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GENERATIVE ARTIFICIAL INTELLIGENCE AND KNOWLEDGE CREATION IN KNOWLEDGE-INTENSIVE ORGANISATIONS: A SYSTEMATIC LITERATURE REVIEW

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Abstract

Purpose: *This study aims to investigate how generative artificial intelligence transforms knowledge systems within knowledge-intensive organisations (KIOs). It specifically explores the interaction between AI capabilities and established organisational knowledge creation processes to determine if AI acts as an independent agent or a supportive tool.*

Design/Methodology/Approach: *Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, a systematic literature review was conducted. The study synthesised twenty peer-reviewed papers published between 2018 and 2026, focusing on sectors such as finance, engineering, IT, and research. Data were analysed using qualitative thematic narrative synthesis, mapping findings onto the SECI model and the Knowledge-Based View (KBV).*

Findings: *The review identifies four primary mechanisms of AI-enabled knowledge creation: co-creation, cognitive augmentation, automation of daily tasks, and knowledge recombination. While generative AI enhances innovation capacity and enterprise knowledge retrieval through retrieval-augmented generation (RAG), it remains susceptible to "epistemic hazards" such as hallucinations and systematic misinformation. The evidence suggests that AI operates most effectively as an amplification feature within human-led learning systems rather than as a replacement for human cognition.*

Implications: *For practitioners, sustainable competitive advantage depends on disciplined integration rather than technology adoption alone. Organisations must implement robust governance structures, human-in-the-loop verification procedures, and hybrid technical architectures (like combining LLMs with knowledge graphs) to mitigate risks of misinformation and professional deskilling.*

Originality/Value: *This research provides conceptual clarity by integrating fragmented scholarly views into a unified theoretical framework. It contributes to the field by specifically linking generative AI capabilities to the SECI spiral and Dynamic Capability Theory, offering a strategic roadmap for responsible AI application in high-stakes knowledge environments.*

Keywords: *Knowledge Creation; Generative Artificial Intelligence; Knowledge-Intensive Organisations; SECI Model; Knowledge-Based Perspective; Organisational Learning.*

Introduction

The rapid expansion of generative artificial intelligence (AI) has significantly reshaped knowledge work across a wide range of sectors, including consultancy, higher education, research, law, finance, and information technology. Large language models and foundational AI systems are no longer experimental tools but have become embedded in routine organisational processes, offering outputs such as analytical reports, design concepts, code, and decision support that closely resemble expert human contributions. This transition marks a decisive shift from AI as a technical novelty to a central infrastructure within knowledge-intensive environments, where intellectual output and problem-solving capacity define institutional relevance and competitiveness.

Knowledge-intensive organisations operate primarily on intangible assets such as expertise, innovation, collaboration, and the ability to synthesise complex information. In such contexts, the generation, integration, and application of knowledge are critical determinants of organisational performance. Emerging empirical evidence suggests that AI-enabled knowledge processes enhance both innovation capacity and operational efficiency, while also reshaping organisational structures and professional roles (Alshammari & Alshammari, 2026; Cui, 2025; Xu et al., 2025). At the same time, generative AI is influencing knowledge hierarchies and redefining how expertise is distributed and accessed within institutions, raising important questions about the future of human-AI collaboration in intellectual work.

Despite these advancements, fundamental conceptual and theoretical tensions remain unresolved. Scholars continue to debate whether generative AI merely reorganises existing information at scale or genuinely contributes to new knowledge creation. While some view it as a transformative force capable of redefining knowledge management paradigms (Kaczorowska-Spychalska et al., 2024), others interpret it as a complementary tool that enhances, rather than replaces, traditional knowledge processes (Neștian et al., 2020). Moreover, concerns about epistemic reliability, including issues of hallucination and misinformation, highlight the need for robust validation frameworks and theoretical grounding (Dehal et al., 2025; Razniewski et al., 2021). In light of these debates, there is a pressing need for a systematic and integrative review that consolidates existing theoretical perspectives and empirical findings to clarify the role of generative AI in knowledge creation within knowledge-intensive organisations.

Conceptual and Theoretical Foundations

The study of generative artificial intelligence (AI) in knowledge-intensive businesses relies on several key frameworks. The Knowledge-Based View (KBV) and the SECI model are the primary lenses used, while organisational learning and dynamic capability theories offer complementary perspectives on how AI transforms knowledge production.

Generative Artificial Intelligence Systems

Generative AI creates new content by analysing statistical patterns in large datasets. Unlike predictive analytics, these systems produce outputs like papers, code, design ideas, and research hypotheses. Applications range from design exploration (Zhu & Luo, 2022) to scientific hypothesis generation (Park et al., 2023), overlapping directly with organisational knowledge generation.

Organisations That Need Knowledge

Knowledge-intensive businesses depend on expertise, intellectual capital, and innovation. Competitive advantage stems from the efficient creation and application of knowledge. Empirical research shows that AI-enabled knowledge sharing enhances creativity and performance (Alshammari & Alshammari, 2026; Cui, 2025).

SECI Model

The SECI paradigm views knowledge generation as a spiral of socialisation, externalisation, combination, and internalisation. Generative AI most clearly affects externalisation and combination. Large language models (LLMs) enable rapid synthesis of information (Neștian et al., 2020) and help codify tacit insights into structured representations. While AI aids in mixing cross-disciplinary knowledge, internalisation still requires human interpretation to turn AI outputs into organisational knowledge.

The Knowledge-Based Perspective: Knowledge as a Strategic Asset

From a KBV perspective, a firm's most important asset is knowledge. AI's value lies in enhancing innovation capacity and integration rather than just automation. Retrieval-augmented systems improve access to corporate data (Mendes et al., 2024), and AI-powered sharing improves learning (Cui, 2025). However, competitive advantage depends on how effectively AI is integrated into existing systems, highlighting the need for governance.

Organisational Learning Theory: Feedback and Adaptation

This theory focuses on learning methods, feedback loops, and adaptation. Generative AI catalyses faster feedback through simulations and alternative generation. While AI-powered sharing improves job performance (Cui, 2025), learning remains a socially embedded process. AI provides inputs, but adaptive change relies on group introspection and leadership.

Dynamic Capability Theory: Reconfiguration and Strategic Renewal

Dynamic capability theory explains how firms sense opportunities, seize them, and reconfigure resources. AI enhances sensing by identifying patterns in large datasets and aids in seizing opportunities by generating strategic alternatives. Implementation can also transform corporate hierarchies and bureaucratic levels (Xu et al., 2025). Ultimately, AI serves as a tool for dynamic capacity, though strategic renewal remains human-driven.

Methodology

This study employed a systematic literature review (SLR) guided by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure a transparent and replicable process. PRISMA offers a structured framework for identifying, screening, and synthesising research through clearly defined questions, search strategies, and selection criteria. The review focused on generative artificial intelligence, particularly large language models, within knowledge-intensive organisational contexts.

Study Approach and Research Protocol

A qualitative synthesis approach was adopted, following five stages: defining research questions, developing a search strategy, applying inclusion and exclusion criteria, assessing full-text relevance, and conducting data extraction and synthesis. Peer-reviewed studies published between 2018 and 2026 were retrieved from Scopus, Web of Science, and Google Scholar using Boolean search strings combining AI-related terms with knowledge process concepts. Searches were limited to English-language publications within relevant disciplines, and reference lists of selected studies were manually reviewed to enhance coverage.

Inclusion and Exclusion Criteria

Included studies explicitly examined generative AI or large language models in organisational knowledge processes, focusing on tools such as GPT, ChatGPT, or Copilot. Both empirical and theoretical studies addressing knowledge creation, sharing, or learning were considered. Excluded were non-peer-reviewed sources, studies lacking organisational relevance, and purely technical research without knowledge implications.

Study Selection Process

The initial search produced 72 records, reduced to 61 after duplicate removal. Following title and abstract screening, 34 studies were excluded. Of the remaining 27 full-text articles assessed, 7 were further excluded for insufficient focus on knowledge creation, resulting in 20 studies included in the final synthesis.

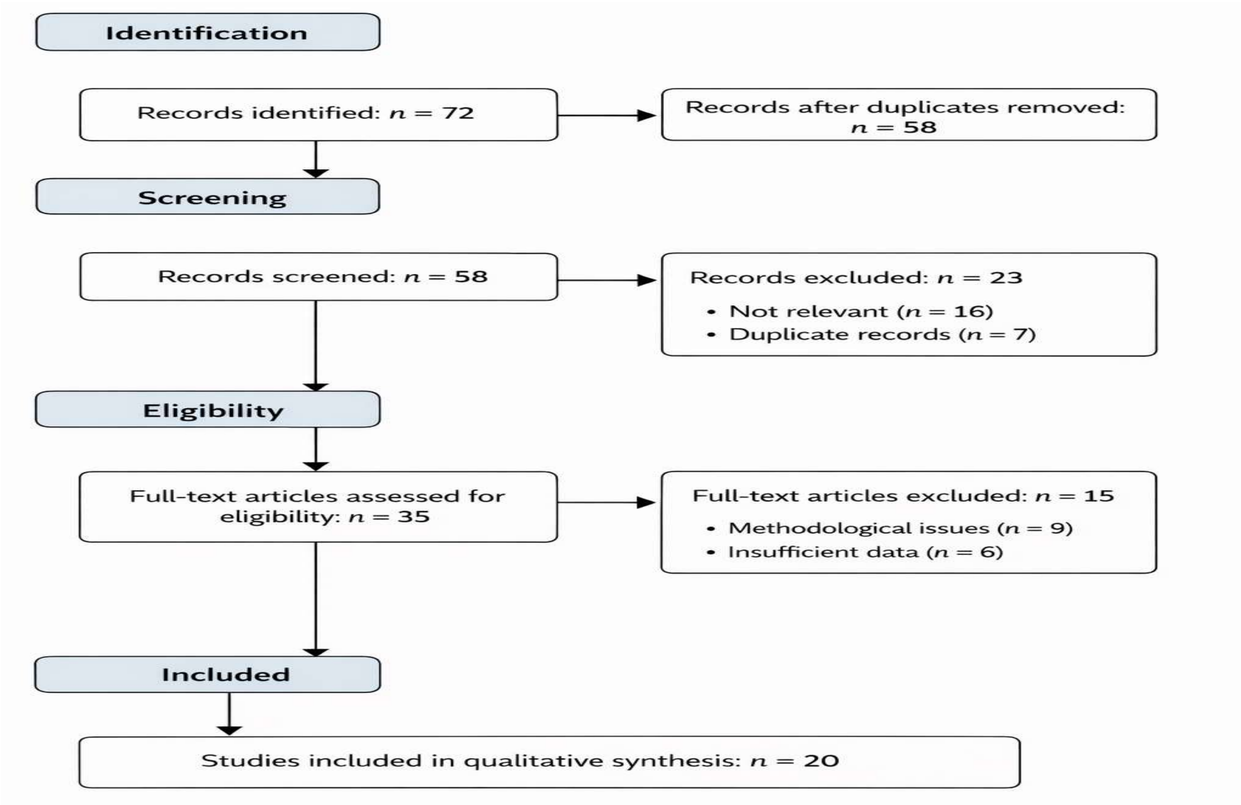

Figure 1: PRISMA Flowchart Source: Created by the author using Google Gemini

Data Extraction and Synthesis

Key data extracted included authorship, methodology, theoretical frameworks, AI tools, and knowledge outcomes. A thematic narrative synthesis grouped findings into conceptualisations, mechanisms, benefits, and risks. Due to methodological diversity, no meta-analysis was conducted; instead, findings were mapped onto theoretical models to develop a conceptual framework explaining AI-enabled knowledge creation

Systematic Literature Synthesis

After the PRISMA-guided selection procedure, the final set of 20 papers underwent methodical synthesis. This section provides a clear summary of the intellectual makeup of the reviewed papers before proceeding to the thematic analysis. Rather than presenting results in isolation, the synthesis begins by noting important features of the selected papers, including publication year, research design, theoretical framework, type of generative artificial intelligence investigated, and specific knowledge processes addressed. These fundamental characteristics are shown in Table 1. This comparative overview sets out the empirical and conceptual terrain of the discipline. It provides the analytical basis for the following study of theoretical trends, AI-enabled knowledge-creation techniques, reported advantages, and related risks.

Table 1: Meta-Analysis Table

S/N	Author and Year	Title	Country	Research Design	Theoretical Framework	AI Type Used	Knowledge Outcomes	Key Findings
1	Jun Cui (2025)	KM Dynamic Capabilities and AI-Driven KS	China	Quantitative (PLS-SEM)	RBT and KBV	AI-driven KS, ChatGPT	Improved skills and continuous learning	Positive impact on organisational performance
2	Kaczorowska-Spychalska et al. (2024)	GenAI and KM Paradigm Change	Poland	Qualitative	SECI, Tacit Knowledge Theory	GenAI, ChatGPT	Tacit knowledge codification automation	Disruptive KM innovation across stages
3	Shan Shan Yang (2024)	Transformative Role of AI in KM	Finland	Qualitative	Nonaka Theory, Wiig Cycle	GenAI, ML, NLP	Streamlined KM processes	Enhances agility and decision-making
4	Brachman et al. (2025)	LLMs for Knowledge Work	USA	Two surveys	Human-Centered Computing	LLMs, ChatGPT, Bard	Idea generation and decision support	Four main LLM usage categories
5	Alshammari & Alshammari (2026)	Digitalisation to Knowledge Innovation	Saudi Arabia	Quantitative (SEM)	KBV and DCT	AI-enabled integration	Enhanced innovation capabilities	Knowledge agility drives innovation
6	Dehal et al. (2025).	Knowledge Graphs and LLMs	Canada	Systematic Review	Symbolic/Neuro-symbolic AI	LLMs, KGs, Hybrid Models	Automated KG construction and grounding	KGs reduce LLM hallucinations
7	Zhiguo Yang et al. (2025)	Era of Misknowledge	USA	Research synthesis	GenAI-aided knowledge framework	GenAI, LLMs	Cognitive automation; misinformation risk	Requires verification-driven adoption
8	Tzirides et al. (2023).	GenAI in Education	USA	Intervention study	Learning by Design taxonomy	C-LLM	Extensive narrative academic feedback	AI feedback exceeds peer reviews
9	Saka et al. (2023).	GPT in Construction	UK / Hong Kong	Qualitative review	NLP vs LLM evaluation	GPT models, BERT	Automated BIM retrieval and optimisation	Useful but hallucination-prone
10	Megahed et al. (2023).	GenAI in SPC Practice	USA / Germany	Exploratory study	SPC-focused analysis	ChatGPT	Code generation and concept explanation	Requires rigorous human validation
11	Neștian et al. (2020)	AI in Knowledge Creation	Romania	Literature study	KBV, SECI	ML, Expert Systems	Tacit knowledge extraction	Enhances externalisation and combination
12	Kang et al. (2023)	Knowledge-Augmented Distillation	S. Korea / Singapore	Experimental	KARD theory	GPT-4, T5	Improved reasoning via knowledge grounding	Small models outperform larger ones

13	Luo et al. (2023)	Parametric Knowledge Guiding	Hong Kong / USA	Experimental	PKG framework	GPT3.5, LLaMA	Enhanced factual and multimodal performance	Access specialised knowledge safely
14	Trajanoska et al. (2023)	KG Construction with LLMs	Macedonia	Experimental	NLP & semantic reasoning	LLMs, ChatGPT	Automated KG population	Higher accuracy than specialized models
15	Zhu & Luo (2022)	Generative Design Ideation	Singapore	Case study	Knowledge Distance Theory	Fine-tuned GPT-2	Novel design idea generation	Synthesises internal and external knowledge
16	Razniewski et al. (2021).	LMs and Knowledge Bases	Germany / Netherlands	Position paper	Latent LMs vs KBs	BERT, GPT-3, T5	Factual retrieval and assertion elicitation	LMs augment, not replace KBs
17	Park et al. (2023).	ChatGPT for Scientific Hypotheses	USA / S. Korea	Technical study	Deductive reasoning	GPT-4	Hypothesis generation from data patterns	Viable for scientific reasoning
18	Mendes et al. (2024).	Enterprise Wikibase Q&A	Brazil	Technical implementation	RAG and EKG ontologies	Gemini 1.0 Pro	Natural language KG access	Accurate SPARQL query translation
19	Suh et al. (2023).	Structured Design Exploration	USA	System study	Human-AI Co-Creation	LLMs	Structured design space exploration	Improves relevance and diversity
20	Xu et al. (2025)	GenAI and Organisational Structure	USA / China	Formal modeling	Organisational hierarchy theory	GenAI, LLMs	Restructured workforce hierarchies	Eliminates layers with reliability

Results

The review of the identified studies yielded insights into publication trends, theoretical frameworks, mechanisms of AI-enabled knowledge creation, reported benefits, and risks in KIOs. These results are summarised below, drawing on the extracted data.

Publication Distribution

As shown in Table 2, there was a slow start, as only 1 study was published each year from 2020-2022. However, the number of studies published increased drastically in 2023, reaching a new high of 6 studies. The number of studies published was reduced to 3 in 2024, but production increased once more in 2025, reaching yet another new high of 6 studies. The number of studies published was reduced to 2 in 2026, implying a fluctuating but increasing interest in the topic.

Table 2: Publication Trends by Year

Year	Number of Studies
2020	1
2021	1
2022	1
2023	6
2024	3
2025	6
2026	2

Dominant Theoretical Frameworks

According to Table 3, the Knowledge-Based View and traditional structures such as the SECI Model underpin much of the material. While Dynamic Capability Theory receives moderate attention, Human-AI Co-Creation and Organisational Hierarchy Models reflect the latest conceptual developments in the field.

Table 3: Most Frequently Used Theories

Theory	Frequency
SECI Model	High
Knowledge-Based View	High
Dynamic Capability Theory	Moderate
Organisational Hierarchy Models	Emerging
Human-AI Co-Creation	Emerging

AI-Enabled Knowledge Creation Process

Table 4 presents four main processes by which artificial intelligence enables knowledge. Research indicates that artificial intelligence acts as a co-creator, helping with group ideation (Suh et al., 2023). It also acts as an augmenting instrument, increasing human cognitive capability (Megahed et al., 2023). Furthermore, AI serves as a knowledge recombination engine producing original syntheses (Zhu & Luo, 2022) and automates repetitive activities (Xu et al., 2025).

Table 4: Identified Mechanisms

Mechanism	Supporting Studies	Description
AI as Co-Creator	Suh et al. (2023)	Collaborative ideation
AI as Augmentation Tool	Megahed et al. (2023)	Cognitive support
AI as an Automation Mechanism	Xu et al. (2025)	Task substitution
Knowledge Recombination Engine	Zhu & Luo (2022)	Novel synthesis

Reported Benefits

Generative artificial intelligence improves technical skills and ongoing learning, hence boosting innovation as seen in Table 5. It helps produce scientific hypotheses and enables organised design exploration. Retrieval-enhanced generation systems increase access to corporate knowledge in organisational contexts. These contributions combine to present generative artificial intelligence as a useful instrument for promoting informed decision-making, research productivity, and creativity across technical and knowledge-intensive sectors.

Table 5: Contributions of Generative AI to Innovation and Knowledge Work

S/N	Contribution Area	Description	Source
1	Enhanced innovation capability	Generative AI improves organisational innovation outcomes and creative problem-solving capacity	Alshammari & Alshammari (2026)
2	Improved technical skills and learning	Supports skill development and continuous learning among users	Cui (2025)
3	Hypothesis generation in science	Assists researchers in generating testable scientific hypotheses	Park et al. (2023)
4	Structured design exploration	Enables systematic and structured exploration of design alternatives	Suh et al. (2023)
5	Enterprise knowledge access through RAG systems	Facilitates the retrieval and integration of internal organisational knowledge	Mendes et al. (2024)

Risks and Limitations

Table 6 lists the main dangers connected to the introduction of generative artificial intelligence. These include hallucinations and real mistakes that may generate false data as well as systematic misinformation that distributes biased narratives. The table also notes data privacy flaws, ethical and copyright risks, and deskilling issues—all of which pose significant professional, legal, and governing problems for responsible artificial intelligence implementation.

Table 6: Key Risks Associated with Generative AI Use

S/N	Risk Category	Description
1	Hallucination and Factual Errors	AI systems may generate inaccurate or fabricated information (Dehal et al., 2025).
2	Systemic Misinformation	AI can amplify biased or false narratives at scale (Yang et al., 2025).
3	Deskilling Concerns	Overreliance on AI may weaken users' critical thinking and professional expertise.

4	Ethical and Copyright Risks	Issues arise around plagiarism, ownership, and responsible use of AI-generated content.
5	Data Privacy Vulnerabilities	Sensitive information may be exposed or misused through AI systems.

Overall, the general trends described in the foregoing paragraphs indicate that there are ongoing relationships among publishing growth, readers' preferences, the effectiveness of artificial intelligence, perceived benefits, and risks. Apart from these general, surface-level trends, more rigorous theoretical analysis is required to further illuminate and clarify the underlying mechanisms and conceptual coherence of these trends.

Discussion

The results of this review indicate that generative artificial intelligence alters organisational knowledge development in practice instead of replacing it. The prevailing pattern in the reviewed papers is augmentation rather than replacement. Generative AI seems to have four connected roles: co-creator, augmentation tool, automation mechanism, and knowledge recombination engine, as shown in Table 4. Although these jobs may seem different, they can be seen as various ways in which AI systems' capacity to expand human cognitive and integrative abilities within organised environments is expressed. Suh et al. (2023) highlight collaborative thinking between humans and artificial intelligence, hence the co-creation role. AI in this setup aids exploratory thought by enlarging design spaces and providing organised options; it does not generate knowledge on its own. This fits very well with the augmentation viewpoint presented by Megahed et al. (2023), in which artificial intelligence supports human judgment and analytic reasoning rather than substituting for them. Both parts support the theory that generative artificial intelligence works inside human-led epistemic processes.

Xu et al.'s (2025) description of the automation mechanism further elaborates on this capacity. Though strategic interpretation and contextual decision-making remain human duties, regular cognitive tasks may be somewhat replaced. Even if artificial intelligence speeds up workflows, epistemic responsibility remains organizationally entrenched. Notably, the fourth mechanism, knowledge recombination (Zhu & Luo, 2022), is important. Generative AI improves cross-domain integration and pattern recognition by combining distributed explicit knowledge at volume. Recombination, though, is not the same as the first discovery.

The quality of the training data and the contextual framing still count.

From a classic theoretical perspective, these processes align naturally. According to Table 3, the SECI paradigm and the Knowledge-Based View control the body of work. From a SECI perspective, generative AI most powerfully improves externalisation and combination. Large language models help to codify hidden insights into ordered representations and mix clearly known material over organisational repositories (Neștian et al., 2020). Still, internalisation, that is, experiential learning and meaning construction, cannot be robotised. Before human performers become organisational knowledge, they must analyse and situate the results of artificial intelligence. In this sense, AI quickens portions of the information spiral but does not independently finish it.

Further explanation comes from the Knowledge-Based Perspective. AI-enabled knowledge integration improves innovation capacity and performance outcomes, as shown in Table 5 (Alshammari & Alshammari, 2026). Through retrieval-augmented generation systems, it promotes hypothesis generation in scientific contexts (Park et al., 2023), improves technical learning (Cui, 2025), and increases enterprise knowledge retrieval (Mendes et al., 2024). These advantages confirm that knowledge remains the primary strategic asset. However, using generative artificial intelligence tools alone does not create a competitive edge. It depends on the organisation's capacity to properly integrate, manage, and contextualise them.

Simultaneously, the hazards shown in Table 6 run counter to the cheery narrative. The epistemological fragility of generative systems is shown by hallucinations and real errors (Dehal et al., 2025). Systematic misinformation (Yang et al., 2025) reveals how quickly mistakes can spread in the absence of appropriate verification procedures. Further evidence of deskilling concerns and ethical weak spots suggests that the adoption of artificial intelligence may change professional standards and cognitive practices. These dangers directly affect the credibility of organisational knowledge outputs rather than being marginal.

The conflict between epistemic risks and innovation rewards indicates that generative artificial intelligence works best as a controlled hybrid performer. It is neither an autonomous knowledge agent nor does it match the conventional definition of a passive tool. Its effectiveness depends on the surrounding institutional architecture. Structural modelling data indicate possible changes in organisational structure (Xu et al., 2025), but trust in the system's dependability determines whether these changes occur. Technical mitigation techniques, including knowledge graphs and retrieval-augmented generation (Dehal et al., 2025; Mendes et al., 2024), demonstrate that accuracy increases when generating systems are trained on curated datasets. This supports the more general conclusion that the organisation of government and the performance of artificial intelligence are linked.

The data taken together point to a consistent conceptual reading. Although it relies on human validation to transform outcomes into trustworthy corporate knowledge, generative artificial intelligence sharpens knowledge externalisation, accelerates recombination, and enhances exploratory capability. Its transforming capacity lies in organised cooperation rather than in independent cognition. Organisations more likely to achieve sustainable innovation outcomes are those that view artificial intelligence as an integrated feature of learning systems, supported by ethical monitoring and verification procedures. Epistemic erosion is caused by those who view it as a replacement for knowledge. In this regard, generative artificial intelligence should be viewed as a capacity multiplier within knowledge-intensive companies. Its value comes from rigorous integration with established knowledge processes rather than from technology innovation alone.

Conclusion

In organisations that rely heavily on knowledge, generative artificial intelligence is changing knowledge systems. Particularly in knowledge recombination and externalisation, the data point towards substantial enhancement effects. Theoretical integration is still developing; epistemic hazards call for organised monitoring. Sustainable competitive advantage results from matching artificial intelligence skills with organisational learning and governance systems.

Recommendations

Organisations need to go beyond haphazard testing of generative AI and embrace established human-AI cooperation frameworks that specify roles and verification obligations. Ensuring that outputs are examined, checked, and contextualised prior to usage, human supervision should be an essential component of workflow design rather than an afterthought. Governance policies must include defined verification procedures to reduce the risk of hallucination and systematic misinformation. These regulations ought to address documentation procedures, fact-checking guidelines, and accountability mechanisms.

Organisational-level, continuous expenditure on artificial intelligence training is quite vital. Employees must understand the possibilities and limits of these systems to avoid overreliance that might compromise clear thought and professional judgment. Technically speaking, the highest priorities ought to be hybrid designs that mix knowledge graphs or retrieval-augmented systems with big language models. These improve factual grounding and lower error rates.

To examine the long-term effects of artificial intelligence-assisted knowledge creation, future studies should conduct longitudinal studies. With respect to policy implications, future studies should focus on developing ethical guidelines for legislation in the following domains: copyright, transparency, data privacy, and accountability in artificial intelligence-assisted knowledge creation.

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