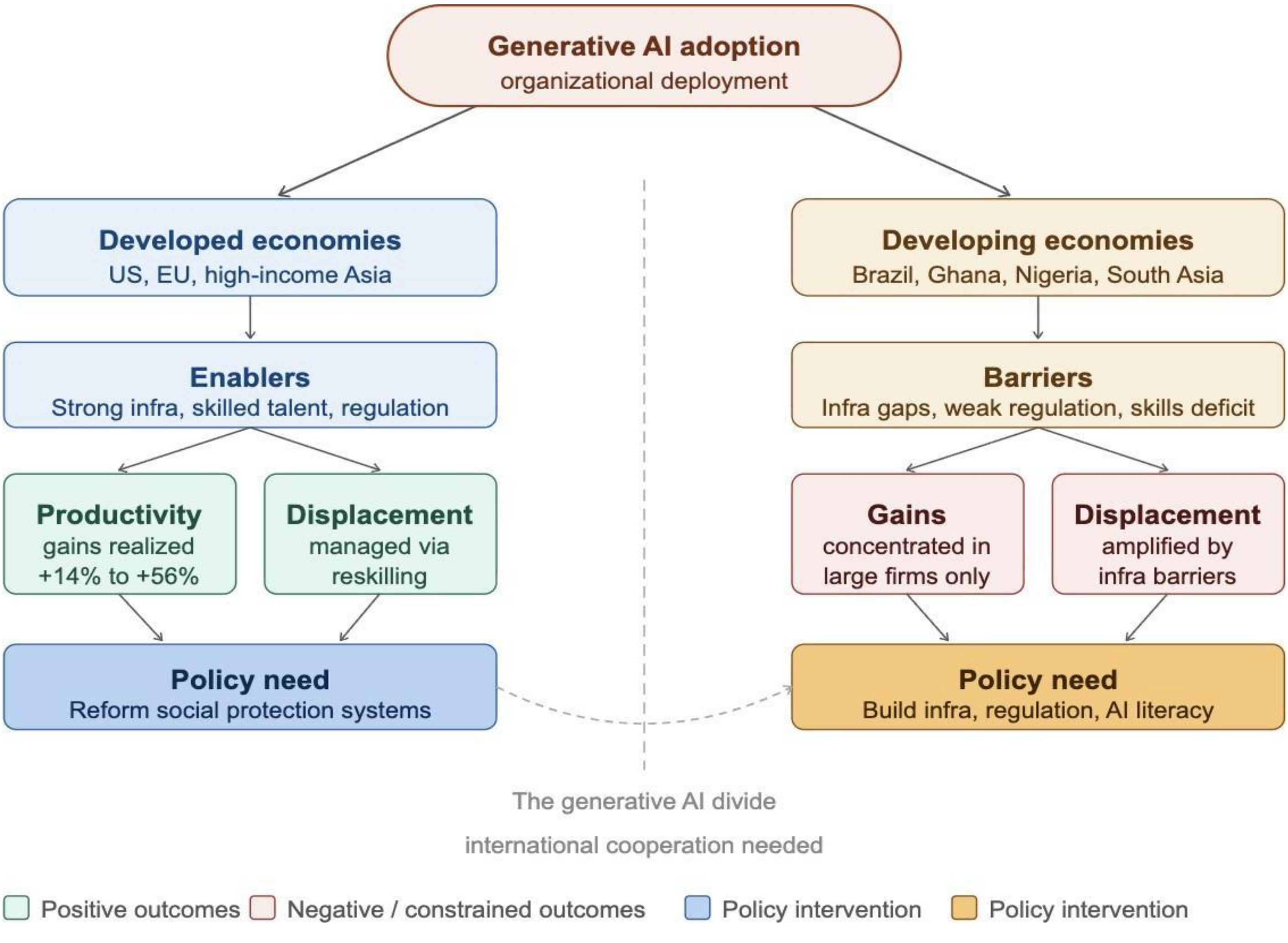

Figure 2 - The Generative AI Divide: Developed vs. Developing Economies

DISCUSSION

Synthesis of Key Findings

The reviewed literature converges on three overarching conclusions. First, productivity gains from generative AI are real, empirically robust, and substantial — but conditional on task-technology fit and organizational deployment logic. The consistent skill-leveling effect across independent studies (Noy & Zhang, 2023; Brynjolfsson et al., 2025) suggests that generative AI raises the performance floor more than the ceiling, reducing intra-occupational productivity inequality. Second, employee perceptions are structurally ambivalent — reflecting generative AI's simultaneous role as a job resource that reduces cognitive load and a job demand that introduces upskilling pressure and identity threat (Liang et al., 2024). This ambivalence is not transitional but a persistent feature of human-AI collaboration that organizations must design around. Third, job insecurity is structurally grounded: the novel pattern of highest LLM exposure among high-wage, high-education occupations (Eloundou et al., 2024) represents a historically unprecedented automation trajectory that existing labor market institutions were not designed to manage.

The Generative AI Divide

The most significant contribution of this review is its documentation of the generative AI divide — a structural asymmetry between developed and developing economies in the capacity to harness AI productivity gains while managing employment disruption. Of the 40 included studies, the majority drew on evidence from high-income economies. The minority addressing developing economy contexts consistently found structural barriers that limit AI benefit realization while amplifying displacement risks (Aderibigbe et al., 2023; Gabas, 2025; Sarfo et al., 2024). This geographic imbalance in the research base risks producing governance frameworks calibrated to high-income economy conditions and inadequate for the majority of the world's workforce. Addressing the generative AI divide requires expanded research in developing economy contexts and AI governance frameworks explicitly designed around distributional — not merely aggregate — outcomes.

Implications for Organizations

Four practical recommendations emerge for managers and HR practitioners. First, AI adoption strategies should prioritize augmentation over automation logic, emphasizing human-AI complementarity rather than workforce substitution (Raisch & Krakowski, 2021). Second, organizations should invest proactively in digital self-efficacy development, given evidence that it moderates the relationship between AI-induced job insecurity and psychological distress (Zhao & Wu, 2024). Third, AI implementation should be accompanied by transparent communication about its intended scope, as information asymmetry is a primary driver of resistance (Lnenicka & Machova, 2024). Fourth, performance management systems should be redesigned to recognize distinctly human contributions — judgment, relational intelligence, ethical reasoning — that generative AI cannot substitute.

Implications for Policymakers

In developed economies, social protection systems require reform to accommodate the novel displacement of high-skill professionals that existing unemployment and retraining frameworks were not designed to support (Eloundou et al., 2024; Autor, 2022). In developing economies, governments face the dual challenge of building digital infrastructure and regulatory capacity while protecting workers from benefit concentration among large firms (Gabas, 2025). International development institutions should incorporate AI readiness — including digital infrastructure, regulatory capacity, and AI literacy — as a core dimension of development assistance, treating the generative AI divide as a structural development challenge rather than a temporary technological lag.

Limitations

This review is subject to three principal limitations.

- **Database coverage:** Scopus and Web of Science were inaccessible due to subscription constraints, limiting formal reproducibility. Future replications should extend the search to Scopus and Web of Science to test the robustness of the current findings. The absence of these databases likely introduced a modest selection bias: Scopus and Web of Science index a higher proportion of established peer-reviewed journals in management, organizational behavior, and human resource management — fields central to this review — meaning some high-quality empirical studies may have been missed. The corpus may therefore slightly overrepresent preprints and open-access publications relative to what a fully indexed search would yield. Future updates of this review should prioritize these databases to address this limitation.

- **Publication lag:** The rapid pace of generative AI development means the evidence base is still emerging. Findings represent a snapshot of an evolving landscape rather than a settled body of evidence.
- **Narrative synthesis:** Heterogeneity across study designs precluded formal meta-analysis. The wide range of productivity estimates — 14% to over 55% — reflects genuine variation in task types, tools, and populations.

Research Gaps and Future Research Directions

The review identifies six significant gaps in the existing literature, each pointing to a corresponding research direction.

- **Developing economy evidence:** The evidence base is overwhelmingly concentrated in developed economies. Comparative studies using matched samples across developed and developing economy organizations are urgently needed to test the generative AI divide hypothesis and generate differentiated policy recommendations (Aderibigbe et al., 2023; Sarfo et al., 2024).
- **Longitudinal research:** Cross-sectional studies dominate the literature. Multi-year longitudinal studies are needed to determine whether AI-driven productivity gains are sustained or eroded as workers adapt and organizational expectations shift (Brynjolfsson et al., 2025).
- **Implementation processes:** Most studies measure AI inputs and outputs without examining organizational mechanisms. Mixed-methods case studies are needed to reveal how leadership, HR practices, and change management mediate employee experiences of AI adoption (Lnenicka & Machova, 2024).
- **Governance and regulation:** Research on governance mechanisms that promote equitable AI outcomes is critically underdeveloped, particularly in developing economy contexts where regulatory capacity is limited (Albaroudi et al., 2024).
- **Mental health and well-being:** AI-induced loneliness, identity threat, and automation anxiety remain understudied. Future research should integrate occupational health psychology with AI adoption research across diverse worker populations (Zhao & Wu, 2024; Patel et al., 2024).
- **Sector-specific evidence:** Systematic evidence from healthcare administration, public sector organizations, and manufacturing management remains sparse. Sector-specific reviews are needed to understand how industry context moderates AI's effects (Al Naqbi et al., 2024).

CONCLUSION

This systematic review has synthesized findings from 40 peer-reviewed studies on the organizational impacts of generative AI, addressing three interconnected themes: productivity effects, employee perceptions, and job insecurity. The evidence is clear that generative AI generates meaningful and measurable productivity gains for knowledge-intensive tasks — but these gains are heterogeneous, conditional on task-technology fit, and shaped by organizational deployment logic. The skill-leveling effect documented consistently across independent studies is particularly significant, suggesting that generative AI has the potential to reduce intra-occupational inequality when deployed with an augmentation rather than automation orientation.

Employee perceptions are structurally ambivalent — not as a transitional phase, but as a persistent feature of human-AI collaboration rooted in generative AI's dual role as simultaneously a job resource and a job demand. Managing this ambivalence requires investment in transparent communication, participatory change management, and digital self-efficacy development. Job insecurity, meanwhile, is structurally grounded in a historically novel pattern of automation that targets high-skill, high-education occupations previously considered immune to technological displacement.

The generative AI divide — the structural asymmetry between developed and developing economies in the capacity to realize AI productivity gains while managing employment disruption — represents the most significant underexplored dimension of this technological transition. Addressing this divide demands expanded empirical research in developing economy contexts, governance frameworks designed around distributional outcomes, and international development strategies that treat AI readiness as a core dimension of economic capacity building. As generative AI continues its rapid diffusion globally, the evidence synthesized here provides a foundation for evidence-based management of AI adoption — but the pace of technological development ensures that the research agenda it identifies remains both urgent and unfinished.

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