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Research Article

Gen AI-Driven Adaptive Clinical Decision Support (GDA-CDSS): Enhancing Patient Outcomes with LLaMA-3 and Federated Learning

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Abstract *- The exponential growth of healthcare data, spanning electronic health records (EHRs), wearable sensors and medical imaging demands a paradigm shift in clinical decision-making. Traditional CDSS, based on rigid rule framework, fail to process unstructured data and cannot adapt well to evolution of medical scenarios. This review explores the transformative potential of GDA-CDSS by combining LLaMA-3, a cutting-edge large language model, with Federated Learning (FL) to enable precision medicine while ensuring data privacy. Unlike conventional CDSS which rely on predefined rules, GDA-CDSS dynamically learns from vast and diverse datasets to give real time recommendations tailored to the context. Furthermore, LLaMA-3 enables deep natural language understanding, improves diagnostic accuracy, generates synthetic patient cases while efficiently processing complex clinical narratives. At the same time, FL ensures that such collaboration between hospitals remains privacy preserving, enabling models to be trained on distributed data without revealing the sensitive patient information while meeting the regulations of HIPAA and GDPR. Although, model interpretability, interoperability and bias mitigation are challenges that would need to be overcome for adoption to be widespread. Explainability for LLaMA-3 and FL leads to transparent, trustable recommendations for clinicians and an equitable model training on diverse populations for scalability and interoperability for easy integration with modern healthcare. GDA-CDSS strives to establish LLaMA-3's lightweight architecture and FL's decentralized approach for the future of AI powered healthcare for adaptive, intelligent and ethically robust.*

Keywords - *Federated Learning; LLaMA-3; Healthcare Data; Electronic Health Records (EHR); Adaptive Clinical Decision Support; HIPAA; Compliance*

I. INTRODUCTION

Clinical decision support system is a standard tool for improving clinical decision making in modern healthcare. These systems are analyzing huge amounts of patient data, medical literature or clinical guidelines to generate actionable insights for healthcare professionals. In the healthcare industry, today there is an unprecedented surge in data generation. As per an example, in 2021 global electronic health records (EHRs) were created at a rate of more than 1.1 billion globally, which is 30% of the world's data [1]. Accelerated by the rise of wearable health technology that is set to become a $186.14 billion market by 2030 and constantly collecting physiological data from patients [2], this exponential growth is only increasing. Furthermore, the amount of medical imaging data to be generated is on the scale of 2.5 petabytes per hospital by 2025 [3], showing how much of the information is being created. Moreover, up to 2023, the number of clinical trials exceeded 400 000 contributed to the medicine field with valuable, but complex evidence [3].

Although these advances have revolutionized patient care, they have also raised clinical challenges inherent to the clinicians. With the volume and complexity of the data, healthcare professionals find it difficult to efficiently retrieve, assess and apply relevant insights. These doctors are clearly struggling to keep up the with rapid pace of medical advancement, as such traditional data management methods are no longer sufficient to handle this type of data deluge anymore. For this reason, there is a need for enhanced tools that enable the efficient analysis of the data and support of clinical decision making in a real time setting.

However, Artificial Intelligence (AI) has shown up to be a transformative force in health care and offering innovative solutions to these challenges. AI is an approach to leverage technology like machine learning (ML), natural language processing (NLP), computer vision, robotics, to replicate human-like intelligence and decision-making processes. AI driven tools are revolutionizing the way healthcare professionals approach disease diagnosis, treatment planning, and predictive analytics in the clinical settings. Using these tools, huge amounts of medical data can be analyzed to detect patterns and generate insights which humans would have difficulty or failure to have identified on its own [7].

We can look at the rise of conversational AI models like ChatGPT as one of AI's most notable examples. These models are popular in deploying advanced NLP to generate human-like text responses and allow for seamless interaction in the chatbots, virtual assistants and customer support systems. Conversational AI is also being used to improve the patient engagement in healthcare, to answer medical queries and medical queries assist physicians with the clinical decision making. These models deliver quick and accurate answers to complex questions aiding the bridge between patients and healthcare providers and as a result, improving the overall care delivery.

Nevertheless, healthcare data continues to present major problems due to its exponential growth. However, to clinicians, this vast and constantly growing pool of information is increasingly overwhelming as they try to dig up, analyze and use appropriate insights from just the information they need. That is, traditional data management methods are unable to keep up and therefore there is a need for better solutions. Here, in comes the use of Generative AI GenAI-Adaptive Clinical Decision Support Systems (CDSS) [4]. Next generation systems leverage the power of GenAI to deliver personalized, context aware recommendations that evolve in real time as a function of patient profile, medical literature and changing clinical guidelines.

CDSS using the genAI models like LLaMA-3 are a huge leap in the capabilities of CDSS. Unlike standard AI models, GenAI models produce dynamic, real-time insights based on the specific needs of each patient in real time, and unlike standard datasets they are based on, which are static. It allows clinicians to make more precise diagnoses, to develop more informative treatment plans, to ultimately improve the outcomes of patients [5][6]. Something that LLaMA-3 can do, for instance, is analyze a patient's past medical history or current symptoms and relevant research to recommend personalized treatment recommendations in line with the most recent clinical guidelines.

Federated Learning is another key advance in healthcare AI, a decentralized model training regime that allows for collaborative training of a medical model amongst multiple healthcare organizations while preserving raw patient data. This offers data privacy and security in healthcare while allowing for the benefit of AI models from diverse datasets. Federated Learning trains models on data from multiple sources and not just from the individual sources used to create the machine learning models. This increases the robustness and generalizability of AI systems that may be more helpful in particular real world clinical settings. Most importantly, this approach makes sure that the data is HIPAA and GDPR compliant, which means it can be used in accordance with some of the strictest rules in the healthcare regulations.

LLaMA-3 and their integration into processors of GenAI-driven CDSS (GDA-CDSS) is a powerful combo that has great potential to disrupt healthcare delivery. By leveraging the strength of both technologies, GDA-CDSS improves evidence-based decision making, reduces diagnostic errors, and improves patient outcomes. For example, using Federated Learning's privacy-preserving framework, one can combine LLaMA-3's ability to generate personalized, context-aware recommendations, along with being highly effective in doing so. This integration enables various datasets from which AI models will be trained to prevent bias and ultimately provide recommendations with greater accuracy.

With the growth of healthcare related data increasing exponentially, clinical decision making would benefit from opportunities and challenges. Conversely, traditional CDSS and data management ideas are outdated while AI, especially GenAI and Federated Learning present new avenues of more complex and smart solutions. Particularly, GDA-CDSS leverages technologies such as LLaMA-3 and Federated Learning to enable the inputs of clinicians and create the capabilities they need to make sense of today's healthcare, ultimately improving the outcomes of patients and efficiency of the health system. These technologies are growing and the promise of delivering personalized, data driven, and transforming healthcare delivery is there for the taking as these technologies continue to advance.

II. OBJECTIVES

This review aims to:

a. Comparative analysis of traditional CDSS and AI- Based CDSS
b. Analyze the integration of LLaMA-3 and Federated Learning in adaptive CDSS, highlighting their impact on personalized patient care and decision-making.
c. Examine the challenges and ethical considerations in implementing AI-driven CDSS, including data privacy, model interpretability, and regulatory compliance.
d. Propose future directions for advancing AI-driven CDSS to improve real-time healthcare decision-making and patient outcomes.

By addressing these aspects, this review provides a comprehensive understanding of LlaMA's transformative potential in clinical decision support, ensuring data-driven, efficient, and personalized healthcare delivery.

III. BACKGROUND

Clinical Decision Support Systems (CDSS) have undergone significant evolution over time, transforming the nature of technical decision making by healthcare professionals. Ledley and Lusted, introduced the idea of computer application for medical decision making in the 1950s and 1960s, the mothers of modern advancements. In the 1970s and 1980s, MYCIN and INTERNIST-1 rule based expert systems were developed which used 'if then' rules to assist in diagnosis and treatment. Nevertheless, these systems were limited in the face of uncertainties.

During the 1990s and 2000s CDSS were integrated with Electronic Health Records (EHRs) to provide access to patient data and to promote interoperability based on standards such as HL7 and CDA. At the same time, the development of evidence-based medicine assured CDSS consistency with clinical guidelines. CDSS was transformed from the 2010s on by artificial intelligence (AI) and machine learning (ML) to predictive analytics, personalized recommendations and automated risk assessment. This has greatly improved the diagnosis, treating planning and patient care. The future lies in interoperability which warrants further work in developing standardized and scalable CDSS frameworks for the improvement in reliability and clinical decision making [8]-[10]. Figure 1 shows the evolution of Clinical Decision Support Systems over decades, and the milestones.

A. Types of Clinical Decision Support Systems (CDSS)

Clinical Decision Support Systems (CDSS) can be categorized based on their approach to capturing, processing and inferring clinical knowledge. They utilize different methods such as the rule-based logic, machine learning, and federated learning to aid healthcare professionals in making the best decision. The main types of CDSS [11] are given below.

a. *Knowledge-Based (Rule-Based) CDSS*:
It uses predefined if–then rules and clinical guidelines such as suggesting antibiotics for bacterial infection.

b. *Non-Knowledge based CDSS (Machine Learning based):*
Uses AI and ML to analyze patient data and predicts outcomes (e.g., neural network for predicting sepsis risk of ICU patients).

c. Federated learning Based CDSS:
ML models are trained across multiple hospitals in a shared training domain (predicting diabetes complications in hospitals), without sharing sensitive data.

d. Passive CDSS:
Provide clinical information only when queried, for example, a doctor of a symptom and the possible diagnosis.

e. ***Active CDSS:***
Automatically alerts clinicians in real-time (e.g., an ICU system notifying doctors of septic shock risk).

B. Transition to Generative AI in CDSS

Traditional AI-based CDSS like rule based and classical ML systems are good for structured environments providing high interpretability and success in tasks e.g., risk prediction, guideline adherence, [12]. However, they are brittle to change as they have a dependency on predefined rules, large annotated datasets and are not adaptive to rare scenarios. On the contrary, Generation AI (GenAI) driven CDSS uses state of the art models such as GAN, VAE, and LLM to deal with unstructured data, generate synthetic patient records, and manufacture customized therapy designs [13]-[15]. Although Creativity and Adaptability are better with GenAI, explainability, validation and data privacy in ethical concerns are encountered as challenges.

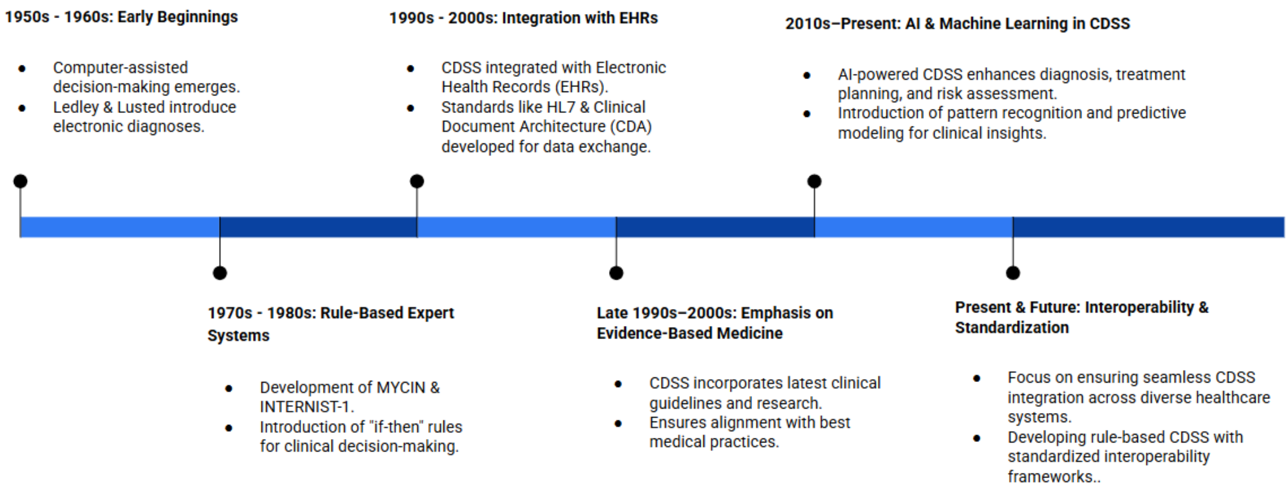

Figure 1. Evolution of Clinical Decision Support System

CDSS that rely on the routines (e.g., rules) and traditional databases are the ones that perform well with structured, rule-based tasks, i.e., with high reliability and interpretability. But with the increasing complexity and unstructured nature of healthcare data, the demand for AI-driven systems capable to process voluminous data, detect intricate patterns and learn in new scenarios is escalating. As a result, more dynamic and context aware decision making has been obtained with the advent of genAI driven models [23].

An approach to the integration of traditional CDSS with Generative AI (GenAI) that uses structured reasoning combined with adaptive learning to improve clinical outcomes. Rule based CDSS is what gives results in the form of consistency and transparency, whereas GenAI based models build themselves in real time and are flexible enough to provide results even in real time with predictive capabilities. LLaMA is an example of this advancement, a family of large language models from Meta engineered to support AI driven decisions now that the boundaries of AI technology. In contrast to traditional CDSSs based on predefined rules, LLaMA models make use of databases of large and deep learning to smartly modify code. Since LLaMA is smaller in parameters (7–65 billion vs. 175 billion), but trained on a larger dataset of tokens, it surpasses InstructGPT on a range of benchmarks. LLaMA 3 further refines these capabilities with 8 to 70 billion parameters for configurations and gives improved efficiency and performance [16].This would also suggest that evolution in language models complements traditional CDSS with interpretability and adaptability in clinical applications.

LLaMA 3 (Large Language Model Meta AI 3) is a major leap forward in Natural Language Processing, by involving architectural refinements to mend its reasoning, stability, and efficiency. It has a structured three phase approach [17]:

a. ***Pre-Training Phase:*** Data collection, preprocessing, tokenization, filtering etc are done in this stage called Pre-Training Phase and these inputs must be correct. Although trained first with an 8K context window, it is later retrained with a 128K context window, thereby letting it deal with much bigger spans of text.

b. ***Core Model Architecture:*** LLaMA 3 is a decoder-only transformer with multi head self-attention for contextual understanding and core model architecture. SwiGLU activation functions are its key enhancement along with RMSNorm for stability, Rotary Positional Embeddings (RoPE) for long range dependency computation, and Grouped Query Attention (GQA) for content efficient computation.
c. ***Fine-Tuning and Post-Training:*** During pretraining, the instance of LLaMA 3 is subject to instruction fine-tuning, as well as safety and alignment mechanisms such as adversarial training and human feedback to ensure responsible AI behavior. Integration of tools to the external API enhances the capability of the model in the reasoning and coding tasks.

Figure 2 shows the structured architecture of LLaMA 3, with core processes like pre-training, core architecture, post training, etc. With these advancements the model can now handle large amounts of context, is stable, can incorporate external tools and has very strong usage in applications which incorporate complex AI.

Key Considerations for LLaMA-3 CDSS in Healthcare

Despite their great potential, LLM driven specially Llama 3 CDSS, should be able to overcome a few major issues in order to be used safely and appropriately in clinical settings.One of the main challenges is how to handle medical data due to the particular nature of privacy and ethics. Given Table 1, medical data is very sensitive and it is imperative that protection is extremely stringent as it can get misused and used as a weapon that can be used for discriminating against an individual.

Table 1. Summary of the consideration involved in Healthcare LLM[22]

Consideration	Safety Aspect	Usefulness Aspect	Fine-Tuning Strategies
Patient Privacy & Data Security	Protecting sensitive information through strict data handling and anonymization.	Balancing data diversity with privacy by limiting identifiable patient data use.	Use differential privacy, synthetic data, or federated learning to protect patient privacy during fine-tuning.
Data Security	information through strict data handling and anonymization.	with privacy by limiting identifiable patient data use.	data, or federated learning to protect patient privacy during fine-tuning.
Clinical Accuracy	Minimizing demographic or clinical biases to prevent unfair recommendations.	Balancing fairness with model performance to avoid overfitting to biased data.	Use fairness-aware training, diverse and representative datasets, and evaluate model performance on different subgroups.
Explainability	Ensuring model decisions are interpretable for clinicians and patients.	Balancing model complexity with interpretability to maintain clinical transparency.	Incorporate attention layers, interpretable surrogate models, and SHAP or LIME for model explainability post-finetuning.
Ethical Considerations	Adhering to ethical healthcare guidelines and preventing harm to patients.	Balancing ethical considerations with potential clinical benefits.	Conduct ethical audits of the model, align outputs with healthcare ethics (e.g., HIPAA compliance), and include human oversight.

A. Federated Learning for Privacy-Preserving AI in Healthcare

In medical research, Large Language Models are used and data privacy and security issues need to be taken very seriously. To make LlaMA-3 dynamic decision support tools during critical medical processes, integrated real time adaptive learning capabilities could enable them. These models would be able to provide timely insights on live data from medical devices to help improve patient outcomes and clinical decision making [18]. A related promising advancement is the use of federated learning in healthcare [19].

With this approach, AI models can learn from the data of multiple institutions directly without having to share any data because it preserves patient privacy while also improving model robustness. Federated learning can enable more generalized and effective healthcare solutions across diverse populations because it can enable more secure and collaborative knowledge propagation.

This research introduces Federated Learning (FL) [20] as a distributed machine learning approach that simultaneously reduces systemic privacy risks and training costs for multiple clients (devices or organizations) that collaboratively train models without sharing their data. FL offers security advantages due to the data being kept local but with secure computing protocols of Homomorphic Encryption (HE), Multi-Party Computation (MPC) and Differential Privacy (DP) [24].

In the FL framework, several privacy preserving algorithms are developed. This includes Vertical Logistic Regression (VLR) using HE, SecureBoost: an FL version of XGBoost and semi-supervised learning techniques for dealing with missing features [21]. Furthermore, Secure Aggregation is provided to build data protection during training. While it can be a hard problem to deal with privacy in decentralized environments, these improvements make FL a promising solution toward privacy preserving machine learning across decentralized environments.

B. Compliance and Ethical Considerations

Healthcare applications are essentially human centric, and hence ethical aspects should be heavily thought through while developing AI based medical systems. Thus, it is very necessary to be aware of sociological needs of targeted users prior to commencing data collection when developing the AI model [30]. If they are to access and analyze personal data, use of large language models such as LLaMA- 3 in many countries are required to follow data protection regulations. Since May 25, 2018, all of this has been regulated with the GDPR throughout the European Union. Such legislation has been followed by many countries, which have also sought to ease regulatory compliance when doing business with Europe [25] - [28]. These regulations were framed to moderate the misuse which is there even in the realms of apparent benign personal data. Some of the legal regulations and ethical principles in Machine Learning and Artificial Intelligence mentioned in Table 2.

The development and release of LlaMA-3 is important because it has ethical and legal considerations. Meeting GDPR, HIPAA regulations, and the like guarantees personal data and individual's rights safety. Ethical AI principles help to foster trust, accountability, and society approval of AI systems. When regulatory frameworks like the EU AI Act appear, every organization needs to remain aware, and should be proactive in incorporating ethical and legal compliance of AI.

C. Model Explainability and Transparency

For healthcare, large language models (LLMs) achieve very little in terms of transparency and explainability due to such challenges that affect their adoption by medical professionals. Clinicians have often been skeptical about the opacity of their nature, as they need clear justifications for the recommendation driven by AI. In addition, training data biases can undermine the accuracy and incorrect diagnoses or treatment plans can be generated [31].

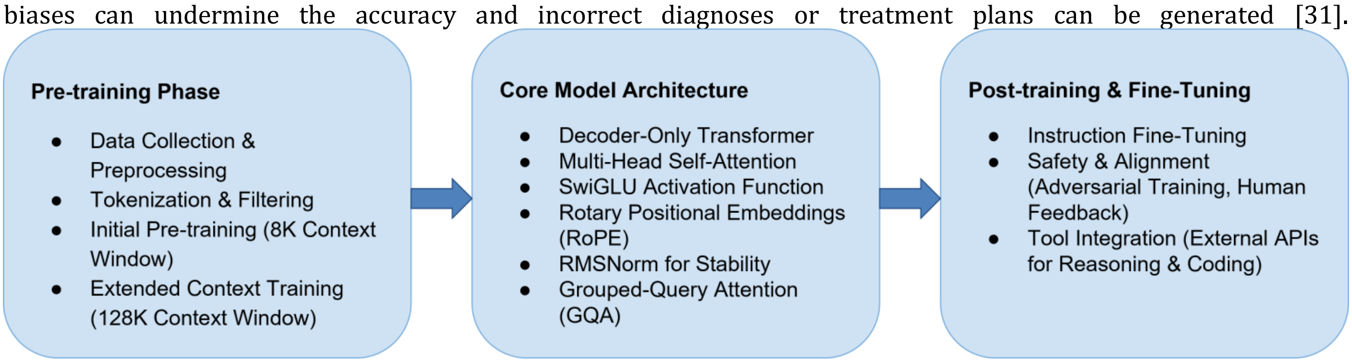

Figure 2. Modular Architecture of LLaMA-3

To alleviate these concerns, LLaMA-3 can improve explainability by offering its reasons in the human readable form, summarizing medical literature, and pointing towards factors that make its decision significant. Moreover, the transparency of federated learning is also enhanced as it allows the decentralized training of a model on multiple healthcare institutions without sharing sensitive patient data leading to their diverse and unbiased learning. In addition, this approach enables institutions to audit model updates and thus create confidence and promote regulatory compliance. By linking federated learning's decentralized and privacy preserving framework with LLaMA-3's interpretability, healthcare AI will be able to be more transparent, reliable, and conform to clinical decision-making requirements.

Table 2. Key legal regulations and ethical principles [29].

Aspect	Description
GDPR	EU regulation focusing on personal data protection, individual rights, data minimization, consent, and data breach notifications. Non-compliance can result in substantial fines.
HIPAA	U.S. law protecting medical records and health information, including privacy and security rules for PHI and e-PHI, with penalties for violations.
Ethical AI Frameworks	Guidelines promoting transparency, fairness, accountability, and human-centric design in AI, including the Asilomar AI Principles, OECD AI Principles, and EU Ethics Guidelines.
EU AI Act	Proposed EU regulation classifying AI systems by risk level, imposing requirements on high-risk AI, prohibiting certain practices, and ensuring trustworthy AI development.
Core Ethical Principles	Transparency and explainability, fairness and non-discrimination, accountability, privacy and data governance, human-centric design.

D. Bias and Fairness

Research towards addressing biases in large language models (LLMs) for healthcare especially is critical due to the potential for misinformation and inequitable treatment recommendations from biased outputs. Vast datasets that LLMs may be trained on can contain biases on things such as gender, race, disease prevalence or treatment outcomes. These biases, if not properly managed, can be institutionalized and amplified and undermine principles of fairness and trust essential to communities supporting AI driven healthcare solutions. Rigorous validation processes, careful data curation and constant model audits are needed to mitigate these risks. In particular, collaboration between domain experts, ethicists, and data scientists is essential for defining what makes for the best practices in detecting and mitigating bias [32].

These challenges can be addressed by LLaMA-3 and federated learning. This can be further improved by the incorporation of fairness aware training mechanisms and explainability features for LLaMA-3 that enable healthcare professionals to better understand and validate AI generated recommendations. Moreover, it can be fine tuned on artificially curated dataset that puts a specific emphasis on diversity and fairness. At the same time, federated learning avoids biases by allowing decentralized model training among multiple institutions while avoiding compromising data privacy by exposing them to a variety of patient populations. The distributed generation of these embeddings allows just enough bias to remove the overfitting bias towards one dataset or demographic, leading to more equitable and unbiased healthcare outcomes. Federated learning paired with natural language understanding present in LLaMA-3 ensures that those involved are aware of how AI driven healthcare is being utilized in their name.

E. Scalability and Interoperability

There are two key challenges with deploying large language models (LLMs) in healthcare: scalability and interoperability. With healthcare systems generating tons of patient data, AI models need to efficiently scale to process and analyse that information in real time. Still, to deal with large scale and diverse datasets, traditional centralized models are unable to balance computational efficiency. Other challenges include interoperability – the capacity for AI systems to seamlessly work with various electronic health record (EHR) systems, clinical workflows and regulatory structures– which continues to be a concern. This may create barriers to adoption of AI driven decision support systems that lack standardized integration protocols, and thus may not have much impact on patient care.

These challenges can be tackled well with LLaMA-3 and federated learning approaches. Since it aims to be lightweight and adaptable, LLaMA-3 can be deployed across any healthcare infrastructure without significant overhead computation. As a gradient model, it remains efficient while it can be fine tuned for a specific medical task. On the other hand, federated learning increases scalability and improves the learning process by distributing model training over several institutions therefore no central storage of data is required for AI to learn from multiple data set. Moreover, it allows for decentralization of approach, which not only enhances model generalization but also guarantees compliance with the data privacy regulations such as HIPAA and GDPR. Federated learning provides interoperability by enabling AI models to be trained on institution specific data while still respecting 'global health standards'. With the help of LLaMA-3's flexibility and federated learning's decentralized training, healthcare AI systems can become scalable, efficient, and interoperable deployments with the aim of reducing patients' failures and helping medical decisions.

While LLaMA-3 as an LLM should observe these ethical principles and legal requirements, it should be used. Specificity of compliance issues includes avoiding bias and ensuring fairness as LLMs may learn whatever biases they encounter in the training data; building trust in the face of such complexities inherent in LLMs; protecting the privacy of data with approaches such as differential privacy and federated learning; setting up mechanisms of accountability for any damages caused by AI systems; and ensuring that the behaviour of AI is in keeping with human values and normative principles.

IV. CONCLUSION AND FUTURE WORK

In this regard, LLaMA-3 is an example of integration of Generative AI and Federated Learning in Clinical Decision Support Systems (CDSS), which constitutes a transformative step in modern healthcare. By harnessing the very latest in natural language processing, as well as decentralized learning, the Generative AI Driven Adaptive CDSS (GDA-CDSS) ensures that each recommendation that it generates is customized to each individual user in real time, is private and secure. In contrast to traditional rule based CDSS that can frequently suffer the problem of rigidity and lack of adaptability, GDA-CDSS learns dynamically from heterogeneous patient data in a data-driven way to make more accurate and semantic contextual clinical decision making.

GDA-CDSS is one of the strongest advantages of the GDA-CDSS in the fact that it can operate in a federated learning mode, where the patient data remains at the local hospital level while contributing to the global model. By doing this, privacy concerns are addressed and meet strict regulations such as HIPAA, GDPR to great trust between healthcare providers and patients. Moreover, being powered by cutting edge natural language models like LLaMA-3 lends itself to more understandable interpretability of clinical insights providing healthcare professionals with more intuitive, human-like engagement with AI systems.

However, there are several issues that must be addressed to widespread adoption and effectiveness of GDA-CDSS. However, ethical concerns related to bias in LLama models must be well managed to prevent healthcare recommendation disparities. Although model explainability is still an important problem to solve, clinicians need transparency in AI driven decision-making processes to maintain trust and accountability. Also, it should be interoperable with existing electronic health record (EHR) systems to readily blend into healthcare workflow. Challenges using both AI and clinicians will need a multidisciplinary effort including researchers, policymakers, clinicians and regulatory bodies.

GDA-CDSS with LLaMA-3 and FL has great potential for future radical changes in healthcare, addressing critical challenges and opening new doors. Another key direction is to enhance real time adaptive learning models that adaptively update on live data streams from medical devices during an emergency or surgery so that rapid and context aware recommendations are made. FL allows for collaborative model training among institutions in a scalable and privacy preserving way by training the model without sharing raw data globally and helping in global collaboration and model robustness. By further optimizing the resource and providing standardized protocols over FL, its scalability and interoperability with existing Electronic Health Record (EHR) systems is also enhanced. There must be a compliance and an ethical consideration part, automated tools to assist with GDPR, HIPAA compliance, ethical audits, and accountability through robust human oversight. GDA-CDSS will expand into use cases such as rare disease diagnosis, precision medicine, and mental health support, thereby increasing its impact, and synthetic data generation can help with data scarcity and privacy concerns. In low resource environments, the use of both energy efficient and cost-effective solutions will make sure of the sustainable deployment.

To address such disparities and keep AI use in healthcare ethical, equitable access and patient consent frameworks are essential. And finally, multimodal AI can come into play to not just integrate text, imaging, genomic and sensor data but create comprehensive patient profiles and more accurate, personalized treatment plans. However, by considering these future directions, such as real-time adaptability, ethical compliance and multimodal integration, GDA-CDSS brings changes to healthcare delivery and can enhance the patient outcomes and realizing the vision of precision medicine. In order for these technologies to be deployed responsibly, equitably and effectively, in the service of patients and healthcare systems worldwide, it will be crucial for the researchers and the clinician to work in collaboration with the policymakers.

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