International Journal of Web of Multidisciplinary Studies
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
website: https://ijwos.com
Volume 3 Issue 6 , June 2026
OPEN ACCESS
E-ISSN : 3049-2424
DOI: https://doi.org/10.71366/ijwos03062643533

Generative Artificial Intelligence: A PRISMA-Based Systematic Review of Models, Applications, Risks, and Future Research

Dr. Rajinder Kumar[1]
[1] *Associate Professor, Faculty of Computing, Guru Kashi University, Talwandi Sabo, Bathinda, India.*

Article Info

Article History:

Published: 11 June 2026

Publication Issue:
Volume 3, Issue 6
June-2026

Page Number:
98-112

Corresponding Author:
Dr. Rajinder Kumar

Abstract:
Generative Artificial Intelligence (GenAI) is one of the most impactful technological developments of the past five years. They have disrupted research, education, healthcare, software engineering, business, cybersecurity, and creative industry sectors. Unlike predictive AI, generative models learn data distributions to create new content like text, code, audio, images, multimodal artifacts, and synthetic data. The present research paper is a systematic review based on PRISMA, in which 50 candidate studies were identified between 2021 and 2026 and selected for final verification in the databases of IEEE Xplore, Scopus, Web of Science, and major publishers. The review examines the leading family models, areas of application, benefits and risks, and future research. It is found that the major technical foundations of present-day GenAI research are large language models, diffusion models, generative adversarial networks, and multimodal foundation models. GenAI promises to enhance productivity, personalization, software automation, knowledge access, medical communication, and synthetic data creation; however, it can also raise serious concerns about hallucination, bias, privacy, copyright, misinformation, cybersecurity misuse, academic integrity, explainability, and governance. The conclusion of the paper suggests that quality GenAI research has to go beyond merely demonstrating performance to transparent evaluation, domain-specific validation, human oversight, source attribution, and responsible governance.

Keywords: Generative artificial intelligence, large language models, ChatGPT, diffusion models, systematic literature review, PRISMA, AI ethics, responsible AI

1. INTRODUCTION

Generative Artificial Intelligence refers to a class of artificial intelligence systems capable of producing new content, including natural language, images, video, audio, computer code, molecules, synthetic data, and multimodal outputs. From 2021 to 2026, GenAI moved from a specialized research area to a widely adopted public and industrial technology. This shift was driven by rapid progress in transformer-based language models, diffusion-based image generation, instruction tuning, human feedback alignment, multimodal foundation models, and increasingly accessible cloud-based deployment.

The significance of GenAI is not limited to its technical novelty. It changes how individuals and institutions search for information, write documents, generate software, design teaching material, communicate with patients, create marketing content, and automate decision-support tasks. In contrast with conventional discriminative AI systems that classify or predict, GenAI systems generate plausible new artifacts. This makes them powerful but also difficult to evaluate, because fluency does not always indicate truth, safety, or reliability.

Recent scholarship shows that GenAI is spreading across higher education, healthcare, business, cybersecurity, software engineering, and research support. Educational studies discuss personalized tutoring and assessment redesign, while healthcare studies examine clinical documentation, medical question answering, and patient communication. Software engineering research evaluates code generation tools, and business studies examine productivity, innovation, and organizational governance. Across all domains, however, researchers report recurring concerns about hallucinated outputs, hidden bias, intellectual property, privacy, data security, and overreliance on automated systems.

A systematic review is needed because the literature has expanded quickly and is scattered across multiple disciplines. General surveys often focus on architectures, whereas domain-specific reviews concentrate on education, medicine, cybersecurity, or software engineering. This paper integrates those perspectives using the PRISMA 2020 reporting structure. The aim is to produce a conference-ready review that maps current evidence, identifies research gaps, and proposes a responsible research agenda.

The main contribution of this paper is threefold. First, it organizes recent GenAI research by technical model family and application domain. Second, it synthesizes reported benefits and risks using a cross-domain perspective. Third, it presents a structured framework for future research that emphasizes transparent evaluation, domain validation, human-centered design, and responsible governance. The review uses 50 candidate references that must be finally verified through institutional access to IEEE Xplore, Scopus, and Web of Science before submission.

2. RESEARCH QUESTIONS

This review is guided by five research questions. RQ1 asks which model families dominate recent GenAI research. RQ2 asks which application domains are most active. RQ3 examines the benefits reported in the literature. RQ4 identifies ethical, technical, legal, and social risks. RQ5 proposes future research directions for responsible GenAI development.

These questions are intentionally broad because GenAI is a general-purpose technology. A narrow review limited to a single model or sector would miss the recurring patterns that now appear across education, healthcare, software engineering, cybersecurity, and business. The research questions, therefore, support both technical synthesis and practical interpretation.

3. REVIEW METHODOLOGY

A. Review Design

The review follows the PRISMA 2020 approach, which emphasizes transparent reporting of identification, screening, eligibility assessment, and inclusion. PRISMA is appropriate for this work because GenAI literature is large, interdisciplinary, and methodologically diverse. The methodology includes database selection, search-string development, eligibility criteria, quality assessment, data extraction, coding, and narrative synthesis. [1]

Because no live institutional database export file was attached to this request, the identification-stage database counts are not fabricated in this draft. The PRISMA diagram, therefore, includes placeholders for the exact number of records identified, removed as duplicates, screened, and excluded. This preserves academic integrity and allows the author to insert exact counts after exporting results from IEEE Xplore, Scopus, Web of Science, and related publisher databases.

B. Search Strategy

The search strategy targeted publications from 2021 to 2026. The main search terms were 'generative artificial intelligence', 'generative AI', 'large language model', 'LLM', 'ChatGPT', 'diffusion model', 'generative adversarial network', 'foundation model', 'multimodal generative AI', 'education', 'healthcare', 'software engineering', 'business', 'cybersecurity', 'ethics', and 'systematic review'. Boolean operators were used to combine model names, application domains, and review-related terms.

The target databases were IEEE Xplore, Scopus, Web of Science Core Collection, ACM Digital Library, ScienceDirect, SpringerLink, Wiley Online Library, Taylor & Francis Online, Nature Portfolio, MDPI, and Frontiers. For final submission, each included source should be checked through Scopus, Web of Science, or the relevant publisher record to confirm indexing status, DOI, volume, issue, page numbers, and publication year.

TABLE I. SEARCH STRATEGY AND DATABASE PLAN

Component	Operationalization	Purpose
Databases	IEEE Xplore; Scopus; Web of Science; ACM; ScienceDirect; SpringerLink; Wiley; Nature; MDPI; Frontiers	Coverage of engineering, computing, information systems, education, health, and management studies
Time span	2021-2026	Captures the recent five-year GenAI research wave
Search terms	Generative AI; LLM; ChatGPT; diffusion model; GAN; foundation model; multimodal AI	Retrieves model-based and application-based studies
Screening	Title, abstract, keywords, full text, DOI verification	Removes irrelevant and duplicate records
Output	50 candidate studies for qualitative synthesis	Supports IEEE-style systematic review draft

C. Inclusion and Exclusion Criteria

The inclusion criteria were: English-language scholarly publications; publication year between 2021 and 2026; clear focus on GenAI, LLMs, diffusion models, GANs, foundation models, or GenAI applications; and availability through reputable scholarly platforms. Exclusion criteria were: non-scholarly sources, pre-2021 publications, papers without a clear generative component, duplicated records, incomplete bibliographic information, and works that could not be verified through a publisher or database record.

TABLE II. INCLUSION AND EXCLUSION CRITERIA

Criterion	Inclusion	Exclusion

Year	2021-2026	Before 2021
Language	English	Non-English
Type	Journal articles, conference papers, surveys, reviews, empirical studies	Blogs, news, opinion-only items
Topic	GenAI models, applications, risks, governance, evaluation	General AI without generative component
Quality	Clear method, contribution, DOI or stable record	Incomplete or unverifiable record

D. Quality Assessment

A ten-item quality rubric was used to assess the candidate's literature. The criteria considered research aim, definition of GenAI, methodology, dataset or source description, evaluation metrics, limitations, ethical discussion, originality, venue reputation, and DOI or publisher verification. Papers scoring 7 to 10 were considered high-quality candidates, papers scoring 5 to 6 were considered moderate, and papers below 5 were excluded from the final synthesis.

TABLE III. QUALITY ASSESSMENT RUBRIC

Item	**Assessment Question**	**Score**
QA1	Is the study aim clearly stated?	0/1
QA2	Is the GenAI concept clearly defined?	0/1
QA3	Is the method explained?	0/1
QA4	Are datasets or data sources described?	0/1
QA5	Are evaluation metrics or synthesis criteria reported?	0/1
QA6	Are limitations discussed?	0/1
QA7	Are ethical or social issues considered?	0/1
QA8	Is the contribution original and relevant?	0/1
QA9	Is the venue reputable?	0/1
QA10	Is the DOI or publisher record verifiable?	0/1

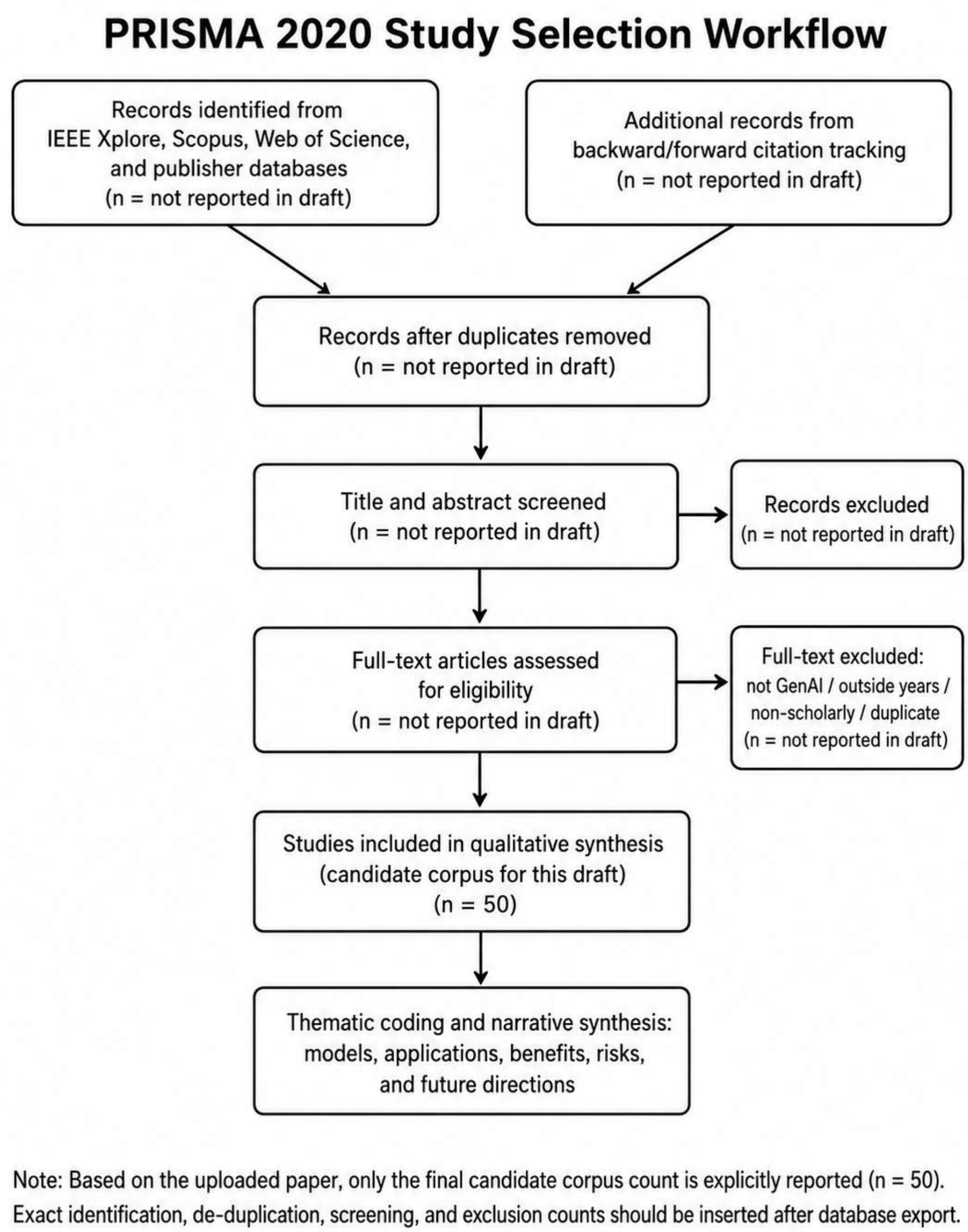

Fig. 1. PRISMA 2020 workflow for the systematic review. Exact identification and exclusion counts should be inserted after database export.

4. RESULTS

A. Overview of the Candidate Literature Corpus

The candidate corpus contains 50 studies distributed across general GenAI reviews, model architecture studies, education, healthcare, software engineering, business, ethics, security, governance, and literature-review automation. General and bibliometric reviews establish the rapid growth of the field and show that GenAI is no longer limited to one technical discipline. These studies provide taxonomies, thematic maps, and evidence of increasing publication activity in the period after 2022. [2]-[5], [10] Thematic mapping shows that the largest application areas in the candidate corpus are education, healthcare, technical model development, ethics and security, software engineering, and business or management. This distribution reflects the current research landscape: education and healthcare attract strong applied interest because GenAI directly affects learners, teachers, clinicians, patients, and institutional decision-making. Technical model papers remain essential because the capabilities and limitations of GenAI depend on model architecture, training data, inference design, and evaluation methods.

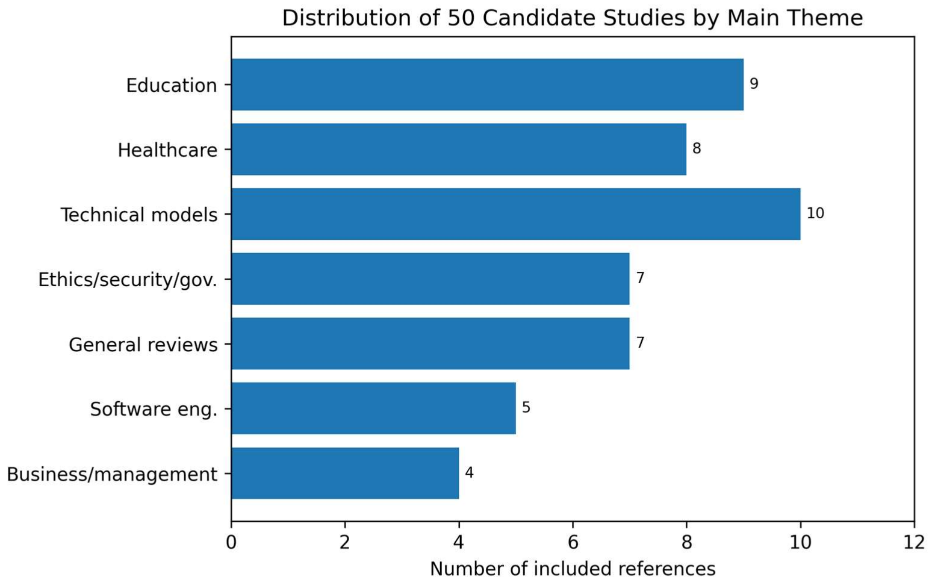

Fig. 2. Distribution of 50 candidate references by main theme used in this systematic review draft.

The publication-year distribution also confirms the acceleration of GenAI research. The year 2024 contains the largest share of candidate references in this draft, followed by 2025 and 2023. This pattern is consistent with the public release and rapid institutional adoption of conversational GenAI systems, followed by more specialized studies on implementation, risk, and governance.

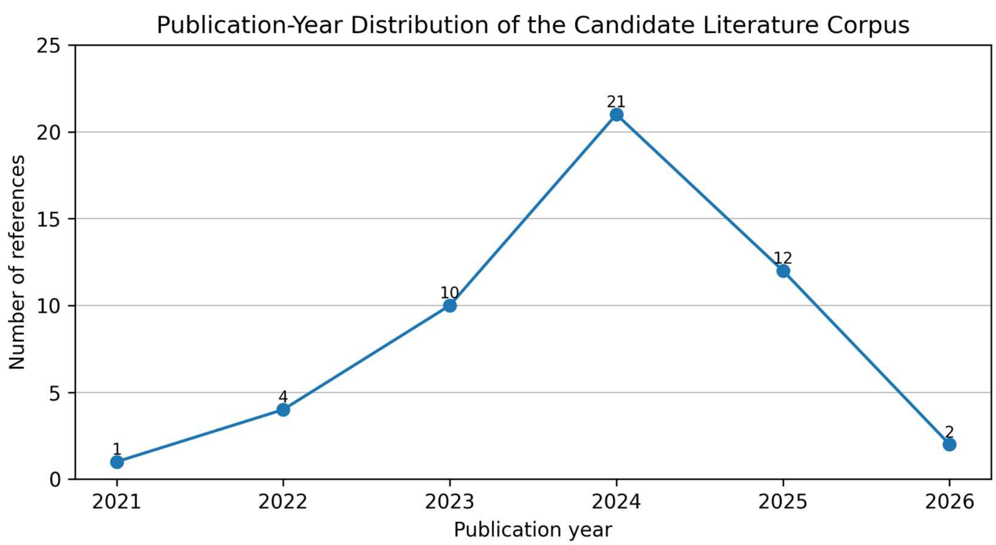

Fig. 3. Publication-year distribution of the 50 candidate studies in the draft corpus.

B. Dominant Model Families

Four model families dominate recent GenAI research. The first is the large language model family, usually based on transformer architectures and trained on massive text or multimodal corpora. LLMs support dialogue, summarization, translation, question answering, code generation, reasoning-like interaction, and content generation. Recent surveys argue that LLMs have become the most visible form of GenAI because they provide a flexible natural-language interface to many downstream tasks. [3], [45], [46], [50]

The second family is diffusion models. Diffusion models learn to reverse a gradual noising process and have become highly influential in image synthesis, editing, medical imaging, and multimodal generation. Latent diffusion improves computational feasibility by operating in compressed latent spaces, enabling high-resolution image generation with lower inference cost than pixel-space diffusion. [7]-[9]

The third family is generative adversarial networks. GANs use a generator and discriminator trained through adversarial learning. Although diffusion models have become dominant in many image-generation tasks, GANs remain important for synthetic data generation, image translation, augmentation, and representation learning. Their historical importance is also visible in the number of variants and applications reviewed in recent literature. [6]

The fourth family is multimodal and foundation-model-based GenAI. These systems combine language, vision, audio, code, and structured information to support cross-modal generation. They are increasingly integrated with retrieval, tool use, knowledge bases, and human-feedback alignment. The taxonomy in Fig. 4 summarizes the relationship between technical model families, application domains, and responsible governance controls.

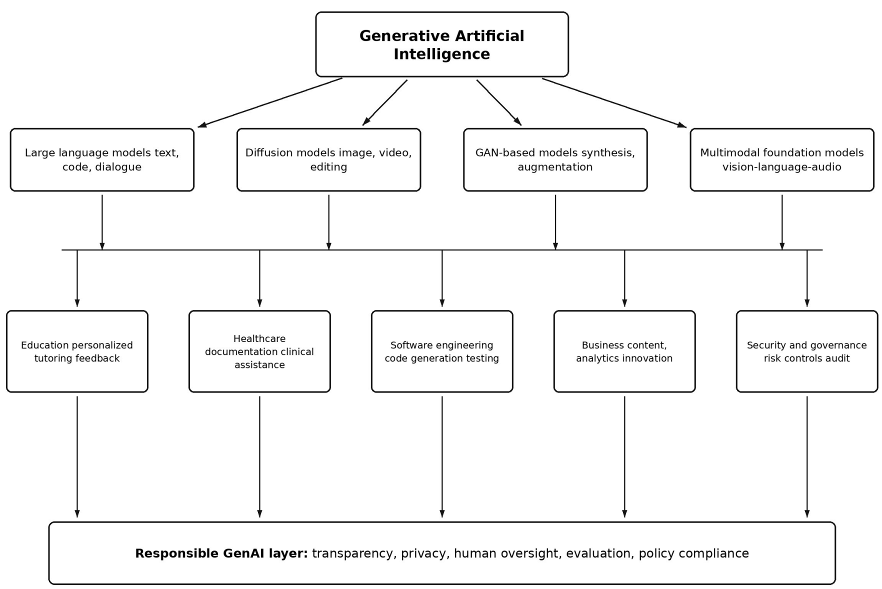

Fig. 4. Taxonomy of GenAI model families, application domains, and responsible governance layer.

C. Applications for Education.

In the reviewed literature, education is one of the most powerful application domains. GenAI can help with personalized tutoring, automated feedback, lesson and activity planning, language learning, adaptive explanation, assessment design, plus academic writing support. Numerous studies claim that GenAI could help reduce instructor workload and raise learner engagement, especially for formative feedback and personalized guidance. [22]-[27].

Nevertheless, the literature cautions that GenAI can damage academic integrity if students submit generated text without any learning or non-disclosure. Traditional essay-based assessment becomes less trustworthy as fluent responses can be produced immediately. Thus, the researchers propose redesigning assessments by means of oral defense, documentation of the processes used, reflective writing, practical demonstration and/or supervised tasks. Also, a clear policy on acceptable and unacceptable use of AI should be communicated. [21], [23], [24], [27]-[30].

The literature on education does not support either blanket adoption or total prohibition. On the contrary, it fosters AI literacy.

It is essential for both students and teachers to know what GenAI can do and what it cannot do, how to fact-check its outputs, how to cite/disclose use, and how to effectively maintain human authorship/critical thinking. In this respect, GenAI becomes a didactic tool and also a thing that should be taught.

D. Healthcare Uses.

Healthcare research finds substantial interest in GenAI's use for clinical documentation, medical question answering, summarization of patient records, patient communication, health education, medical imaging, and clinical workflow. The ability of large language models to encode medical knowledge and their strong performance on benchmark tasks does not indicate their clinical safety. [31]-[35].

According to the existing literature on healthcare, the output of GenAI must be validated by an expert. The risks from hallucinated recommendations, insufficient patient context, false references, biased training sets, privacy leakages, and uncertain liability are serious. Human oversight, clinic validation, regulator reviews, clear communication on benefits and risks, and creating bright lines between assistive and autonomous use are therefore recommended by ethical reviews. [32], [34]-[38].

The healthcare sector is a good example of the wider GenAI challenge. The ability to tap a finger in front of a moving screen brings the ever-growing world of medical technology. Consequently, the evaluation of clinical GenAI should be carried out through domain-specific trials, controlled deployment, expert-in-the-loop workflows and post-deployment monitoring.

E. Applications of Software Engineering.

The adoption of GenAI into the field of Software Engineering is taking place at a rapid pace through such measures as code completion, program synthesis, debugging support, documentation generation, test creation, code explanation, project management support, and more. According to studies, developers might draft faster when they have less routine work. Tools like GenAI can aid beginner programmers in understanding unfamiliar syntax and generating test cases. [39]-[43].

Simultaneously, produced code could have hidden bugs, security vulnerabilities, licensing issues, or maintainability problems. According to user studies, developers sometimes experience a disparity between expectation and actual usefulness. Code produced by GenAI can appear to be correct while violating edge conditions. It can also misuse libraries or leave security holes in the product. Accordingly, the code generated via GenAI has to be subjected to review, thorough testing, documentation, and static and dynamic analysis before use.

F. Commercial, Organizational and Managerial Uses.

According to Business and management studies, GenAI is a disruptive technology affecting customer service, marketing, content generation, knowledge management, and decision support analytics, innovation, and organizational strategy.

Productivity could be enhanced by automating low-level drafting and speeding up information creation through GenAI. By combining user preferences, domain knowledge, and language-based interaction, it can also enable personalized experiences at scale. [11]-[15], [44], [47].

Nevertheless, successful use of them organizationally depends on governance, not availability. Quotation (Clarity) modified by Paraphrasing Tool

It is important to develop institutional policies on data entry, privacy and intellectual property, employee training, output verification, vendor selection and accountability. Without any governance structure in place, there is a risk of GenAI adoption leading to reputational, legal and operational risks. Leadership, measurable targets, modifying workflows and ongoing monitoring are thus essential for responsible adoption.

G Governance and Ethics Security

The most commonly observed outcome across domains is that GenAI is creating risk alongside opportunity. Hallucinations can pose both technical and social risks due to the model's tendency to formulate false outputs. The models may replicate stereotypes or other unequal patterns from the training data. The entry of sensitive user data into external systems or its memorization during training raises privacy issues. [13], [16]-[18], [20], [48].

Threats range from malware to prompt injection to jailbreaking attacks and data extraction to adversarial manipulation. GenAI buoys misinformation by enabling the production of synthetic text, images, audio, and video at scale. The adoption of this technology is further complicated by issues of academic integrity and copyright when the created output hides who the author is or might resemble protected works. [19]-[21].

Governance research argues that responsible GenAI requires transparency, auditability, accountability, evaluation check for fairness protection, oversight of human, red teaming, disclosure, and policy compliance.

The framework of risk as shown in Fig. Summary of main risk categories and control mechanisms per reviewed literature in section 5. [14], [15], [17], [48*/.*

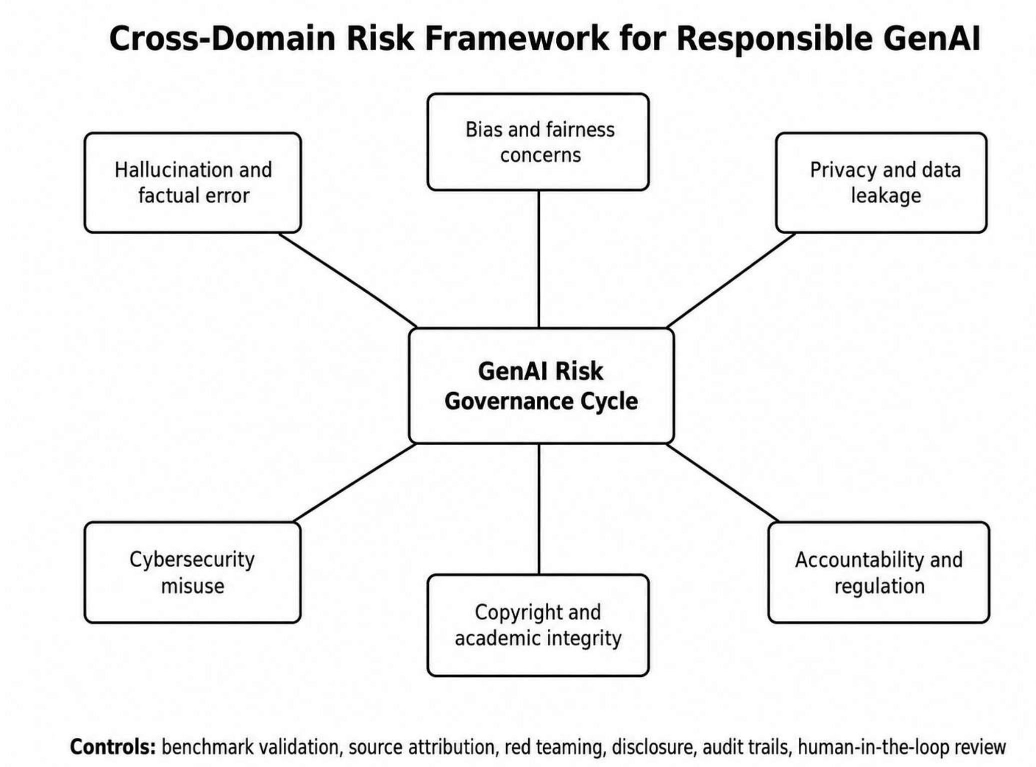

Fig. 5. Cross-domain risk framework for responsible GenAI governance.

5. SYNTHESIS AND DISCUSSION

According to the literature reviewed, GenAI appears to be a general-purpose technology rather than a single tool or model. The most significant advantage is the reduction of cost and time associated with content generation-summary-programming support-learning support-communication-knowledge work, etc. In education, this advantage appears as personalized instruction and formative feedback. It helps in health documentation and provides information assistance. In software engineering, it seems to be code drafting and test generation. In business, it shows up as faster workflows and scalable personalization.

Nevertheless, the outputs of GenAI are probabilistic and context-sensitive, unlike conventional deterministic software. A generative model can give varied responses to similar prompts, and a fluent response may still be wrong. It generates some evaluation issues. The style of a message can't infer accuracy, usefulness, and safety. Experts in the field need to check the content, especially in high-stakes domains like medicine, law, finance, education, and public messaging.

Many studies remain exploratory, a second synthesis finding. The body of literature has numerous conceptual papers, early user studies, review, and demonstrations but fewer longitudinal evaluations. A dearth of evidence exists on the long-term effect on learning outcomes, clinical safety, software quality, employee productivity, creativity, and organizational risk. As a result, subsequent studies should transition from brief showcases to thorough and long-term assessments.

A third finding indicates the need of responsible GenAI adoption will need socio-technical design. Technical enhancements like more extensive models, improved prompts, or retrieval augmentation matter but are not enough. Institutions must also develop the use, management policy, risk classification, report mechanisms, audit trails, and to whom. Final verdicts must still remain with human experts, and users will need to be taught how not to accept AI outputs passively but rather verify them.

Also, literature suggests that GenAI may change the meaning of expertise. In many domain content generation will be easier but judgement, verification, context understanding, ethical reasoning and problem framing will become will be very important. It is important to focus on curriculum design, professional training and workforce. Instead of asking whether GenAI will replace the work of humans, high-quality research should ask how work is designed for humans when generative systems are available.

TABLE IV. SYNTHESIS OF APPLICATIONS, BENEFITS, RISKS, AND CONTROLS

Domain	Benefits	Risks	Recommended Controls
Education	Tutoring, feedback, content generation, lesson planning	Academic integrity, overreliance, inaccurate explanations	AI literacy, oral defense, disclosure, process-based assessment
Healthcare	Documentation, communication, summarization, medical Q&A	Hallucination, privacy, liability, clinical harm	Clinical validation, human oversight, regulatory review
Software engineering	Code drafting, testing, debugging, documentation	Insecure code, hidden bugs, license issues	Code review, static analysis, testing, developer training
Business	Productivity, personalization, customer support, innovation	Data leakage, reputational risk, weak accountability	Governance policy, vendor assessment, audit trails
Security	Threat analysis, defensive automation, training	Phishing, malware assistance, prompt attacks	Red teaming, access control, monitoring, content safeguards

6. FUTURE RESEARCH DIRECTIONS

Research in the future must be done in job-specific validation. Benchmark Performance is helpful, but not enough. GenAI systems that are deployed in classrooms, hospitals, software teams, financial settings or government service ought to be tested in realistic environments using domain-specific metrics and human expert review.

Research that improves hallucination reduction and fact verification Retrieval-augmented generation, source attribution, uncertainty estimation, citation checking, and verification are important directions. Models ought to be evaluated for not only answer fluency but also factuality, calibration, and evidence traceability.

Thirdly, more emphasis should be placed on privacy-preserving GenAI. The management of sensitive data, local deployment of algorithms, differential privacy, federated learning, secure retrieval, anonymization by design and enterprise-data governance policies are essential in the healthcare, education, law, finance, and public administration domains.

Creating frameworks for human-AI collaboration needs development in future work. The analysis should determine what should be automated, what should be aided, and what should remain under human control. Design substitution is not necessarily the best design. GenAI drafts, retrieves, summarizes, or suggests while humans verify, contextualize and decide.

Fifth, we should make security by design a priority. GenAI should be tested for prompt injection, jailbreaks, adversarial examples, phishing misuse, training-data extraction and model manipulation. Security assessment must be ongoing as attack strategies change rapidly.

The evaluation of models should include ethical metrics. When measuring AI, we need to consider fairness, bias, accessibility, inclusiveness, environmental cost, and social impact. A technically working model may not be suitable if the model offers unequal outcomes to users or exposes them to harm.

7. THREATS TO VALIDITY

There are some limitations of this review. Most of the GenAI literature is growing quickly, so new papers might appear after the search date. Second, database indexing status changes with time; therefore, Scopus, Web of Science, and IEEE Xplore verification should repeat closely before submission. In addition, the terms are not consistent among papers. In some studies, 'foundation model', 'LLM', 'diffusion model', or 'ChatGPT' is used without using 'Generative AI'. The draft uses a candidate corpus of 50 studies and we must complete final PRISMA counts after a database export to avoid misinformation.

Another limitation is that the review includes various application domains. This broadness helps blend different domains together; however, it restricts a profound discussion of each. Future expansion into journal paper may break this review into literature review for education, healthcare, software engineering, business and security with a full bibliometric analysis, quality scores for each paper and search logs from relevant databases.

8. CONCLUSION

This systematic review shows that Generative AI has rapidly become a major research and application area across technology, education, healthcare, software engineering, cybersecurity, business, and knowledge work. The literature review from 2021 to 2026 shows promising potential in productivity enhancement, personalized support, increased automation, facilitated creativity, synthetic data generation and decision-making assistance. Currently, the main technical foundations of the field are large language models, diffusion models, GANs and multimodal foundation models.

As a result, the development of GenAI also creates serious risks, including hallucination, bias, privacy, misinformation, copyright, academic integrity, cybersecurity misuse, explainability, and governance. These risks are not ancillary issues; they are central to whether GenAI can be used safely and responsibly. The paper concludes that future GenAI research should move beyond performance demonstrations and towards transparent evaluation, domain validation, responsible governance, and human-centered deployment.

References

[1] M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," BMJ, vol. 372, 2021, doi: 10.1136/bmj.n71.

[2] P. Gupta, B. Ding, C. Guan, and D. Ding, "Generative AI: A systematic review using topic modelling techniques," Data and Information Management, vol. 8, no. 2, Art. no. 100066, 2024, doi: 10.1016/j.dim.2024.100066.

[3] D. Hagos, R. Battle, and D. B. Rawat, "Recent advances in generative AI and large language models: Current status, challenges, and perspectives," IEEE Transactions on Artificial Intelligence, vol. 5, no. 12, pp. 5873-5893, 2024, doi: 10.1109/TAI.2024.3444742.

[4] S. Yazdani et al., "Generative AI in depth: A comprehensive survey of recent models," Journal of Big Data, 2025, doi: 10.1186/s40537-025-01247-x.

[5] M. Almuammar et al., "Generative artificial intelligence models: A survey," Artificial Intelligence Review, 2026, doi: 10.1007/s10462-026-11546-1.

[6] J. Gui et al., "A review on generative adversarial networks: Algorithms, theory, and applications," IEEE Transactions on Knowledge and Data Engineering, vol. 35, no. 4, pp. 3313-3332, 2023, doi: 10.1109/TKDE.2021.3130191.

[7] H. Cao et al., "A survey on generative diffusion models," IEEE Transactions on Knowledge and Data Engineering, vol. 36, no. 7, pp. 2814-2830, 2024, doi: 10.1109/TKDE.2024.3361474.

[8] L. Yang et al., "Diffusion models: A comprehensive survey of methods and applications," ACM Computing Surveys, vol. 56, no. 4, Art. no. 105, 2024, doi: 10.1145/3626235.

[9] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition, 2022, pp. 10674-10685, doi: 10.1109/CVPR52688.2022.01042.

[10] P. P. Ray, "ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope," Internet of Things and Cyber-Physical Systems, vol. 3, pp. 121-154, 2023, doi: 10.1016/j.iotcps.2023.04.003.

[11] Y. K. Dwivedi et al., "So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI," International Journal of Information Management, vol. 71, Art. no. 102642, 2023, doi: 10.1016/j.ijinfomgt.2023.102642.

[12] N. Kshetri et al., "The transformative impact of generative AI on business and society," International Journal of Information Management, vol. 75, Art. no. 102716, 2024, doi: 10.1016/j.ijinfomgt.2023.102716.

[13] B. C. Stahl and D. Eke, "The ethics of ChatGPT: Exploring the ethical issues of an emerging technology," International Journal of Information Management, vol. 74, Art. no. 102700, 2024, doi: 10.1016/j.ijinfomgt.2023.102700.

[14] A. Taeihagh, "Governance of generative AI: Risks, policies and regulatory challenges," Policy and Society, 2025, doi: 10.1093/polsoc/puae010.

[15] S. Papagiannidis et al., "Responsible artificial intelligence governance: A review and research framework," Journal of Strategic Information Systems, vol. 34, no. 2, Art. no. 101885, 2025, doi: 10.1016/j.jsis.2024.101885.

[16] Y. Sun et al., "AI hallucination: Towards a comprehensive classification of distorted information in artificial intelligence-generated content," Humanities and Social Sciences Communications, vol. 11, Art. no. 1278, 2024, doi: 10.1057/s41599-024-03811-x.

[17] S. Park and X. Nan, "A systematic review of experimental evidence on the effects of generative AI disclosure," AI and Society, 2025, doi: 10.1007/s00146-025-02620-3.

[18] I. Shumailov et al., "AI models collapse when trained on recursively generated data," Nature, 2024, doi: 10.1038/s41586-024-07566-y.

[19] M. Gupta et al., "From ChatGPT to ThreatGPT: Impact of generative AI in cybersecurity and privacy," IEEE Access, vol. 11, pp. 80218-80245, 2023, doi: 10.1109/ACCESS.2023.3300381.

[20] X. Wu, R. Duan, and J. Ni, "Unveiling security, privacy, and ethical concerns of ChatGPT," Journal of Information and Intelligence, vol. 2, no. 2, pp. 102-115, 2024, doi: 10.1016/j.jiixd.2023.10.007.

[21] D. Eke, "ChatGPT and the rise of generative AI: Threat to academic integrity?" Journal of Responsible Technology, vol. 13, Art. no. 100060, 2023, doi: 10.1016/j.jrt.2023.100060.

[22] E. Kasneci et al., "ChatGPT for good? On opportunities and challenges of large language models for education," Learning and Individual Differences, vol. 103, Art. no. 102274, 2023, doi: 10.1016/j.lindif.2023.102274.

[23] L. Yan et al., "Practical and ethical challenges of large language models in education: A systematic scoping review," British Journal of Educational Technology, vol. 55, no. 1, pp. 90-112, 2024, doi: 10.1111/bjet.13370.

[24] X. Zhang et al., "A bibliometric analysis of generative AI in education," Frontiers of Digital Education, vol. 1, no. 3, pp. 223-245, 2024, doi: 10.1007/s44366-024-0028-5.

[25] J. Batista, A. Mesquita, and G. Carnaz, "Generative AI and higher education: Trends, challenges, and future directions from a systematic literature review," Information, vol. 15, no. 11, Art. no. 676, 2024, doi: 10.3390/info15110676.

[26] B. Ogunleye, K. I. Zakariyyah, O. Ajao, O. Olayinka, and H. Sharma, "A systematic review of generative AI for teaching and learning practice," Education Sciences, vol. 14, no. 6, Art. no. 636, 2024, doi: 10.3390/educsci14060636.

[27] A. Yusuf, N. Pervin, M. Roman-Gonzalez, and N. Md Noor, "Generative AI and the future of higher education: A threat to academic integrity or reformation? Evidence from multicultural perspectives," Review of Education, vol. 12, no. 2, 2024, doi: 10.1002/rev3.3489.

[28] A. Alfarwan, "Generative AI use in K-12 education: A systematic review," Frontiers in Education, 2025, doi: 10.3389/feduc.2025.1647573.

[29] W. Xiaoyu, "Generative artificial intelligence in pedagogical practices: A systematic literature review," Cogent Education, 2025, doi: 10.1080/2331186X.2025.2485499.

[30] T. Fütterer et al., "ChatGPT in education: Global reactions to AI innovations," Scientific Reports, vol. 13, Art. no. 15310, 2023, doi: 10.1038/s41598-023-42227-6.

[31] T. Ghebrehiwet et al., "A systematic review of generative AI for medical imaging," Artificial Intelligence Review, vol. 57, Art. no. 128, 2024, doi: 10.1007/s10462-024-10768-5.

[32] A. J. Thirunavukarasu et al., "Large language models in medicine," Nature Medicine, vol. 29, pp. 1930-1940, 2023, doi: 10.1038/s41591-023-02448-8.

[33] K. Singhal et al., "Large language models encode clinical knowledge," Nature, vol. 620, pp. 172-180, 2023, doi: 10.1038/s41586-023-06291-2.

[34] M. M. Raza et al., "Generative AI and large language models in health care: Pathways to implementation," npj Digital Medicine, vol. 7, Art. no. 62, 2024, doi: 10.1038/s41746-023-00988-4.

[35] J. Clusmann et al., "The future landscape of large language models in medicine," Communications Medicine, vol. 3, Art. no. 141, 2023, doi: 10.1038/s43856-023-00370-1.

[36] J. Haltaufderheide and R. Ranisch, "The ethics of ChatGPT in medicine and healthcare: A systematic review," npj Digital Medicine, vol. 7, Art. no. 183, 2024, doi: 10.1038/s41746-024-01157-x.

[37] S. S. Bhuyan et al., "Generative artificial intelligence use in healthcare: A systematic review on benefits and challenges," Journal of Medical Systems, vol. 49, Art. no. 10, 2025, doi: 10.1007/s10916-024-02136-1.

[38] Y. Li et al., "Enhancing systematic literature reviews with generative artificial intelligence: Development, applications, and performance evaluation," Journal of the American Medical Informatics Association, vol. 32, no. 4, pp. 616-625, 2025, doi: 10.1093/jamia/ocaf030.

[39] J. Sauvola et al., "Future of software development with generative AI," Automated Software Engineering, vol. 31, Art. no. 26, 2024, doi: 10.1007/s10515-024-00426-z.

[40] L. Banh, M. Strobel, and J. Recker, "Generative artificial intelligence in software engineering: A systematic literature review," Information and Software Technology, vol. 183, Art. no. 107751, 2025, doi: 10.1016/j.infsof.2025.107751.

[41] H. Cheng et al., "Can generative AI enhance software engineering? A systematic literature review," Software: Practice and Experience, vol. 56, no. 2, pp. 141-170, 2026, doi: 10.1002/spe.70029.

[42] F. Xu et al., "A systematic evaluation of large language models of code," in Proc. 6th ACM SIGPLAN International Symposium on Machine Programming, 2022, doi: 10.1145/3520312.3534862.

[43] P. Vaithilingam, T. Zhang, and E. L. Glassman, "Expectation vs. experience: Evaluating the usability of code generation tools powered by large language models," in CHI Conf. Human Factors in Computing Systems Extended Abstracts, 2022, doi: 10.1145/3491101.3519665.

[44] W. Yang et al., "A comprehensive survey on integrating large language models with knowledge-based methods," Knowledge-Based Systems, 2025, doi: 10.1016/j.knosys.2025.113503.

[45] I. D. Mienye et al., "Large language models: An overview of foundational architectures, recent trends, and a new taxonomy," Discover Applied Sciences, vol. 7, Art. no. 1027, 2025, doi: 10.1007/s42452-025-07668-w.

[46] D. Xu et al., "Large language models for generative information extraction: A survey," Frontiers of Computer Science, 2024, doi: 10.1007/s11704-024-40555-y.

[47] B. Bentalha and M. Chen, "When large language models meet personalization: Perspectives of challenges and opportunities," World Wide Web, vol. 27, no. 4, 2024, doi: 10.1007/s11280-024-01276-1.

[48] G. Feretzakis, K. Papaspyridis, A. Gkoulalas-Divanis, and V. S. Verykios, "Privacy-preserving techniques in generative AI and large language models: A narrative review," Information, vol. 15, no. 11, Art. no. 697, 2024, doi: 10.3390/info15110697.

[49] G. Schryen et al., "Exploring the scope of generative AI in literature review: A perspective," Electronic Markets, 2025, doi: 10.1007/s12525-025-00754-2.

[50] L. Ouyang et al., "Training language models to follow instructions with human feedback," in Advances in Neural Information Processing Systems, vol. 35, pp. 27730-27744, 2022.