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Generative Artificial Intelligence and Employee Productivity: A Global Bibliometric and Science-Mapping Analysis

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Abstract
This study maps global research on generative artificial intelligence (GenAI) and employee productivity, separating workplace outcomes from consumer, student, technical, and financial-market applications. A Scopus search for 2023–2026 identified 237 English-language open-access business and economics journal articles. Title–abstract screening retained 61 articles. Performance analysis was integrated with VOSviewer-compatible author-keyword co-occurrence, overlay, and density mapping. Output increased from 2 articles in 2023 to 27 articles in 2026 as of the search date. The corpus covered 31 journals, 194 authors, and 37 countries; 37.7% of articles involved international collaboration. Five keyword clusters linked workplace adoption and human outcomes; LLM-enabled professional work; creativity, work design, and HRM; productivity realization; and agency in platform labor. Themes shifted from prompts and tools toward productivity, collaboration, well-being, and agency, although objective productivity measures remained peripheral. Researchers and managers should evaluate quality-adjusted net productivity, including verification, coordination, learning, governance, and employee well-being, rather than infer performance from adoption or task speed alone. The study offers a screened, outcome-centered, multilevel map of a rapidly emerging field and identifies its transition from technology adoption to human and organizational consequences.

Keywords: generative artificial intelligence; employee productivity; human–AI collaboration; bibliometric analysis; science mapping

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INTRODUCTION

Generative artificial intelligence has moved from a general-purpose technological novelty to a workplace infrastructure for producing text, code, images, analyses, recommendations, and decisions. Experimental and field evidence outside the present filtered corpus indicates that GenAI can shorten task-completion time and improve output quality, but that gains vary across tasks, baseline skill, and the worker's capacity to evaluate model output (Noy & Zhang, 2023; Dell'Acqua et al., 2023; Peng et al., 2023; Brynjolfsson et al., 2025). This heterogeneity is consistent with task–technology fit and the automation–augmentation paradox: performance improves when system capabilities match task requirements and when human judgment complements, rather than merely follows, machine output (Goodhue & Thompson, 1995; Raisch & Krakowski, 2021).

The business and management literature has consequently expanded from speculative accounts of automation toward studies of HRM, project management, marketing, software development, accounting, professional services, entrepreneurship, and platform work. GenAI has been associated with employee performance and engagement in HRM (Prasad & De, 2024), project-manager appropriation (Felicetti et al., 2024), accounting efficiency (Zhao & Wang, 2024), developer utilization (Suryavanshi et al., 2025), sales-unit performance (Saadé & Sabri, 2026), and author productivity in financial analysis (Bradshaw et al., 2026). At the same time, the literature increasingly recognizes verification burden, distrust, ethical risk, work intensification, and erosion of agency (Wach et al., 2023; Polyportis & Pahos, 2024; Hartyándi, 2025; Andraschko & Weritz, 2026).

Employee productivity is therefore not equivalent to adoption, perceived usefulness, or faster completion of a single task. At the task level, productivity may be reflected in speed, quantity, accuracy, or quality. At the employee level, it includes performance across a portfolio of tasks, learning, job crafting, creativity, and sustainable workload. Team and process productivity depend on coordination, handoffs, shared understanding, and error propagation, while organizational productivity requires that gross task gains exceed training, licensing, integration, verification, security, and governance costs. Research on meaningful creative work, collective intelligence, and human–AI teaming further shows that economic output cannot be separated fully from autonomy, skill development, and human agency (Hernández-Ramírez & Ferreira, 2024; Montefiore et al., 2026; Patel & Dey, 2026; Park, 2026).

The speed of publication creates a second challenge. Raw citation rankings privilege the earliest papers in a field that is only a few years old. The first highly cited contributions have concentrated on risks, prompt engineering, and broad marketing applications (Wach et al., 2023; Korzynski et al., 2023; Grewal et al., 2025), whereas the newest work studies employee well-being, agency, collective cognition, and task-level professional performance (Filippelli et al., 2026; Taş et al., 2026; Zhang et al., 2026). Bibliometric analysis is valuable because it can distinguish established intellectual attention from emerging thematic momentum and reveal whether the field's conceptual structure is becoming more outcome-centered.

Existing reviews often map AI, algorithmic management, HRM, or the future of work broadly. Such boundaries mix predictive AI with generative systems and frequently combine consumer, student, and technical-model research with employee outcomes. The present study uses a narrower GenAI-specific, productivity-centered boundary. It analyzes a Scopus export produced by the user-specified query, screens records for direct workplace relevance, and integrates publication performance with VOSviewer-compatible network, overlay, and density mapping. The analysis asks not only which technologies and domains dominate, but also whether productivity, quality, well-being, and human agency are becoming central components of the field.

Research gaps

Five gaps motivate the analysis. First, technology-boundary ambiguity often combines GenAI with general AI and algorithmic management. Second, outcome ambiguity conflates adoption and attitudes with productivity. Third, task-level speed is often generalized to employee or organizational performance. Fourth, the citation youth of the field can hide emerging work on well-being, agency, and collaboration. Fifth, occupational and geographic evidence remains uneven, with knowledge-intensive and English-language contexts receiving disproportionate attention. These gaps are summarized in Table 1.

Table 1. Research Gaps and Bibliometric Implications

Gap	Unresolved issue and bibliometric implication
Technology boundary	General AI, predictive analytics, and GenAI are often merged, obscuring the distinctive structure around LLMs, ChatGPT, and workplace copilots.
Outcome boundary	Adoption, trust, and intention are frequently treated as productivity despite different constructs and measurement requirements.
Level of analysis	Task speed, employee performance, team coordination, and organizational productivity are not consistently separated.
Benefit–friction balance	Gains are mapped more often than verification, correction, integration, work-intensity, and well-being costs.
Temporal and contextual representation	Recent fronts and underrepresented occupations or countries can be missed by raw citations and broad global summaries.

Novelty and contributions

The study contributes an empirically populated, GenAI-specific map rather than a general framework shell. Its novelty lies in combining a screened workplace corpus with a multilevel productivity interpretation, using temporal overlay to identify the transition from tool-oriented themes to human outcomes, and providing reproducible VOSviewer-compatible files. The five- cluster solution is interpreted through task–technology fit, sociotechnical realization, job demands–resources, and human-agency perspectives. The contributions are summarized in Table 2.

Table 2. Study Contributions and Scientific Value

Contribution	Scientific value
Screened productivity corpus	Removes records centered on students, consumers, technical benchmarking, or financial markets without an employee-productivity relationship.
Young-field mapping	Uses occurrence, total link strength, and average publication year rather than relying only on total citations.
Multilevel interpretation	Separates task, employee, team/process, and organizational productivity.
Benefit–friction synthesis	Interprets augmentation and automation alongside verification, coordination, trust, well-being, and agency.
Reproducible VOSviewer package	Provides map, network, thesaurus, screened-corpus, and figure files for independent inspection.

The reminder of the paper reviews the theoretical foundations and develops the research questions, explains the bibliometric method, presents and discusses the science-mapping results, and concludes with implications, limitations, and recommendations for future research.

Literature Review and Research Question Development

Productivity as a Multilevel Construct

Task productivity concerns time, throughput, and output quality for a bounded activity. Employee productivity concerns sustained output across multiple tasks and includes learning, workload, creativity, and adaptive performance. Team and process productivity depend on coordination and collective cognition, while organizational productivity compares quality-adjusted value with labor, technology, integration, and governance inputs. The distinction matters because a system may accelerate drafting while increasing review time or may improve individual output while weakening knowledge retention and collaboration.

Task–Technology Fit and Sociotechnical Realization

Task–Technology Fit theory predicts that performance effects depend on alignment between task requirements and technological functionality (Goodhue & Thompson, 1995). The jagged technological frontier extends this insight by emphasizing that model capability varies sharply across superficially similar tasks (Dell'Acqua et al., 2023). Sociotechnical and work-design perspectives add that performance is jointly determined by technology, expertise, workflow, responsibility, and organizational arrangements (Jarrahi, 2018; Parker et al., 2017; Raisch & Krakowski, 2021).

Resources, Demands, and Human Agency

The Job Demands–Resources model suggests that GenAI can operate simultaneously as a resource—reducing cognitive effort or enabling learning—and as a demand through verification, monitoring, uncertainty, or work intensification (Bakker & Demerouti, 2007). Employee-outcome research already connects GenAI with job crafting, career commitment, trust, and well-being (Liu et al., 2025; Hartyándi, 2025; Filippelli et al., 2026). Agency-oriented studies further show that workers develop oversight and reassertion practices rather than accepting model output passively (Andraschko & Weritz, 2026; Taş et al., 2026).

Research Questions

The study addresses seven questions. RQ1 asks how publication output and citation impact have developed. RQ2 identifies the most productive sources, authors, and countries. RQ3 examines the conceptual communities visible in the keyword network. RQ4 determines how themes shift over time in the overlay visualization. RQ5 identifies the knowledge-density core and peripheral outcomes. RQ6 interprets how productivity benefits and realization frictions are distributed across clusters. RQ7 derives priorities for theory, measurement, and future workplace research.

RESEARCH METHOD

The study follows established bibliometric and science-mapping guidance (Aria & Cuccurullo, 2017; Zupic & Čater, 2015; Donthu et al., 2021). PRISMA 2020 is used as a transparency framework for identification, screening, and inclusion rather than as a claim that the study is an effect-size systematic review (Page et al., 2021). Performance analysis describes the corpus, while keyword co-occurrence mapping reveals its conceptual and temporal structure. The workflow is shown in Figure 1.

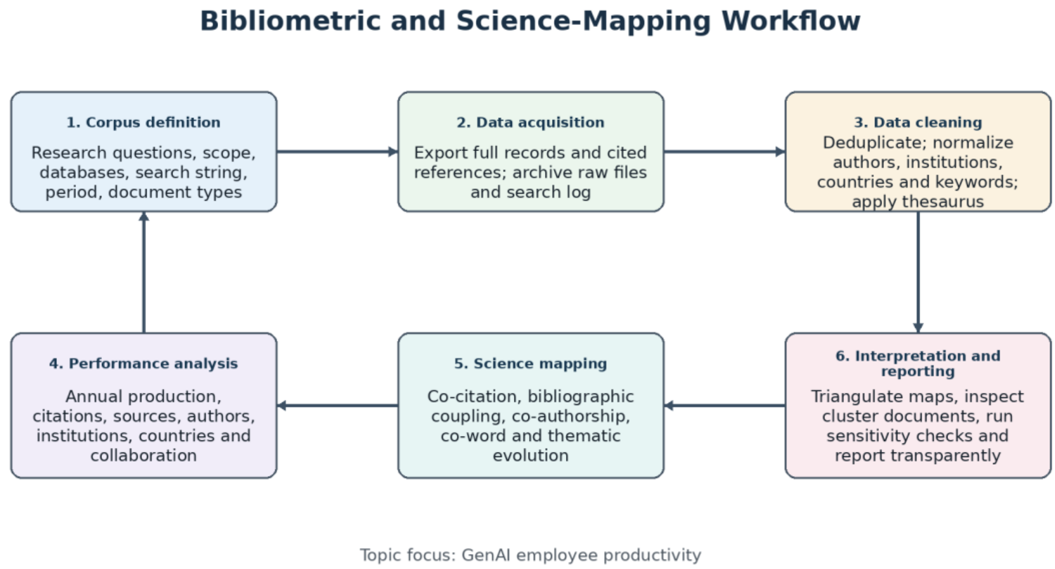

Figure 1. Reproducible bibliometric and science-mapping workflow.

Search strategy and database

Scopus was used because the supplied export contained full bibliographic records, abstracts, author keywords, affiliations, citation counts, and cited references. The search was limited to English-language, open-access journal articles in business and economics, published from 2023 through 2026. The exact query was:

(TITLE-ABS-KEY ("generative artificial intelligence" OR "generative AI" OR genai OR "large language model" OR llm OR chatgpt OR "AI copilot" OR "coding assistant") AND ALL (employee OR worker OR workforce OR "knowledge worker" OR professional OR developer OR agent OR manager) AND ALL (productiv OR performance OR efficien OR throughput OR output OR quality OR accuracy OR "task completion" OR "time saving" OR "work pattern" OR "labor hour" OR "labour hour" OR revenue OR sales)) AND PUBYEAR > 2022 AND PUBYEAR < 2027 AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (OA, "all")) AND (LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "ECON")) AND (LIMIT-TO (DOCTYPE, "ar"))

Screening and eligibility

The export contained 237 unique records and no duplicate DOIs or titles. Two eligibility conditions were applied during title–abstract screening: the study had to concern GenAI, ChatGPT, an LLM, or a comparable generative system in a workplace or professional context; and it had to address productivity, efficiency, performance, quality, creativity, learning, work design, well-being, human agency, or another outcome that can influence work performance. Studies centered only on students, consumers, tourism, investments, model benchmarking, translation quality, or the use of LLMs merely as an analytical method were excluded. Sixty-one articles met the final boundary. Table 3 summarizes the eligibility criteria, and Figure 2 shows the screening flow.

Table 3. Screening Eligibility Criteria

Decision	Operational criterion
Include	GenAI/LLM use or effects involving employees, workers, professionals, managers, entrepreneurs, teams, or workplace processes, with an explicit productivity- or performance-related outcome.
Exclude	Student-only learning, consumer-only adoption, tourism behavior, financial-market prediction, technical model evaluation, or method-only LLM applications without workplace productivity relevance.
Retain for context	Conceptual or review articles were retained when they explicitly analyzed work design, HRM, professional practice, organizational coordination, or labor-market consequences.

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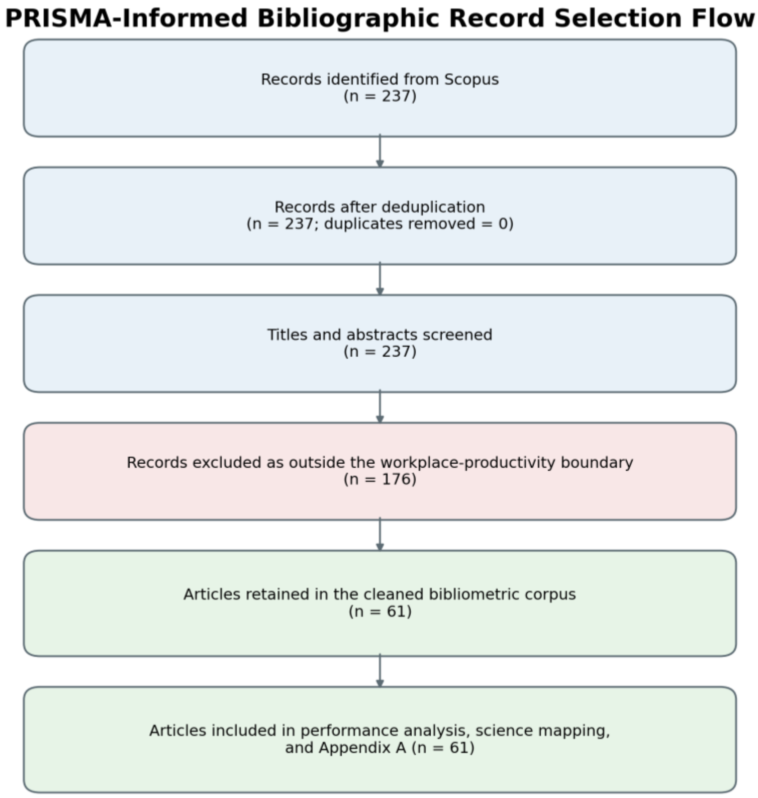

Figure 2. PRISMA-informed record identification, screening, and inclusion flow.

The 176 excluded records were classified for audit purposes as follows: 90 lacked an explicit GenAI–employee/workplace productivity relationship, 37 focused on consumer, tourism, retail, or financial-market contexts, 26 focused on education or students without an employee outcome, and 23 were technical, model-evaluation, or method-use studies without a workplace-productivity focus.

Data cleaning and VOSviewer mapping

Author keywords were separated, lowercased, and standardized with a thesaurus. GenAI, generative AI, GAI, and generative artificial intelligence were merged; LLM and LLMs were merged with large language models; human–machine teaming and AI-as-teammate terms were merged with human–AI collaboration; and HRM variants were merged with human resource management. Country and method labels that did not represent substantive concepts were removed. A minimum occurrence threshold of two generated a connected network of 22 terms and 70 links. Node size represents keyword occurrence, edge weight represents co-occurrence strength, cluster color represents community membership, and overlay color represents average publication year. VOSviewer-compatible map and network files were written with item coordinates, clusters, occurrence weights, total link strength, and average-year scores, following the VOSviewer file structure described by van Eck and Waltman (2010).

The included figures were generated from the same map and network attributes, and the accompanying text files can be opened directly in VOSviewer for independent reproduction. The clustering solution produced five communities. Because clusters can be sensitive to thresholds and thesaurus decisions, labels were based on term content and inspection of the articles represented by each community rather than on color alone.

Performance indicators

The analysis calculated annual production, source and author productivity, country participation, international co-authorship, total and median citation impact, keyword occurrence, total link strength, and average publication year. Full counting was used for descriptive country participation, while

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fractional country counts were retained in the reproducibility files. Citation results are interpreted cautiously because the field is young and the 2026 publication year is incomplete.

RESULTS AND DISCUSSION

Analysis Results

Corpus Profile and Publication Growth

The cleaned corpus contains 61 articles published between 2023 and 2026. Output increased from 2 articles in 2023 to 10 in 2024, 22 in 2025, and 27 in the partial 2026 year. Thus, 80.3% of the corpus was published in 2025–2026. The corpus spans 31 journals and 194 unique authors, with an average of 3.33 authors per article. Only five papers were single-authored. Affiliations represented 37 countries, and 23 papers (37.7%) involved more than one country. Figure 3 shows annual production, and Table 4 summarizes the corpus profile.

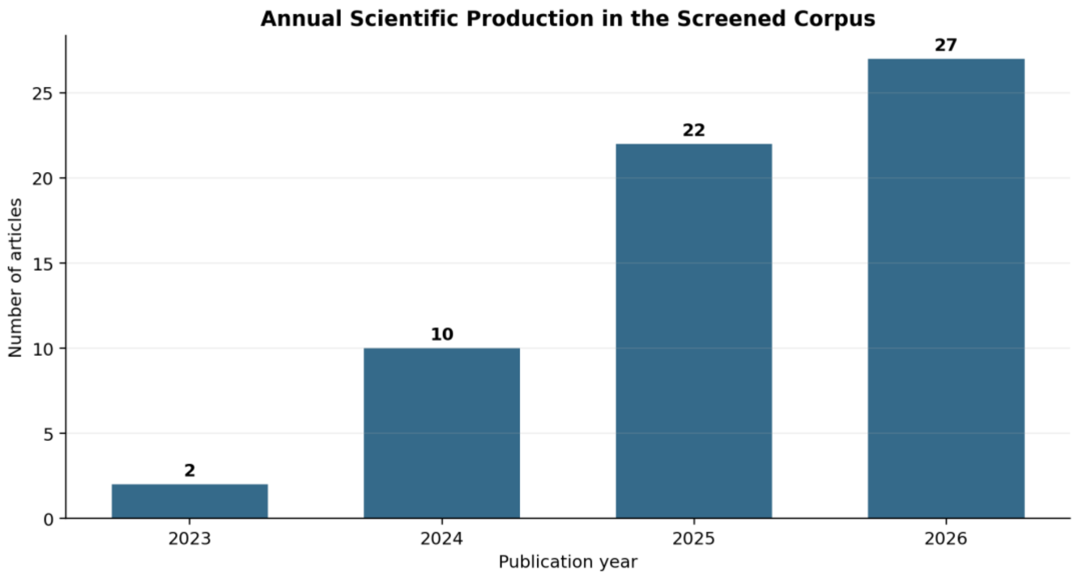

Figure 3. Annual scientific production in the screened corpus.

Table 4. Corpus Profile and Publication Growth

Indicator	Verified value	Interpretation
Articles	61	Screened workplace-productivity corpus from 237 Scopus records
Timespan	2023–2026	The 2026 count is partial as of the analysis date
Sources	31	High interdisciplinary dispersion
Unique authors	194	Most contributors have one publication
Average authors/article	3.33	Collaborative field with relatively large teams
Countries represented	37	Global authorship, but concentrated in a few countries
International co-authorship	23 articles (37.7%)	More than one affiliation country
Total citations	1,477	Strongly affected by a small number of early papers
Mean / median citations	24.2 / 3	Highly right-skewed citation distribution

Leading Sources, Documents, Authors, and Countries

The Journal of Innovation and Knowledge was the most productive outlet with 12 articles, followed by Humanities and Social Sciences Communications with 7. Journal of Business Ethics, Journal of Public Policy and Marketing, Electronic Markets, and International Journal of Accounting Information Systems each contributed three articles. This distribution shows that the field is not located in a single disciplinary home; it spans innovation, management, ethics, information systems, accounting, marketing, and communication. Table 5 lists the leading publication sources.

Table 5. Leading Publication Sources

Source	Articles
Journal of Innovation and Knowledge	12
Humanities and Social Sciences Communications	7

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Source	Articles
Journal of Business Ethics	3
Journal of Public Policy and Marketing	3
Electronic Markets	3
International Journal of Accounting Information Systems	3
Journal of the Academy of Marketing Science	2
Journal of Accounting Research	2
Entrepreneurial Business and Economics Review	2
Business and Professional Communication Quarterly	2

Citation influence is more concentrated than publication volume. Wach et al. (2023) received 576 citations and Korzynski et al. (2023) received 195, reflecting early interest in GenAI risks and prompt engineering. Grewal et al. (2025) and Cillo and Rubera (2025) became influential marketing and innovation contributions with 114 and 98 citations. The most cited domain review was Dong et al. (2024) with 74 citations, while Felicetti et al. (2024) and Zhao and Wang (2024) represent early project-management and accounting applications. Table 6 presents the most-cited documents.

Table 6. Most-Cited Documents

Lead author	Year	Document	Citations
Wach K.	2023	The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT	576
Korzynski P.	2023	Artificial intelligence prompt engineering as a new digital competence: Analysis of generative AI technologies such as ChatGPT	195
Grewal D.	2025	How generative AI Is shaping the future of marketing	114
Cillo P.	2025	Generative AI in innovation and marketing processes: A roadmap of research opportunities	98
Dong M.M.	2024	A scoping review of ChatGPT research in accounting and finance	74
Felicetti A.M.	2024	Artificial intelligence and project management: An empirical investigation on the appropriation of generative Chatbots by project managers	51
Zhao J.	2024	Unleashing efficiency and insights: Exploring the potential applications and challenges of ChatGPT in accounting	49
Polyportis A.	2024	Navigating the perils of artificial intelligence: a focused review on ChatGPT and responsible research and innovation	47
Hermann E.	2025	Generative AI in Marketing and Principles for Ethical Design and Deployment	42
Prasad K.D.V.	2024	Generative AI as a catalyst for HRM practices: mediating effects of trust	26

Author productivity was diffuse. Liu Y. authored three articles; Li Y., Sheng F., Stratopoulos T. C., Wang V. X., Korzynski P., Mazurek G., and Liu W. authored two each. The United States led full-count participation with 15 articles, followed by the United Kingdom (9), China (7), India (5), and Italy (5). The concentration in the United States, United Kingdom, and China indicates that the global label should be interpreted as broad participation rather than balanced representation. Table 7 reports country participation.

Table 7. Country Participation

Country	Full-count articles	Fractional count
United States	15	10.58
United Kingdom	9	3.67
China	7	4.98
India	5	4.14
Italy	5	4.50
Malaysia	4	2.64
Saudi Arabia	4	2.00
Germany	4	1.42
Canada	3	1.25
Poland	3	2.50

VOSviewer Network Visualization

The cleaned author-keyword network contains 22 terms, 70 links, and five clusters. Generative artificial intelligence is the dominant node, occurring in 41 articles with a total link strength of 71. Artificial intelligence occurs 20 times, ChatGPT 13 times, large language models 12 times, and technology adoption 7 times. Employee productivity appears only four times, despite being the focal outcome of the search. This contrast is a central result: the literature is still organized more strongly around technologies and adoption than around standardized productivity constructs. Figure 4 shows the network, and Table 8 summarizes the clusters.

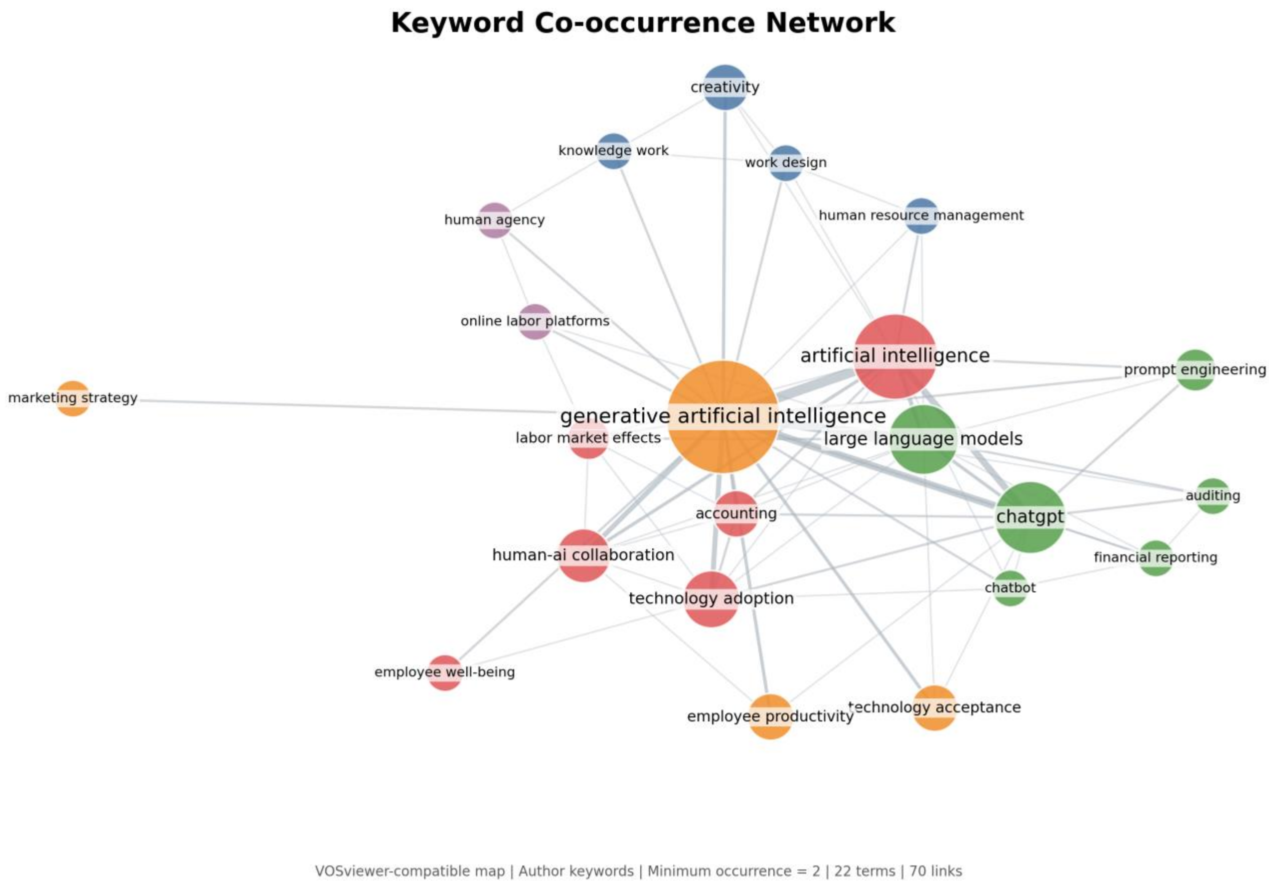

Figure 4. VOSviewer-compatible author-keyword co-occurrence network. Node size indicates occurrence; line thickness indicates co-occurrence strength; color indicates cluster.

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Table 8. Keyword Clusters and Interpretations

Cluster	Main terms	Interpretation
1. Workplace adoption and human outcomes	Artificial intelligence; technology adoption; human–AI collaboration; accounting; labor-market effects; employee well-being	Connects implementation with collaboration, professional domains, labor consequences, and employee experience.
2. LLM-enabled professional work	ChatGPT; large language models; prompt engineering; auditing; chatbot; financial reporting	Represents tool-specific use in accounting, assurance, reporting, and professional problem solving.
3. Creativity, work design, and HRM	Creativity; work design; human resource management; knowledge work	Frames GenAI as a change in job content, competence, creativity, and organizational design.
4. Productivity realization and market-facing use	Generative artificial intelligence; employee productivity; technology acceptance; marketing strategy	Links the core technology label to performance realization, acceptance, and market-facing work.
5. Agency and platform labor	Human agency; online labor platforms	Highlights worker autonomy, contestation, and changes in digital labor demand.

Overlay Visualization: Thematic Evolution

The overlay map reveals a temporal shift. Prompt engineering has the earliest average publication year (2024.00), followed by ChatGPT (2024.38), auditing and work design (both approximately 2024.50). These earlier terms reflect the first phase of tool exploration, prompt competence, and professional application. By contrast, employee productivity has an average year of 2025.75, human–AI collaboration 2025.67, creativity and technology acceptance 2025.50, and human agency and employee well-being 2026.00. The newest work is therefore less tool-centric and more focused on human consequences, sustained use, collaboration, and the distribution of control. Figure 5 shows this thematic evolution.

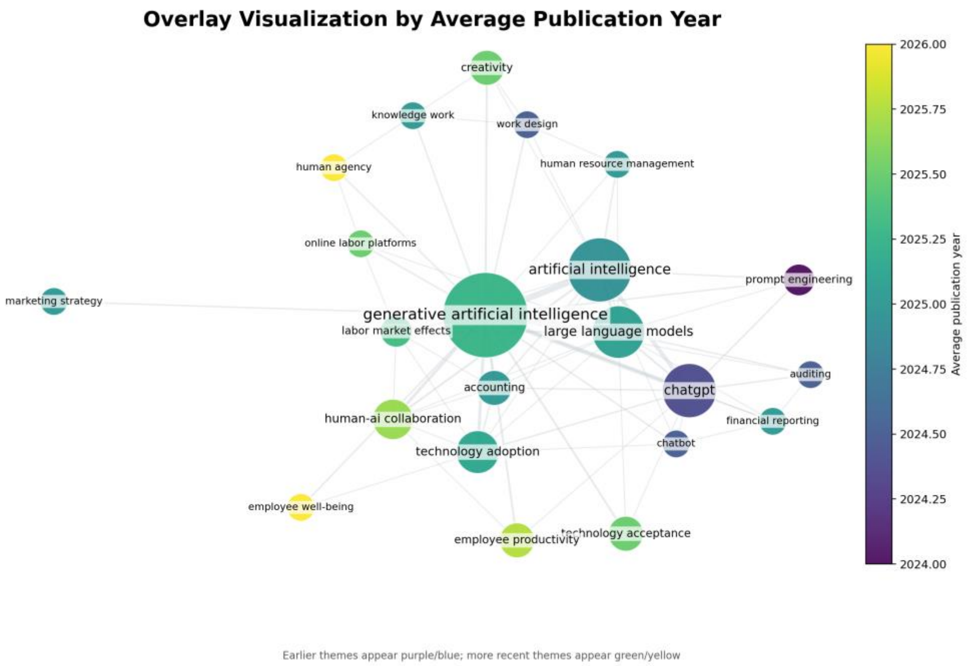

Figure 5. Overlay visualization based on average publication year. Purple/blue terms are earlier; green/yellow terms are more recent.

The transition is also visible in the underlying publications. Earlier work emphasizes prompt engineering, broad risks, project-manager appropriation, and ChatGPT applications (Korzynski et al., 2023; Wach et al., 2023; Felicetti et al., 2024; Zhao & Wang, 2024). More recent work examines employee well-being, collective cognition, meaningful creative work, human agency, and firm-level sales or accounting performance (Saadé & Sabri, 2026; Montefiore et al., 2026; Zhang et al., 2026; Filippelli et al., 2026; Andraschko & Weritz, 2026; Choi & Xie, 2026).

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Density Visualization and Conceptual Maturity

The density map shows a bright core around generative artificial intelligence, artificial intelligence, large language models, ChatGPT, technology adoption, and human–AI collaboration. In contrast, employee productivity, employee well-being, human agency, and online labor platforms remain lower-density or peripheral. The pattern indicates that the field has a mature technology-and-adoption vocabulary but a less consolidated outcome vocabulary. Productivity is often implied through efficiency, innovation, creativity, or performance rather than measured through a consistent set of time, quantity, quality, error, and cost indicators. Figure 6 shows the density pattern.

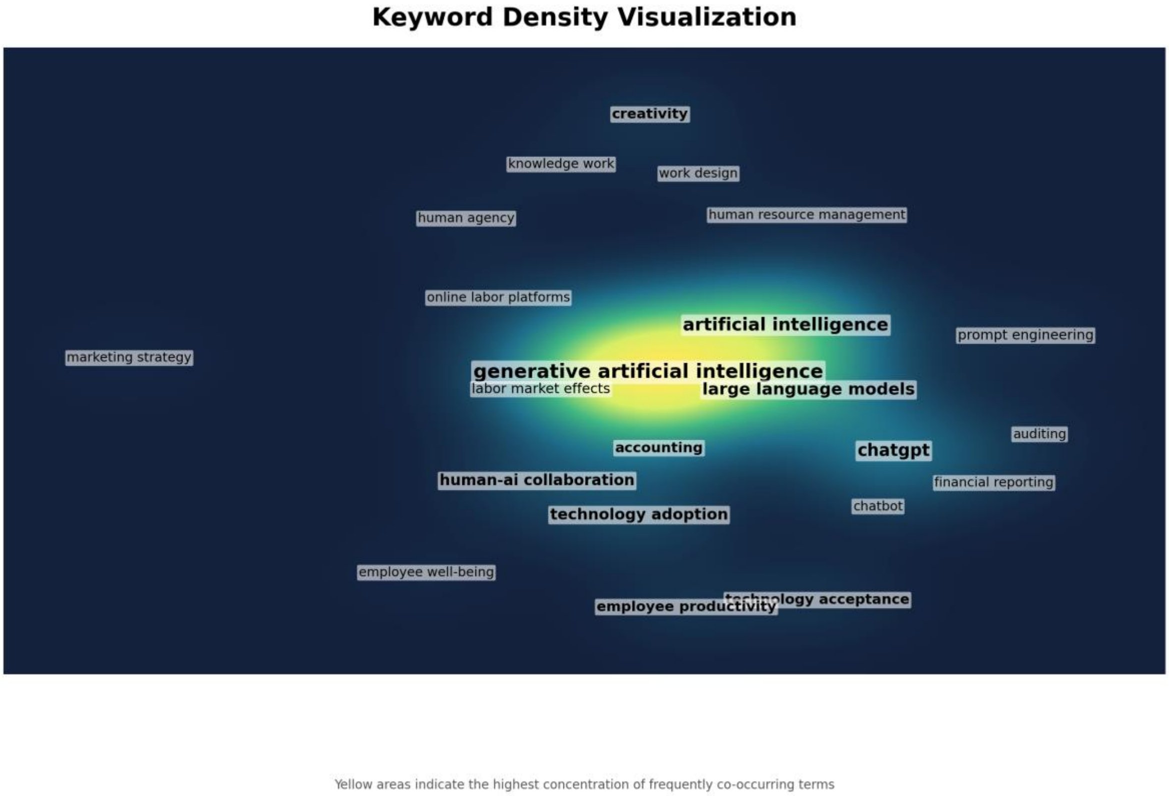

Figure 6. Keyword density visualization. Yellow areas show the highest concentration of frequently co-occurring terms.

Integrated Benefit–Friction Interpretation

Across clusters, four benefit mechanisms recur: production automation, cognitive augmentation, knowledge diffusion, and coordination support. Studies of marketing content, accounting advice, and sales systems emphasize faster production and quality improvement (Dubé & Xu, 2026; Tocev & Atanasovski, 2026; Saadé & Sabri, 2026). Studies of entrepreneurship, innovation, and new-product development emphasize ideation and collective cognition (Li et al., 2025; Park, 2026; Zhang et al., 2026). HRM and work-design research emphasizes competence, trust, engagement, job crafting, and meaningfulness (Prasad & De, 2024; Liu et al., 2025; Montefiore et al., 2026).

The friction side is less densely represented but conceptually important. It includes hallucination and verification, ethical and privacy risk, distrust, dependence, reduced autonomy, and unequal labor-market effects (Polyportis & Pahos, 2024; Wach et al., 2023; Hartyándi, 2025; Teutloff et al., 2025; Andraschko & Weritz, 2026). The network therefore supports a gross-to-net interpretation: GenAI may raise task output, but net employee or organizational productivity depends on whether verification, integration, coordination, and human costs remain below the realized benefit.

Discussion

From Adoption Discourse to Productivity Realization

The most important temporal finding is the movement from tool-centered discourse toward outcome-centered research. ChatGPT, prompt engineering, and technology adoption dominate the early structure because organizations first had to understand access, usability, and competence. The newest terms—employee productivity, well-being, human–AI collaboration, and human agency—suggest that

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the field is entering a realization phase in which researchers ask what sustained use does to work rather than whether employees intend to use a tool. This progression mirrors the broader technology-adoption literature, where acceptance is a necessary but insufficient condition for performance (Venkatesh et al., 2003; Goodhue & Thompson, 1995).

Nevertheless, the low occurrence of employee productivity shows that the transition is incomplete. Many studies continue to infer productivity from acceptance, perceived quality, creativity, or organizational capability. Direct workplace studies are emerging in sales, accounting, marketing content, and platform labor, but objective measures remain fragmented (Dubé & Xu, 2026; Saadé & Sabri, 2026; Choi & Xie, 2026; Bradshaw et al., 2026; Teutloff et al., 2025). The field would benefit from a common minimum measurement set covering time, quantity, quality, errors, verification effort, learning, and coordination.

Task Gains Do Not Automatically Become Organizational Productivity

The bibliometric structure reinforces the need to distinguish gross task gains from net organizational productivity. Experimental benchmark studies show that GenAI can improve speed and quality for selected writing, consulting, customer-service, and coding tasks, often with larger benefits for less-experienced workers (Noy & Zhang, 2023; Dell'Acqua et al., 2023; Peng et al., 2023; Brynjolfsson et al., 2025). Yet the present corpus shows that workplace research is expanding into domains with higher accountability and verification requirements, including auditing, financial reporting, tax, and project management (Felicetti et al., 2024; Dong et al., 2024; Fotoh & Mugwira, 2025; Sugahara & Kano, 2026; Al Najjar et al., 2024). In these domains, saved drafting time may be offset by review, correction, explanation, or governance work.

A stronger productivity model should therefore estimate net value as quality-adjusted output minus prompting, training, verification, integration, coordination, security, and error costs. It should also identify who captures saved time. Organizations may convert it into greater output, shorter workdays, higher work intensity, or expanded service scope. These alternatives have different implications for employee well-being and sustainability. The emergence of the well-being node in 2026 indicates growing awareness of this issue (Filippelli et al., 2026; Zhang et al., 2026).

Human–AI Collaboration, Creativity, and Skill Distribution

Human–AI collaboration links the central technology node to work design, knowledge work, and employee outcomes. This position is theoretically important. GenAI is not only an automation device; it can function as a cognitive partner that changes problem framing, information search, and collective reasoning (Jarrahi, 2018; Park, 2026; Patel & Dey, 2026). In new-product development, LLM tools can support collective cognition, while in marketing and entrepreneurship they can expand idea generation and information access (Zhang et al., 2026; Grewal et al., 2025; Li et al., 2025).

The same mechanism can create creative fixation, homogenization, or reduced skill cultivation. Research on creative work and LLM-supported tasks shows that output improvement and meaningfulness need not move together (Doshi & Hauser, 2024; Cheng & Zhang, 2025; Montefiore et al., 2026). Future studies should therefore evaluate not only immediate output but also retention, independent performance after tool removal, diversity of ideas, and long-term expertise. This is particularly important when GenAI equalizes short-term performance by helping novices while potentially reducing the practice through which expertise is developed.

Agency, Trust, and the Contested Workplace

The small but newest agency cluster suggests an emerging corrective to adoption-centered research. Workers do not merely accept or reject GenAI; they develop routines to contest, verify, reinterpret, and selectively use model output. Studies of online labor platforms and early-adopting technology firms describe deliberate reassertion and episodic oversight (Andraschko & Weritz, 2026; Taş et al., 2026). Distrust may reflect irrational resistance, but it may also signal legitimate concerns about accountability, surveillance, deskilling, or hidden organizational objectives (Hartyándi, 2025; Kellogg et al., 2020).

This finding has implications for implementation. Trust should not be maximized indiscriminately; calibrated trust is preferable. Employees need information about model limitations, approved data sources, escalation paths, and responsibility for final decisions. Human oversight should be designed into workflow checkpoints rather than added after errors occur. Such arrangements preserve agency and can reduce the verification burden by focusing attention on high-risk steps.

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Theoretical Contribution

The study contributes a bibliometric realization model that connects five mapped communities. Task–Technology Fit explains why the same system produces different outcomes across tasks. Automation–augmentation theory explains the coexistence of substitution and complementarity. The Job Demands–Resources model explains why GenAI can reduce effort while simultaneously generating verification demands and uncertainty. Human-agency and work-design perspectives explain why productivity effects depend on autonomy, meaning, responsibility, and skill development. Together, these perspectives suggest that GenAI productivity is an emergent property of a technology–task–worker–workflow–governance configuration rather than an intrinsic attribute of the model.

Managerial and Policy Implications

Managers should evaluate GenAI at the task and workflow levels before making organization-wide productivity claims. A credible deployment scorecard should record baseline time, output quantity, quality, error rates, review time, escalation frequency, employee experience, and downstream rework. Training should combine prompting with domain verification, data governance, and responsibility. Saved capacity should be allocated deliberately; otherwise, apparent efficiency may become work intensification rather than sustainable productivity.

Policymakers, professional bodies, and labor institutions should note the geographic and occupational concentration of the evidence. The United States, United Kingdom, and China account for a large share of authorship, and knowledge work dominates the thematic structure. Evidence from multilingual, frontline, public-sector, small-firm, and lower-infrastructure settings remains limited. Standards for transparency, employee consultation, privacy, and contestability should accompany productivity-oriented deployment.

Concluding Remarks and Recommendation

This study examined how research on generative AI and employee productivity has developed, which sources and countries shape the field, how its conceptual clusters are organized, and how its themes have shifted over time. A screened Scopus corpus of 61 workplace-relevant articles was analyzed through performance indicators and VOSviewer-compatible network, overlay, and density mapping. The results show rapid publication growth, five connected thematic communities, and a clear transition from prompt engineering and tool adoption toward employee productivity, human–AI collaboration, well-being, and human agency.

The study contributes an outcome-centered and multilevel interpretation of GenAI productivity. Its originality lies in separating employee and workplace outcomes from consumer, student, technical-model, and financial-market applications, and in showing that productivity is an emergent property of the technology–task–worker–workflow–governance configuration. The findings also integrate task–technology fit, automation–augmentation, job demands–resources, work-design, and human-agency perspectives into a bibliometric realization model.

For managers, productivity claims should be based on quality-adjusted net value rather than adoption or task speed alone. Evaluation should include output quantity and quality, errors, verification time, rework, learning, coordination, employee experience, and governance costs. Policymakers and professional bodies should support transparency, privacy, employee consultation, calibrated oversight, and evidence from multilingual, frontline, public-sector, small-firm, and lower-infrastructure settings.

The findings are limited by the Scopus search boundary, the English-language and open-access journal filters, the short 2023–2026 period, author-supplied keywords, and judgment in title–abstract screening. Bibliometric density indicates scholarly attention rather than causal effect size. Future studies should therefore use longitudinal workplace deployments, objective workflow data, quality and cost accounting, team-level designs, delayed learning measures, and cross-country or multilingual comparisons. The recommended agenda below translates these limitations into testable priorities. Table 9 summarizes the recommended research agenda.

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Recommended Research Agenda

Table 9. Recommended Future Research Agenda

Priority	Research question	Preferred design/data
Net productivity	When do task-level gains survive verification, integration, coordination, and technology costs at employee, process, and firm levels?	Longitudinal enterprise deployments; workflow logs; quality and cost accounting
Learning and expertise	Does sustained GenAI use build, redistribute, or erode domain expertise and independent problem-solving capability?	Longitudinal experiments; delayed retention tests; skill telemetry
Teams and coordination	How does GenAI affect handoffs, shared mental models, collective creativity, and error propagation?	Team experiments; communication networks; process mining
Well-being and work intensity	Are saved minutes converted into autonomy, higher output, surveillance, or additional workload?	Experience sampling; digital trace data; job demands–resources measures
Agency and governance	Which oversight arrangements produce calibrated trust, accountability, and contestability?	Comparative field studies; governance experiments; incident logs
Global and multilingual settings	How do language quality, infrastructure, regulation, and work organization change productivity effects?	Multi-country field studies; multilingual workplace benchmarks
Measurement standardization	What minimum set captures time, quantity, quality, errors, verification, learning, coordination, and employee experience?	Delphi study; validated toolkit; open reporting standard

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