The Uses of Large Language Models in Healthcare: A Literature Review

Introduction

Artificial intelligence is moving into hospitals and clinics faster than most people realize, and at the front of that wave sit Large Language Models (LLMs) like OpenAIs GPT family and Googles PaLM. Backed by deep-learning math and hefty libraries of online text, these programs can read, summarize, and even compose sentences that sound surprisingly human. So far they have tackled everyday chores-drafting emails or sorting records-as well as weightier jobs such as advising doctors, answering patient questions, and tightening medical notes. Because lives hang on every word, this review surveys what researchers say about the strengths, weaknesses, and ethical knots of using LLMs in medicine. It also flags shaky rules and points toward fresh studies needed to plug gaps and keep these tools safe, useful, and trustworthy once they move from the lab into routine care.

Applications of LLMs in Healthcare

Clinical Decision Support Systems (CDSS)

One of the most exciting places to spot large language models in health care is inside clinical-decision support systems (CDSS). These tools pull together medical facts and a patients history to help clinicians choose the best path forward. By combing through mountains of journals, guidelines, and lab results, LLMs can flag possible diagnoses, ipgrade triage, and even outline treatment options. Singhal and colleagues (2023) showed that Med-PaLM, a model built for healthcare, answered USMLE questions at an expert level, hinting at its power to back up human reasoning. Such support proves invaluable in bustling emergency rooms, far-off rural clinics, or simply on shifts when staff are thin. Still, every algorithmic insight needs a doctor in the loop, lest teams lean on code instead of their own judgment.

Patient Communication and Education

Clear communication sits at the heart of good care. When doctors and patients talk past each other, treatment plans slip, worry grows, and risks rise. Large language models (LLMs) now help turn complex terms into everyday language about diagnoses, drugs, and tests. Nori and colleagues (2023) found that GPT-4 could craft friendly summaries that patients both understood and felt at ease reading. In addition, LLM-powered chatbots can field routine questions, book visits, and even offer basic mental-health check-ins. These digital helpers promise to lighten staff workloads and reach people with low literacy or language struggles.

Medical Documentation and Administration

Paperwork eats up a huge chunk of clinicians hours and feeds burnout. LLMs already draft visit notes, boil discharge slips down to plain notes, and build referral letters. Rajkomar et al. (2022) note that offloading these tasks lets doctors spend more minutes beside their patients. Hooked to voice-recognition systems, the models can listen to a room, pull out key facts, and shape them into the clinics format while the visit unfolds. This blend of tech not only speeds administrative work but also makes charts steadier and more complete.

Benefits and Opportunities

Scalability and Accessibility

A key strength of large language models (LLMs) is how easily they scale. After a model is trained and tested, it can be rolled out to thousands of clinics at once with little extra work. That feature is especially valuable where specialists are thin on the ground and resources are tight. Khan et al. (2023) give examples from rural clinics across Sub-Saharan Africa, where LLMs now offer local-language clinical guidance and basic health lessons, steadily raising the standard of care.

Multilingual Capabilities

Models like GPT-4 and PaLM 2 learn from texts in many tongues, so they can draft medical replies in more than one hundred languages. Such language range matters in worldwide health work and in culturally mixed city hospitals alike. Imagine an LLM printing discharge notes in a patients mother tongue; that small act cuts confusion and lifts recovery rates. According to Khan et al. (2023), broad language support thus moves the field closer to equal, dependable care for everyone, no matter the language spoken.

Personalisation of Care

Large language models (LLMs) can shape replies by looking at a patients chart, risk factors, and what the person has already said they want. Because of this, the model can send reminders, tips, and follow-up notes that feel much more relevant. Imagine it crafting a meal plan or exercise suggestion that fits a 50-year-old office worker with diabetes, not a generic list. When that kind of smart conversation happens, people tend to stick with their plan, feel heard, and, in the end, rate their care higher.

Challenges and Limitations

Hallucinations and Inaccuracy

Yet one major weak spot is the models habit of hallucinating-sounding confident while saying something that never happened or is plain wrong. In health settings, that slip can lead to misguided tests, the wrong meds, or real harm to patients. Bender and colleagues (2021) warn that we should not welcome these systems blindly, since even their best reply may rest on shaky premises. The danger grows if the tool runs unsupervised or if busy staff skip the step of double-checking what it spits out.

Bias and Inequity

Large language models learn from old internet scraps, news articles, and other text that carry the weight of past prejudice. When doctors use these models in clinics, hidden bias can slip into who is diagnosed, who gets treatment first, and even who is told to worry about future illness. Obermeyer and colleagues showed this clearly in 2019, revealing that a common risk-score tool overlooked many Black patients simply because it had learned from data that tied health needs to cost rather than to actual wellbeing. Without deliberate work to clean the training data and check the results, the same models will keep widening the gap instead of closing it.

Data Privacy and Security

Medical records contain some of the most private details of a persons life, from birth to illness to death. Plugging language models into hospitals therefore sparks urgent questions about keeping that information safe and following the law. Wang and co-authors pointed out in 2022 that any data sent to an AI must still obey HIPAA in the United States or GDPR across Europe. That means doing more than writing good code; hospitals need solid encryption, strict visitor controls, and clear answers for patients about what the model reads, remembers, and deletes.

Limited Explainability

Large language models work like black boxes, and that secrecy causes real trouble in health care. Unlike older, straightforward stats tools, these models rarely show clear logic behind any answer they give. Mitchell and colleagues (2022) note that this haze erodes trust and makes it hard to spot mistakes. Doctors need more than a recommendation-they must grasp the reason behind it before deciding to act. If the reasoning stays hidden, clinicians may push back or apply the advice incorrectly.

Ethical and Regulatory Considerations

Regulatory Gaps

The fast roll-out of large language models (LLMs) has already outpaced officials efforts to write sensible rules. Agencies such as the U.S. Food and Drug Administration (FDA) are starting to look at software-based medical devices, yet plain guidance on testing LLM safety and usefulness is still missing. Topol (2023) argues that oversight must include honest-to-goodness clinical trials, watchdog checking once a product is in the wild, and routine model revalidation. Without these guardrails, hospitals are left guessing whether an LLM tool is ready to go or simply risky.

Human Oversight and Accountability

Ethically bringing LLMs into health care means keeping a clinician in the drivers seat at all times. The software should act as a smart co-pilot, not as a self-flying plane. Human-in-the-loop (HITL) systems require that a trained expert read, question, and approve each AI suggestion before a patient sees it. That practice protects medical accountability and gives doctors a chance to fix any glitchy output. Moreover, bringing end-users into design and testing keeps tools friendly and eases most hesitancy about using them.

Transparency and Public Trust

Trust is the bedrock of good healthcare. Developers of large language models (LLMs) therefore should be open about how they train these systems, which datasets go in, and what harms might follow. Mitchell and coworkers (2022) even recommend using so-called model cards to spell out each models limits, target tasks, and identified biases. Sharing this information invites outside audit and lets doctors and patients weigh risks for themselves. Without such clarity, new tools may look secretive and evasive, eroding confidence in both the algorithm and the health system that uses it.

Future Directions

Integration with Electronic Health Records (EHRs)

Linking LLMs smoothly to Electronic Health Records is one of the biggest opportunities ahead. Doing so could supply on-the-spot advice, craft care plans tailored to each person, and cut time spent writing notes. Yet for that to happen, systems must talk through open, secure APIs, and the underlying data needs to follow common standards. Research should look for ways to bring in language models while interrupting daily clinical routines as little as possible.

Development of Specialised Medical Models

Instead of relying on one-size-fits-all LLMs, the medical field is already moving toward narrow models tuned for specific areas of care. Med-PaLM shows how this approach can work in practice. Singhal and colleagues (2023) point out that specialty models tend to be more accurate and safer than their general counterparts. Ongoing work should create and test versions for oncology, psychiatry, infectious disease, and other fields.

Establishing Evaluation Standards

At the moment no single yardstick exists for measuring LLMs in health settings. Rajkomar et al. (2022) emphasize that assessments must cover varied patient groups, conditions, and care environments. Before any model goes wide, it should pass solid clinical trials and run in real service on units that manage living patients. Clear, repeatable standards will boost trust and encourage hospitals to adopt these tools long term.

Conclusion

Large language models are ready to change how doctors diagnose, patients understand their plans, and clinics handle paperwork. Early pilots show practical gains, yet problems such as false outputs, hidden bias, and murky logic still worry stakeholders. Policymakers, engineers, and ethicists must tackle these issues early so that the benefits reach everyone fairly and safely.

Looking ahead, large language models wont be winning any stethoscopes; their real utility lies in giving doctors an extra pair of hands and a faster brain. When raw computing muscle is blended with clinical know-how, the result can be faster diagnoses, easier access to guidelines, and smoother day-to-day tasks. Reaching that goal hinges on doctors, data scientists, regulators, and ethicists working side by side instead of in silos. Only then can health-care teams unlock LLMs potential without running into avoidable harms.

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