

Generative artificial intelligence in healthcare: A comparative analysis of clinical and administrative applications

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ABSTRACT

Objectives: This study aims to systematically identify, classify, and evaluate generative artificial intelligence (GAI) tools used in healthcare. The research focuses on examining the application areas of these tools in both clinical and administrative contexts and analyzing their technological and operational characteristics.

Materials and methods: A scoping review methodology was employed following the framework proposed by Arksey and O'Malley. Data were collected from academic databases, technology platforms, and publicly available sources to identify GAI tools related to healthcare. After applying the inclusion criteria, a dataset of 80 GAI tools developed between 2010 and 2025 was compiled. The collected data were analyzed using descriptive statistics and content analysis to classify the tools according to their application domains, development origins, platform availability, and pricing models.

Results: The findings indicate that the majority of GAI tools in healthcare were developed in the United States, followed by other technologically advanced countries. The tools are widely used in areas such as medical imaging, clinical documentation, decision support systems, and drug discovery. Additionally, most of the identified tools operate through web-based platforms, while many follow commercial or freemium pricing models, reflecting the increasing commercialization of digital health technologies.

Conclusion: Generative AI technologies have significant potential to transform healthcare systems by improving diagnostic accuracy, supporting clinical decision-making, enhancing operational efficiency, and enabling personalized medicine approaches. However, issues related to ethics, data privacy, regulatory frameworks, and equitable access must be carefully addressed to ensure the sustainable and responsible integration of GAI into healthcare services.

Keywords: Artificial intelligence tools, clinical decision support, digital health, generative artificial intelligence, healthcare management.

Artificial intelligence (AI) can be broadly understood as technologies that mimic human thinking abilities, such as learning, reasoning, decision-making, and even creativity.^[1] In recent years, advances in machine learning and natural language processing (NLP) have accelerated the emergence of generative AI (GAI), which goes a

step further by creating new content based on existing data.^[2]

At the same time, healthcare systems around the world are experiencing a major digital shift. Technologies like electronic health records (EHRs), telemedicine, wearable devices, and AI-driven decision support systems are becoming increasingly embedded in everyday healthcare practice.^[3] Within this broader transformation, GAI has started to stand out due to its ability to handle complex tasks and produce outputs that are clinically meaningful.

Research shows that AI-based systems can enhance diagnostic accuracy, anticipate disease progression, and improve the overall efficiency of healthcare management.^[2,4,5] For example, some AI models have reached dermatologist-level performance in identifying skin cancer from medical images.^[6] Beyond diagnosis, GAI

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tools are also being used to streamline clinical documentation, suggest treatment options, and support administrative workflows.

This study aims to explore GAI tools used in healthcare by identifying, classifying, and evaluating them across both clinical and managerial contexts. In doing so, it seeks to offer a comprehensive perspective on how these tools can contribute to healthcare professionals, managers, and decision-makers.

This study seeks to answer the following research questions:

RQ1: What are the main characteristics of GAI tools used in healthcare?

RQ2: How are GAI tools distributed across clinical and administrative applications?

RQ3: What patterns emerge regarding the technological, geographical, and economic aspects of these tools?

RQ4: How do GAI tools contribute to digital transformation in healthcare systems?

This study is grounded in the theoretical perspectives of digital transformation, healthcare management, and platform economy. Generative AI tools are conceptualized as technological enablers that support both clinical decision-making and administrative efficiency.

The framework assumes that GAI contributes to healthcare transformation through three main dimensions: (1) clinical value creation (diagnostics, treatment, research); (2) managerial efficiency (workflow, communication, planning); and (3) platform-based digital ecosystems (web-based AI tools and commercialization).

This conceptualization allows the study to position GAI not only as a technological innovation but also as a driver of organizational and systemic change in healthcare.

Generative artificial intelligence in healthcare

Generative AI has quickly become one of the most transformative technologies in modern healthcare. Unlike traditional AI systems, which mainly focus on tasks like classification, prediction, or pattern recognition, GAI can actually create new outputs—whether that's text, images, audio, or structured data—by

learning from existing datasets.^[2] It relies on advanced machine learning approaches such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), transformer-based models, and diffusion techniques to produce outputs that are both realistic and clinically meaningful.^[7] This capability opens up new possibilities for supporting clinical decisions and improving healthcare management.

At the same time, healthcare systems are going through a rapid digital transformation. Hospitals and healthcare organizations are increasingly adopting digital tools to handle growing volumes of medical data, enhance diagnostic accuracy, and improve operational efficiency.^[8] Within this evolving landscape, GAI is gaining attention as a powerful tool that can address complex challenges, whether by generating new insights, summarizing clinical information, or assisting healthcare professionals in their decision-making processes.^[5]

One of the most visible use cases of GAI in healthcare is clinical documentation. Healthcare professionals spend a considerable amount of time on administrative tasks, including writing patient reports, documenting clinical encounters, and preparing discharge summaries. Generative AI models, especially those built on NLP, can automate much of this work by generating clinical notes, summarizing patient histories, and supporting documentation workflows. As a result, these systems help reduce administrative burden and allow clinicians to focus more on patient care.^[7,9]

Another important area is medical imaging and diagnostic support. Generative AI models can create realistic medical images, such as magnetic resonance imaging (MRI), computed tomography (CT), and X-ray scans, which can be used to enrich training datasets for diagnostic systems. This is particularly useful when available data is limited or unbalanced. By generating high-quality synthetic data, these models can improve the performance of diagnostic algorithms and contribute to more accurate disease detection.^[9]

Generative AI is also making a strong impact in drug discovery and pharmaceutical research. Traditional drug development is often slow and costly, requiring years of experimentation

and clinical trials. Generative AI can help accelerate this process by predicting molecular structures, simulating chemical interactions, and identifying promising drug candidates. Research suggests that AI-driven approaches can significantly reduce both the time and cost of drug development while increasing the likelihood of finding effective treatments.^[10]

Beyond clinical applications, GAI also plays a key role in healthcare management. Healthcare organizations face ongoing challenges in areas such as resource allocation, patient flow, and service planning. By analyzing historical data, GAI systems can generate predictive scenarios that support strategic decision-making. For example, AI-based models can forecast patient admission rates, optimize hospital capacity, and assist in workforce planning.^[11]

In addition, GAI contributes to the advancement of personalized medicine. By integrating data such as genetic information, medical history, and lifestyle factors, these systems can generate tailored treatment recommendations and predict how individual patients might respond to specific therapies.^[4] This approach has the potential to improve treatment outcomes while reducing unnecessary interventions.

Despite all these advantages, integrating GAI into healthcare is not without challenges. Concerns around data privacy, algorithmic transparency, and accountability for AI-generated decisions remain significant. Addressing these ethical and regulatory issues is essential to ensure safe implementation and to build trust among both healthcare professionals and patients.^[7]

Digital transformation and artificial intelligence in healthcare

In recent years, healthcare systems have been going through a major digital transformation, largely driven by rapid developments in information and communication technologies. At its core, digital transformation refers to the use of technology to reshape how organizations create value, redesign their processes, and introduce new service models.^[12] In healthcare, this shift is reflected in the growing integration of tools such as EHRs, telemedicine platforms,

mobile health applications, big data analytics, and AI into everyday service delivery.

The main goal of this digitalization process is to improve the quality of care, make healthcare services more accessible, reduce costs, and support better clinical decision-making. Traditionally, healthcare systems have relied on manual ways of managing and analyzing large volumes of medical data. Today, however, digital technologies allow healthcare organizations to process this data much more efficiently and turn it into meaningful, actionable insights.^[11] In this transformation, big data analytics and AI play a particularly central role.

Artificial intelligence, in simple terms, refers to systems that enable computers to perform tasks that normally require human intelligence, such as learning, reasoning, and decision-making.^[9] In healthcare, AI is already being used in a wide range of applications, from disease diagnosis and medical image analysis to treatment planning, clinical decision support, and the optimization of healthcare operations.^[4]

Among these applications, machine learning and deep learning stand out for their ability to analyze complex healthcare data. In particular, deep learning models have shown strong performance in medical imaging. They can examine radiological images and assist in the early detection of diseases. For instance, some deep learning algorithms have achieved diagnostic accuracy comparable to dermatologists when identifying skin cancer from medical images.^[6] Developments like these clearly indicate that AI will continue to play an increasingly important role in clinical practice.

Beyond clinical use, AI is also becoming a key tool in healthcare management and administrative processes. Healthcare organizations must deal with complex challenges such as managing patient flow, planning hospital capacity, allocating workforce resources, and controlling costs. AI-based systems can analyze large datasets and provide insights that support more effective and strategic decision-making.^[8]

At the same time, integrating AI into healthcare is not without its challenges. Concerns around data privacy, ethical considerations, algorithmic bias, and the lack of

clear regulatory frameworks remain significant barriers.^[13,14] Given the sensitive nature of healthcare data, ensuring its secure handling and protection is absolutely critical.

Finally, digital transformation is also closely linked to the shift toward more patient-centered care. AI-powered systems can analyze individual patient data and support the development of personalized treatment plans. In doing so, they not only improve treatment outcomes but also encourage patients to take a more active role in managing their own health, ultimately contributing to a more efficient and sustainable healthcare system.

Generative AI models

Generative AI models are a class of machine learning approaches designed to create new data that closely resembles patterns found in existing datasets. Unlike discriminative models, which are mainly used for classification or prediction, generative models focus on learning the underlying structure of the data itself and then producing new samples based on that learned distribution.^[3] In healthcare, these models have attracted growing attention due to their ability to generate synthetic medical data, produce clinical text, enrich imaging datasets, and support biomedical research in innovative ways. Among the most commonly used generative approaches are GANs, VAEs, autoregressive transformer models, and diffusion models, each offering distinct advantages depending on the application.^[4,9]

Generative Adversarial Networks, first introduced by Goodfellow,^[3] are among the most widely adopted generative models. They are built around two neural networks, a generator and a discriminator, that are trained simultaneously. The generator creates synthetic data, while the discriminator evaluates how realistic that data is compared to actual samples. Over time, this adversarial process pushes the generator to produce increasingly convincing outputs. In healthcare, GANs are especially valuable for medical image synthesis and data augmentation.^[3] Since medical imaging datasets are often limited due to privacy concerns and data availability, GANs can generate realistic images, such as MRI or CT scans, to support the training of diagnostic algorithms.^[5] They are also

used to enhance image quality, reduce noise, and even reconstruct missing parts of medical images. Another important use case is the creation of synthetic patient data, which allows researchers to work with realistic datasets while protecting patient privacy and addressing ethical concerns around data sharing.

Variational Autoencoders represent another important type of generative model. These models work by compressing input data into a latent (hidden) representation and then reconstructing new data from that representation. What makes VAEs distinct is their probabilistic approach, which enables them to generate diverse variations of the original data rather than simple reconstructions.^[9] In healthcare, VAEs are often used for generating biomedical data and detecting anomalies. For example, they can create synthetic medical images or genomic data to support research in areas where real-world data is limited, such as rare diseases.^[15] They are also useful for identifying unusual patterns in patient data, which can help with early diagnosis and predictive analytics.

Another strength of VAEs lies in their ability to handle multimodal data. In healthcare, different types of data, such as imaging, clinical notes, and laboratory results, can be integrated into a shared latent space. This makes it possible to explore complex relationships across data types and gain more comprehensive insights into patient conditions.^[10]

Autoregressive models form another key category of GAI systems. These models generate data step by step, predicting each new element based on previously generated ones. With the development of transformer architectures, autoregressive models have become highly effective in NLP tasks. Large language models, such as the Generative Pre-trained Transformer-based systems, are well-known examples of this approach and have shown strong potential in healthcare applications.^[16]

In clinical settings, transformer-based models can support a range of tasks, including generating clinical documentation, summarizing patient records, assisting with literature reviews, and even contributing to clinical decision-making.^[17] By automating

time-consuming administrative work, such as writing patient notes or discharge summaries, these systems help reduce the workload on healthcare professionals and improve overall efficiency.^[15]

More recently, diffusion models have emerged as a powerful new approach in GAI. These models work by gradually transforming random noise into structured data through a sequence of denoising steps. They have shown impressive performance, particularly in generating high-quality images and complex data structures.^[13] In healthcare, diffusion models are increasingly used for producing high-resolution medical images, creating simulation environments, and generating datasets for research and education.^[14] Their ability to generate highly detailed and realistic outputs makes them especially valuable for training diagnostic systems and supporting medical learning.

Overall, each type of GAI model brings unique strengths to healthcare applications. Their suitability depends on the specific task, whether it involves image generation, text processing, data synthesis, or predictive analysis. Table 1 provides a comparative overview of the key characteristics of these commonly used GAI models in healthcare.

Despite their strong potential, GAI models also come with important challenges in healthcare settings. One of the main concerns is related to data reliability and model transparency. Healthcare decisions demand a high level of accuracy and clear reasoning, yet many GAI systems function as “black boxes,” making it difficult to fully understand how they arrive at their outputs.^[11]

Ethical and regulatory issues also remain a significant challenge. Since these models are often trained on highly sensitive healthcare data, protecting patient privacy and ensuring data security is critical. At the same time, any synthetic data generated by AI systems needs to be carefully validated to ensure it is clinically sound and free from bias. Without proper oversight, there is a risk that these systems could reinforce existing inequalities or lead to unreliable outcomes.

MATERIALS AND METHODS

This study adopts a descriptive and exploratory research design to identify and classify GAI tools used in healthcare. To achieve this, a scoping review approach was used to systematically explore the current landscape of GAI technologies and their applications across both clinical practice and healthcare management. Scoping reviews are particularly useful when examining emerging fields, as they help map existing knowledge and highlight potential research gaps.^[18]

This study used exclusively publicly available data and did not involve human participants, patient data, or clinical interventions. Therefore, ethical approval and informed consent were not required. All data were obtained from publicly accessible sources and used in accordance with relevant guidelines and principles of research integrity.

The main objective of the study is to identify GAI tools relevant to healthcare and classify them based on their functional features, development background, technological foundations, and areas of use. The research process was structured into four key stages:

Table 1. Comparison of generative AI models in healthcare

Model type	Key characteristics	Healthcare applications
GANS	Adversarial training between generator and discriminator	Medical image synthesis, data augmentation
VAEs	Probabilistic latent representation of data	Anomaly detection, biomedical data generation
Transformer models	Sequential text generation using attention mechanisms	Clinical documentation, medical text generation
Diffusion models	Noise-based image generation with iterative refinement	High-resolution medical image synthesis

GANS, Generative Adversarial Networks; VAEs, Variational Autoencoders.

literature search, tool identification, data extraction, and classification analysis.

Data collection and search strategy

The search process focused on tools developed between 2010 and 2025, a period during which GAI technologies began to gain substantial momentum. A comprehensive search and final data retrieval were performed to ensure the inclusion of the most up-to-date evidence available. Data for this study were collected through a comprehensive search of multiple sources to ensure a broad technological and clinical perspective. The search included academic databases such as Google Scholar, PubMed, and Scopus, as well as gray literature from technology company websites, digital health platforms, and AI tool directories. Additionally, conference proceedings, project reports, and the official websites of AI startups and healthcare technology companies were reviewed to identify emerging GAI tools.

During the initial stage of the research, a list of relevant keywords was developed in order to identify GAI tools used in healthcare. The primary keywords and their combinations included 'generative AI,' 'AI healthcare tools,' 'digital health AI,' 'AI clinical decision support,' and 'medical generative AI.'

To ensure the quality and relevance of the dataset, clear inclusion and exclusion criteria were applied throughout the selection process. Tools were included in the study if they were based on GAI technologies, had potential applications in healthcare or health-related services, were publicly documented through websites, reports, or academic publications, and were actively available or recently developed. Conversely, tools were excluded from the dataset if they were purely predictive or analytical AI systems without generative capabilities, had no direct or indirect application in healthcare, or if insufficient information was available regarding their functionality or developer. This initial search resulted in a broad pool of GAI tools. After applying these inclusion criteria and removing irrelevant entries, a total of 80 tools specifically related to healthcare applications were selected for the final dataset.

Data extraction and classification

After identifying the eligible GAI tools, relevant information about each tool was systematically extracted and organized into a structured dataset. The following variables were recorded for each tool: name of the tool, developer organization, country of origin, year of development or release, main application area, platform availability (web, mobile, or hybrid), pricing model (free, paid, freemium), and functional characteristics. Following the data extraction process, the tools were classified into two main categories based on their application domains: 'Clinical Applications' and 'Administrative and Managerial Applications.' Clinical applications included tools used for tasks such as medical imaging analysis, clinical documentation, diagnostic support, and drug discovery. Administrative applications included tools designed for healthcare management tasks such as workflow automation, patient communication, operational planning, and health information management.

Data analysis

The collected data were analyzed using a combination of descriptive statistics and content analysis. Descriptive statistical methods were applied to examine how GAI tools are distributed across key variables, such as country of development, year of release, platform availability, and pricing models. In addition, content analysis was used to classify the tools based on their functional features and application areas. This approach made it possible to identify recurring patterns in how GAI technologies are developed and implemented within the healthcare sector. To support and clarify these findings, the results were also presented through visual elements such as tables and figures, providing a clearer overview of the distribution and classification of the tools in the dataset.

RESULTS

The findings highlight important patterns in both the global distribution and functional characteristics of GAI technologies in healthcare. The analysis indicates that most GAI tools in healthcare are developed in

technologically advanced countries. The United States stands out as the leading contributor in this area. This can largely be attributed to its strong technological infrastructure, substantial investment in AI research, and a well-established digital health ecosystem.

Other countries also play a role in this landscape, particularly the United Kingdom, Israel, and Canada, although their contributions are more limited in scale. In addition, a number of other countries are represented by smaller numbers of AI-driven healthcare solutions. Table 2 provides a detailed overview of how these tools are distributed according to their country of origin.

The temporal distribution of GAI tools shows a clear surge in development activity in recent years. In particular, the period following the COVID-19 pandemic appears to have accelerated investments in AI by both healthcare organizations and technology companies.

The data indicate that 2023 and 2024 stand out as the years with the highest number of newly developed GAI tools. This upward trend suggests that GAI is becoming more deeply embedded in digital health solutions. Figure 1 illustrates how these tools are distributed over time based on their year of development.

The sharp increase observed after 2022 suggests that GAI is rapidly becoming a core driver of innovation in digital health.

Another key finding relates to the pricing models of these tools. The analysis shows that most GAI solutions in healthcare follow commercial business models. In many cases, access is provided through paid or subscription-based services, while only a limited number of tools are entirely free. A considerable portion

also adopts a freemium approach, where basic features are available at no cost, but more advanced functionalities require payment.

As shown in Table 3, the results suggest that the digital health ecosystem is increasingly moving toward sustainable commercial business models.

The analysis of platform availability indicates that most GAI tools operate through web-based platforms, which facilitate accessibility and ease of use for healthcare professionals and organizations. Web-based systems allow users to access AI tools without requiring complex installations or hardware infrastructure. In addition, some tools offer mobile applications or hybrid platforms to support cross-device compatibility.

The dominance of web-based platforms demonstrates the importance of accessibility and scalability in digital health technologies.

The findings indicate that a significant proportion of GAI tools are used in healthcare management and administrative processes, such as clinical documentation, workflow automation, and patient communication systems. However, a growing number of tools are also used in clinical applications, including medical imaging analysis, diagnostic support systems, and drug discovery

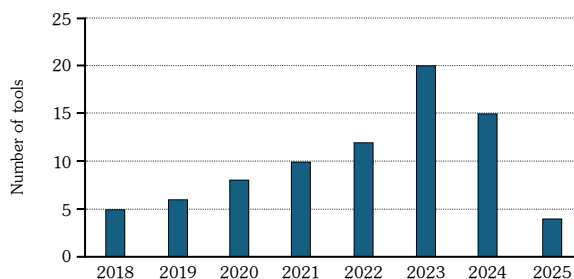


Figure 1. Distribution of generative AI tools by year.

Table 2. Distribution of generative AI tools by country

Country	Number of tools	%
United States	45	56.3
United Kingdom	12	15.0
Israel	4	5.0
Canada	4	5.0
Other countries	15	18.7
Total	80	100

Table 3. Distribution of generative AI tools by pricing model

Pricing model	Number of tools	%
Paid	40	50
Freemium	25	31.3
Free	15	18.7
Total	80	100

Table 4. Distribution of generative AI tools by platform type

Platform model	Number of tools	%
Web-based	46	57.5
Mobile + Web	20	25.0
Mobile only	14	17.5
Total	80	100

Table 5. Application domains of generative AI tools

Application domain	Number of tools	%
Administrative/management	45	56.3
Clinical applications	35	43.7
Total	80	100

research. A total of 45 tools (56.3%) were classified under administrative and managerial applications, whereas 35 tools (43.7%) were categorized as clinical applications. Administrative tools were primarily associated with workflow automation, clinical documentation, and patient communication systems.

Overall, the findings demonstrate that generative AI tools in healthcare are predominantly concentrated in technologically advanced countries and increasingly operate through commercially oriented digital platforms. More than half of the identified tools were developed in the United States, while web-based systems and paid business models represented the dominant operational structure. Additionally, administrative and managerial applications slightly exceeded clinical applications, indicating the growing role of generative AI in healthcare management and organizational efficiency.

These findings in Table 5 demonstrate that GAI technologies play a critical role not only in clinical environments but also in improving healthcare management and operational efficiency.

DISCUSSION

The findings of this study offer valuable insight into the expanding role of GAI in healthcare systems. Overall, the results show that GAI tools are increasingly being adopted

across both clinical and administrative settings, underlining their growing importance in driving digital transformation in healthcare. The clear dominance of technologically advanced countries, particularly the United States, in developing these tools highlights the critical role of strong research infrastructure, sustained technological investment, and well-established innovation ecosystems in advancing AI-based healthcare solutions.

Another notable finding is the sharp rise in the number of GAI tools in recent years, especially following the COVID-19 pandemic. This trend suggests that healthcare systems have accelerated their adoption of digital technologies in response to challenges related to access, efficiency, and patient care management. Similar patterns have been reported in earlier studies, which emphasize the increasing reliance on AI in both healthcare decision-making and service delivery.^[8,11]

The results also indicate that a significant portion of GAI tools are designed to support administrative and managerial functions, such as clinical documentation, workflow automation, and patient communication. This points to a broader transformation in healthcare, where AI is not only enhancing diagnostic capabilities but also improving operational processes. By reducing administrative workload, these tools allow healthcare professionals to focus more on patient care while contributing to greater efficiency within healthcare organizations.

Despite these promising developments, several challenges continue to shape the integration of GAI into healthcare systems. Concerns around data privacy, algorithmic transparency, ethical implications, and the lack of clear regulatory frameworks remain key issues. Addressing these challenges will be essential to ensure that GAI is implemented in a way that is safe, ethical, and trustworthy.

From a broader perspective, GAI technologies are reshaping organizational structures in healthcare. The increasing reliance on AI tools introduces a level of technological dependency, which may affect decision-making autonomy and professional roles within healthcare systems. In addition, the integration of AI into healthcare workflows may lead to organizational restructuring, requiring new

competencies and redefining traditional roles. This transformation aligns with the principles of digital transformation and platform economy, where value creation is increasingly driven by data and algorithmic systems.

The ethical dimension of GAI should also be considered in relation to emerging regulatory frameworks such as the European Union AI Act and global data protection regulations. These frameworks aim to ensure transparency, accountability, and safety in AI applications, particularly in high-risk domains such as healthcare.

Aligning GAI tools with such regulations will be essential for ensuring their responsible and sustainable use in clinical and administrative contexts.

The findings also reflect broader structural transformations in healthcare systems. The dominance of web-based platforms and commercial pricing models indicates the emergence of a platform-based healthcare economy. Generative AI tools are not only technological innovations but also components of a digital ecosystem shaped by commercialization and data-driven value creation. Furthermore, the increasing use of GAI in administrative processes highlights a shift toward organizational efficiency and digital transformation in healthcare management. This suggests that GAI plays a dual role in both clinical innovation and systemic restructuring. This study contributes to the literature by providing a structured classification of GAI tools across clinical and administrative domains and by linking these tools to broader concepts such as digital transformation and platform economy. Unlike previous studies, this research integrates technological, managerial, and economic perspectives into a unified analytical framework. The findings of this study also contribute to understanding how GAI supports digital transformation in healthcare by enhancing data-driven decision-making, improving operational efficiency, and enabling new digital service models.

This study has several limitations that should be acknowledged. First, the analysis was limited to publicly available generative AI tools and accessible data sources, which may have excluded proprietary or newly emerging

technologies. Second, the study primarily relied on descriptive analysis and did not evaluate the real-world clinical performance or effectiveness of the identified tools. Third, the rapidly evolving nature of generative AI technologies means that the findings may become outdated as new tools and applications continue to emerge. Finally, the study focused mainly on the classification and general characteristics of generative AI tools rather than conducting in-depth technical validation or comparative performance testing. Future studies should include empirical evaluations, clinical validation processes, and longitudinal analyses to better understand the practical impact of generative AI in healthcare systems.

In conclusion, GAI holds significant potential to improve healthcare delivery, strengthen clinical decision-making, and enhance management processes. Future research should focus on assessing the real-world impact of these technologies in clinical settings and on developing regulatory frameworks that support their responsible and sustainable use in healthcare systems.

Data Sharing Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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