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Original Article

Automating FHIR Compliance Audits with Large Language Models (LLMs) for Real-Time Healthcare Data Validation

Srinivas Bangalore Sujayendra Rao¹, Lalitha Amarapalli², Lakshmi Durga Panguluri³

¹ZS Associates, USA ²Fresenius-Kabi, USA ³Finch AI, USA

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Abstract - The digitization of healthcare records has revolutionized data exchange but introduced challenges in ensuring Fast Healthcare Interoperability Resources (FHIR) compliance, particularly with the heterogeneity of Electronic Health Records (EHRs) and unstructured data. Traditional compliance audits often require significant time and effort, prone to errors and inefficient (given the complexity and volume) healthcare data, but this study derives Large language models to automate FHIR compliance audits to perform real time validation of structured and unstructured healthcare data. The modern models leveraging advanced natural language processing techniques tackle real world problems like data mapping and interoperability testing, as well as regulatory compliance via frameworks such as HIPAA and GDPR. This allows for automation of key processes such as data analysis, anomaly detection, and compliance reporting which in turn helps improve accuracy, scale and efficiency with minimal manual audits but ethically significant check like bias, accountability and data privacy are still the prime concerns. For building trust in automated system it is imperative to create fair and transparent AI driven compliance solutions. The more recent advances in blockchain, edge computing, as well as federated learning appear to be very promising in enhancing the security of data, real time processing and decentralized compliance monitoring for health care organizations. When these advancements are leveraged, health care organizations can build more trustworthy and adaptive compliance frameworks which can improve global health care interoperability. Automated FHIR compliance audits have the ability to transform regulatory adherence in terms of leveraging streamlining, data integrity, and enabling innovation in healthcare data management as this research suggests.

Keywords - FHIR Compliance, Large Language Models (LLMs), Healthcare Interoperability, Electronic Health Records (EHRs).

I. INTRODUCTION

In order for patients to move through the healthcare system, their EHRs must be available, discoverable, and understandable. In order to make this exchange possible, application programming interfaces (APIs) act as the key by creating a standardized and secure method to share the data. The European Institute of Innovation and Technology acknowledges the significance of such digital health initiatives on advancing healthcare delivery and driving innovation [1]. Furthermore, automated clinical decision support and technologically based health processes require structured and standardized data.

But that has led to new complexities due to the shift to digital records. There is a huge volume and rich mix of healthcare data (EHRs, free text clinical notes, imaging reports, genomic data, etc.) that all need to be as complete, consistent, accurate, and interoperable as possible. According to 2021, in the U.S., 96% of hospitals and 86% of office based physicians use certified EHR system [8]. Nevertheless, this hasn't helped pave the way for interoperability. According to a 2022 Office of the National Coordinator for Health Information Technology (ONC) report only 38% of U.S. hospitals could electronically find, send, receive, or integrate patient health information across external sources [9]. It is because of this complexity that there is room for strong frameworks which standardize data formats, enforce compliance, and facilitate seamless data interchange. Without such frameworks healthcare organization will become lack of efficiency, errors and non fulfillment of regulations resulting in patient care and safety.

To solve these challenges, Fast Healthcare Interoperability Resources (FHIR) has become a global standard to ensure that healthcare data exchange is fast and efficient. Based on previous HL7 standards and with

a new 'resources' based representation of clinical concepts, FHIR organizes health information in a unified manner. That said, these resources can even be customized to various healthcare scenarios. FHIR provides implementors with efficient data interoperability using RESTful APIs based on internet standards [3]. Introducing this framework is essential for harmonizing digital health products and services across all platforms [2]. For example, states like California and New York have begun using FHIR based systems for better care coordination for Medicaid beneficiaries, which demonstrates the value it can bring in closing care gaps within fragmented healthcare systems.

However, the real time FHIR compliance is difficult to guarantee. Another problem is the diversity of EHR systems that all have different coding of physician observations, such as ICD (International Classification of Diseases), CPT (Current Procedural Terminology) and LOINC (Logical Observation Identifiers Names and Codes). This is a rather tricky and time consuming exercise trying to map these codes accurately. For instance, a pull from Texas discovered that greater than 30 percent of the healthcare suppliers have struggled in mapping ICD-10 codes to indigenous terminologies, which resulted in delays in exchanging and billing data [24]. There are also variations on data formats, terminologies and standards from different vendors which makes integration even harder, especially with the inconsistencies of synonyms, abbreviations and terminology usage [7]. Adding another layer of complexity, those real time information extraction and validation become difficult if it is based on unstructured data like clinical notes or imaging reports [5][6]. However, privacy concerns might also hinder its use as EHRs contain sensitive patient information. HIPAA in the US and GDPR in the EU have strict data protection regulations and make de-identification, a privacy preserving techniques, both expensive and technically difficult [6][7]. For instance, a 2023 audit in Florida revealed that '15 percent of health care organizations failed to meet HIPAA's de-identification requirement' [22], thus underlining the requirement for solutions on a scalable scale.

To address these challenges, advanced language models have become a powerful automation for compliance audits and real time healthcare data validation. These models are able to analyse large amounts of structured and unstructured data and to follow FHIR standards and its regulatory requirements. They can be better used to improve medical entity recognition by using natural language processing, to assist coding system mappings, and to help in data standardization efforts. And, for example, pilot projects in Massachusetts have demonstrated that these models can lower coding errors by 25% and help interoperability by 40% in multihospital networks [23]. In addition, they can also help with health communications tailored to the individual patient by delivering personalized health information, drug reminders, and wellness advice. But, data security regulations must be enforced through advanced encryption, secure processing protocols and local data handling when deploying. Accurate and relevant generated content is also crucial, which is continuously trained on verified medical datasets and constantly overseen by the healthcare professionals.

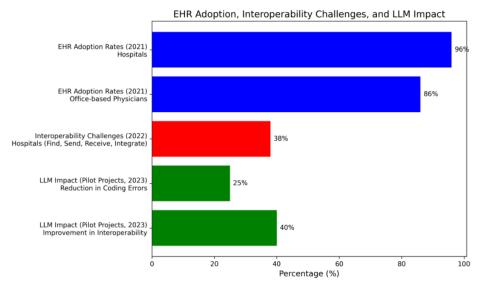


Figure 1. EHR Adoption, Interoperability Challenges, and LLM Impact

An effective method to make rules simpler, improve data interoperability, and validate healthcare data promptly is through the automation of FHIR compliance audits using advanced language models. These models tackle issues that include coding system differences, data inconsistency, unstructured text processing, as well as privacy risk, and they provide efficient and scalable solutions to the challenges in compliance of the healthcare sector.

II. FHIR COMPLIANCE CHALLENGES

If the healthcare organization is FHIR compliant, rest assured that the organization uses standardized format, structure and communication protocol used in exchanging information through different applications to achieve interoperability and improve patient care, and to meet regulatory directions. This is compliance, it has guidelines of the structuring, exchanging and safe storing of Electronic Health Records (EHRs) so that things can run consistently across all other healthcare systems. FHIR standardizes data exchange, enabling smooth communication between platforms for clinical as well as administrative processes and improving the patient outcomes.

Yet, there are major challenges to the traditional ways of ensuring FHIR compliance. Manual audits are also slow, extremely labor intensive, and prone to errors, thus difficult to apply to large and complex healthcare datasets. Structured data is easy to work with using rule-based systems, but unstructured records like clinical notes and imaging reports are non-tradable by rule based systems. There are also differences in EHR systems and a need to accurately map many result coding schemes —such as ICD and LOINC as well as SNOMED CT (OMOP). Such these difficulties raise the necessity for automated solutions designed to deal with both the structured and unstructured data and with the changing FHIR standards and regulations.

These problems have a practical solution in the form of advanced language models. Because it uses natural language processing and pattern recognition, they can enable the automation of the analysis, validation, and enforcement of FHIR compliance standards. The models are able processes unstructured data, find inconsistencies and conform to FHIR guidelines. Thus, they can be continuous learning and adpate to the new requirements, which makes them flexible and fit to the hospital environment changed. This makes them a useful tool for resolving issues of FHIR compliance and improve data interoperability between healthcare systems.

Furthermore, these hospital models enable information tailored to the patient that assists the client engage more with his or her health by offering customized health information, medication reminders and wellness advice. This enhances teamwork between patients and healthcare providers so that better treatment adherence is encouraged. Despite the advances of blockchain and the blockchain eHealth projects, there are still issues to resolve, notably the protection of health sensitive data and the compliance of data protection regulations such as GDPR and HIPAA.

III. KEY REGULATORY AND INTEROPERABILITY STANDARDS

To comply with FHIR, healthcare organizations must follow essential regulatory and interoperability guidelines:

A. HIPAA (Health Insurance Portability and Accountability Act)

HIPAA sets standards of how to protect patient data. To protect the vulnerable and sensitive Protected Health Information (PHI), organizations handling PHI must implement security measures as physical, network, and process level. To keep data private and secure which is also a need of HIPAA compliance, FHIR compliance requires the processes to be aligned with HIPAA [8].

B. ONC Cures Act Final Rule

In terms of the 21st Century Cures Act, that's the work of the Office of the National Coordinator for Health Information Technology (ONC), which aims to improve interoperability and to help prevent case of data access. The Final Rule required the use of FHIR based APIs that allow patients to obtain the electronic health record without unnecessary barriers [9].

C. HL7 FHIR Standards

The framework for healthcare data exchanging is provided by HL7 FHIR standards. Compliance helps with the coordination of the communication between the healthcare systems, thus ensuring both the clinical and administrative workflow [10].

These are the requirements that the FHIR is supposed to comply with but they also increase the complexity due to real time adherence requirements across different types of data and systems. To meet these demands, efficient solutions from address these challenges by being able to process structured and unstructured data and will adapt with respect to the changes in the regulatory environment.

IV. COMMON CHALLENGES IN TRADITIONAL FHIR AUDITS

Compliance audits of FHIR (Fast Healthcare Interoperability Resources) ensure that healthcare facilities comply with the set data exchange standards and regulatory guidelines so that the data is exchanged by

healthcare organizations. These audits confirm the accuracy, security and interoperability of electronic health records (EHR). Nevertheless, the conventional FHIR audits suffer especially with several limitations that adversely affect their efficiency as well as their reliability. Compliance audits can be complex, time consuming and manual verification, different data formats used in memberships, changing regulations are a few. It is imperative to overcome these challenges to develop the healthcare data management and maintain the smooth follow of the industry standards.

A. Data Mapping and Transformation

One difficulty of FHIR audits is to convert data from previous systems to FHIR readable structures. The variety of data structures [11] makes this process prone to error, and therefore complicated. Automated data mapping reduces errors and reduces conversion time. Data can be accurately read, interpreted and transformed into FHIR compatible formats with language based processing.

B. Interoperability Testing

FHIR APIs and different systems need to communicate with each other easily. Testing must be thorough enough to catch the whole range of compliant [12].

Solution: Through automated testing you can check data exchange reliability with different conditions. It helps to discover the gaps and has the assurance that the FHIR implementations are working correctly across various platforms.

C. Security and Privacy Concerns

Data protection is an issue when data is shared, but FHIR enables more data sharing. It is important to ensure compliance with HIPAA and other security regulations [13].

Solution: The solution is advanced encryption and privacy related techniques such as secure data processing which can be applied to protect sensitive patient information through audits.

D. Resource Profiling and Customization

FHIR provides capability of custom resource profiling, but potential inconsistency. In order to achieve interoperability [14], the custom profiles that auditors need to verify that they follow core FHIR guidelines.

Solution: Automated validation for FHIR check can verify custom profiles, identify substandard parts, and suggest corrections to keep up with FHIR standards.

Comparative analysis is required to better understand the advantages of automation over ordinary manual methods for FHIR compliance audits. The Table 1 lists several key difference in terms of accuracy, scalability, adaptability and other important aspects.

V. LARGE LANGUAGE MODELS (LLMS)

Advanced artificial intelligence system that can process and understand human language is known as Large Language Models (LLMs). Such models as OpenAI Generative Pre trained Transformer (GPT) use deep learning approaches to learn about large amounts of textual data. LLMs use transformer architectures with self attention mechanisms to discover patterns, relationships and context of meanings in text, to perform tasks such as Text Generation, Summarization, Translation, Question answering [15].

Lacking the capability to make sense of input is one of the primary problems tackling from unsupervised sufficiency of pre-training and supervised (refered) sufficiency of fine tunning of LLMs. Models are pre-trained during which they learn the general language patterns in books, articles and so on across a variety of sources. It gives them this broad exposure of the language structure and grammar so they know the basics of grammar and structure. On the other hand, when these models are fine-tuned, they make them task and domain specific by fine tuning the models for task or a particular industry so that the output of the models starts to align with domain specific requirements [16].

Due to the ability of LLMs to process structured as well unrestructured data, LLMs are found in many areas, including healthcare. To improve patient care, often we have such important information buried in various medical records, clinical notes, or research papers, which would be otherwise so difficult to extract. The LLMs are tremendously helpful in organizing, summarizing, and analyzing the large volumes of medical data that can be used for compliance audits, clinical decision support and research [16].

The scope of Healthcare applications that LLMs are suitable for in healthcare spans from regulatory compliance check to assisting in diagnostic processes. And as these models continue to mature, they are expected to increasingly take a lead role in improving the efficiency, accuracy and of healthcare. While responsibility deployment is important, issues like bias, transparency and accountability are to be addressed in order to provide use of data in healthcare systems in a fair and ethical way.

Feature	Large Language Models (LLMs)	Traditional Machine Learning (ML)
Accuracy	High accuracy with unstructured data.	Accurate for structured data.
	Handles complex scenarios.	Struggles with unstructured inputs. Rule-
	Requires fine-tuning.	dependent.
Scalability	Highly scalable.	Limited scalability.
	Handles diverse data types.	Manual updates.
	Cloud-enabled.	Resource-constrained.
Adaptability	Adapts to new tasks.	Hard to adapt.
	Learns from new data.	Requires manual updates.
	Supports dynamic environments.	Rigid frameworks.
Data Handling	Excels with unstructured data.	Best for structured data.
	Extracts insights from free-text.	Limited unstructured data processing.
Implementation	High initial cost.	Low initial cost.
Cost	Long-term savings through automation.	High long-term maintenance costs.
Real-Time	Enables real-time validation.	Limited real-time processing.
Processing	Supports continuous monitoring.	Relies on periodic audits.
Interoperability	Enhances interoperability. Adapts to multiple	Limited interoperability.
	coding systems.	Requires manual mapping.
Privacy and	Uses advanced encryption.	Relies on external security measures.
Security	Employs federated learning for privacy.	Centralized data increases risks.

VI. APPLICATIONS OF LLMS IN HEALTHCARE

Large Language Models (LLMs) are being incorporated into healthcare to change how medical data is managed as well as analyzed and used. All driven models get these processes automated, help improve decision making and also help with patient care. They are helping to shape a more efficient and reliable healthcare system from continued data accuracy to assisting with compliance and patient interactions.

A. Data Validation

LLMs aid in the accuracy of healthcare data by identifying inconsistencies, missing data, or errors in electronic health records (EHRs). By doing so they can check up on patient details, results of the test and medication records against the established standards to improve data integrity[17].

B. Regulatory Compliance

That means that you must ensure seniority with certain healthcare regulations, such as HIPAA and the ONC Cures Act. On its part LLMs help by examining medical documentation, ensuring privacy and security compliancy and detecting potential violations to enable reporting that is more effective[18].

C. Clinical Decision Support

LLMs analyze patient information in real time and suggest a treatment options based on medical evidence. Further they help detect potential drug interaction and adverse effects in order to assist health providers in informed decision making and improve the patients safety[19].

D. Processing Unstructured Data

LLMs extract value from unstructured sources such as clinical notes, radiology reports and discharge summaries. It makes the usage of health data for research, analytics and decision making more feasible in operational terms[20].

E. Patient Communication

LLMs also power virtual assistants and chatbots to better communicate with patients' medical queries, recommending health advice and even personalized recommendations. These tools enhance patients' involvement and access to healthcare information [21].

To reap the benefit of LLMs in improving the healthcare outcomes, healthcare organization can achieve the best data management, guarantee regulatory compliance, aid clinical decision making and engage with patients more well.

VII. AUTOMATING FHIR COMPLIANCE AUDITS WITH LLMS

Auto-enforcing FHIR (Fast Healthcare Interoperability Resources) compliance rules can be achieved using Large Language Models (LLMs) which facilitates streamlining the data validation, analysis and rule checks.

A. Data Analysis and Validation

This generates the superior deal, not only because LLMs can process extremely large amounts of healthcare data, no matter what the format (structured or unstructured), in order to identify inconsistencies and, where necessary, confirm compliance with FHIR standards. They make sure that the Patient and Observation data that need to be met with the necessary suppliers.

B. Processing Compliance Data

Using clinical documentation, audit logs, and other records, they can also surface compliance with things like HIPAA and the ONC Cures Act. This allows them to extract pivotal details and flag critical issues such as the absence of patient consent or incorrect access to the data.

C. Rule Enforcement

FHIR rules can be enforced with LLMs by ensuring required fields, data formats and structural constraints as needed. In addition, they guarantee that customized FHIR profiles are in tandem with standard guidelines, leading to a minimized risk of interopability.

D. Automated Reporting

LLMs provide comprehensive audit reports containing compliance gaps and suggested remedial actions. By doing so, this automation reduces the manual workload and supports healthcare organizations to keep up to regulation compliance at ease.

Healthcare providers can boost accuracy, efficiency and consistency in FHIR compliance audits, while following up regulatory guidelines by exploiting LLMs.

VIII. WORKFLOW OF AN AUTOMATED FHIR AUDIT SYSTEM USING LLMS

A structured process consisting of an automated FHIR audit system follows to check whether the healthcare data standards are followed or not. This workflow has following key steps:

A. Data Collection

It collects information from EHRs, FHIR APIs, and clinical data bases. The data comprises FHIR resources, audit logs, clinical notes, and other data that may be part of the clinical information artifact system.

B. Data Preparation

Processed to be consistent, the collected data is analysed. It could be either structuring unstructured text, or standardize FHIR resources for coherence.

C. Compliance Check

Then, the system reviews the data for adherence to FHIR standards as well as healthcare regulations. That includes checking accuracy and completeness, or determining whether it complies with FHIR guidelines.

D. Detection of Errors

It detects the problems: there is no address information, it is in wrong format or it does not follow FHIR rules. As such, it can also alert on possible privacy risks for users or on restricted data sharing.

E. Audit Reports and Suggestions

Analysis of the system results in the creation of reports indicating compliance failures and recommendations for corrective actions. These reports allow the stakeholders problem to be addressed in its most efficient way.

F. Continuous Monitoring

The system always tracks the flow of the data and the update, to keep compliance and all the records follow the FHIR standards over the time.

IX. INTEGRATION OF LLMS WITH EXISTING FHIR-BASED SYSTEMS AND APIS

To effectively integrate LLMs with FHIR based systems, planning must be carefully done to gain access to the LLMs while making sure that it is actually being used in the FHIR-based systems. In fact, there are a few important factors to be kept in mind:

A. API Integration

Since HLTs and LLMs could read and write, they can connect with FHIR APIs and read the healthcare records directly. Thus data is able to be verified on the fly and the data follows the desired standards [11].

B. Middleware Solutions

Its role is to act between LLMs and FHIR systems, providing secure exchange of data. Hence, existing operations do not get disrupted as it ensures seamless integration [12].

A. Cloud-Based Deployment

With LLMs, it is easy to deploy on cloud platforms to handle large datasets efficiently. Updates and maintenance also occur with less complexity in the form of cloud solutions [19].

B. Security and Privacy

In the scenario of LLMs working with FHIR systems is sensitive health data. [18] Encryption, access restriction, and regulatory compliance have to be guaranteed.

The inclusion of Large Language Models (LLMs) in FHIR (Fast Healthcare Interoperability Resources) audits ensures better data management in healthcare data management in various ways. Manual data checks for traditional audits take up time and introduce errors. This makes the process much simpler and uses LLMs to automate analysis, validation and reporting tasks. They evaluate the FHIR resources according to some predefined criteria, point out discrepancies and provide in depth audit reports with minimum manual work. It will speed up the auditing process and keep it consistent.

Therefore large amounts of structured (EHRs, FHIR resources) and unstructured (clinical notes, radiology reports) data come from healthcare systems. Handling the data described above is difficult (if not impossible) for the rule based systems, especially when the data is unstructured. As

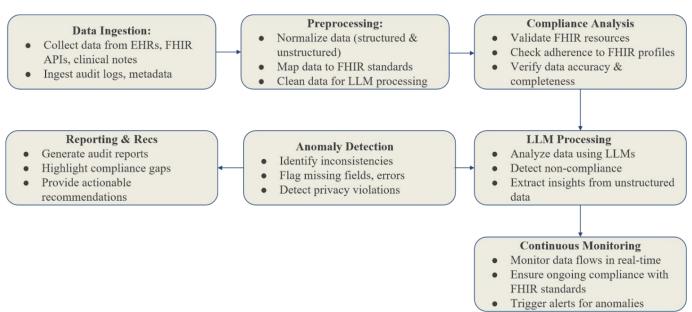


Figure 2. Automated FHIR Compliance Audit Workflow Using LLMs

large datasets, LLMs are quite efficient and can be used for compliance audits within multiple healthcare settings. The work load is handled well by LLMs whether reviewing thousands of patient records or analyzing complex clinical notes. This ensures that healthcare organizations stay in compliance as data continues to increase.

Rule based approach builds a system on predefined rules which may not be able to find complex erroring in health care data. Advanced Natural Language Processing (NLP) allows the LLMs to analyze info with precision. They can recognize missing fields, wrong formats or data inconsistencies that ordinary methods may not. They can also be

used to extract information from unstructured text: for example, to assess privacy risks in clinical notes or to verify participant consent verification forms are displayed. It improves compliance audits and lessens the potential of regulatory violations.

Periodically, the traditional audits may re-capture the compliance gaps. Continuous data flow monitoring using LLMs ensures that data flows are monitored all time at regulatory standard. They real time detect irregularities such as non compliance of FHIR guidelines or unauthorized access and enable immediate corrective action. This proactive approach will still enhance healthcare data security and also maintain compliance.

Incorporating the LLMs can facilitate the management of healthcare data in compliance audits. It reduces the manual work, allows for efficient handling of the large data sets, increases the accuracy, and provides real-time monitoring of the data. By following the approach outlined, healthcare organizations can maintain secure, interoperable and compliant data system.

X. ETHICAL CONCERNS IN USING LLMS FOR FHIR COMPLIANCE

FHIR compliance checks using Large Language Models (LLMs) is an efficient way to use LLMs but also an ethical one. Issues like these should be addressed since fair, reliable and in line with healthcare ethics are important.

A. Bias in LLMs

LLMs learn from vast amounts of data, which may contain biases. If the data is not diverse, the model might produce unfair results, affecting healthcare decisions.

Demographic Bias: If an LLM is mainly trained on data from a certain group (such as a specific age, gender, or ethnicity), it may not work well for others who are less represented.

Clinical Bias: If certain diseases are underrepresented in medical records, the model may provide incorrect compliance checks or recommendations.

Table 2. Bias Detection and Mitigation Strategies

Type of Bias	Potential Impact	Mitigation Strategies
Demographic	Inequitable treatment for	Use diverse training datasets; apply fairness-aware
Bias	underrepresented groups	algorithms.
Clinical Bias	Misdiagnosis or under diagnosis of rare	Include rare disease data in training; collaborate with
	conditions	specialists for validation.
Data Source	Over-reliance on data from specific	Aggregate data from multiple sources; ensure geographic
Bias	institutions	and institutional diversity.

B. Accountability

When using LLMs for compliance checks, it is important to define clear responsibility. If the model makes a mistake, it should be clear who is accountable—whether it is the developers, the healthcare providers, or the regulators overseeing the process.

Table 3. Accountability Roles and Mitigation

Stakeholder	Role	Accountability Measures
Developers	Design and train the LLM	Ensure model fairness, transparency, and compliance
		with ethical guidelines.
Healthcare	Deploy and use the LLM for	Provide human oversight; report and address errors.
Organization	compliance audits	
Regulatory Body	Oversee compliance and audit	Establish guidelines for LLM usage; enforce
	processes	accountability measures.

C. Ethical AI Frameworks

To address ethical concerns, healthcare organizations can adopt ethical AI frameworks for LLM usage. These frameworks should include:

Table 4. Ethical AI Framework for LLMs in FHIR Compliance

Component	Description	Examples/Techniques
Fairness	Ensures LLMs do not perpetuate biases or inequities	Bias detection, diverse datasets, fairness
	in healthcare data.	metrics.
Transparency	Makes LLM decision-making processes	Explainable AI (XAI), audit trails, user-friendly
	understandable to stakeholders.	dashboards.
Accountability	Defines clear roles and responsibilities for LLM	Human oversight, error reporting, regulatory
	usage and error handling.	compliance.

FHIR compliance checks can immensely benefit from the use of Blockchain, edge computing, federated learning and other technologies to power large language models (LLMs). Blockchain forces all records to be maintained securely, by creating an irreversible diary of data activity, thus being accurate and legible. This builds health care provider trust and security, and ensures verification compliance with FHIR rules without tampering.

The real time data processing enabled by edge computing is very useful in places that have limited resources or are remote areas. Raising LLMs on edge devices, for instance, the Internet of Things (IoT) medical equipment through the Internet, supplying the data so that it can be operated locally. Such reduction in delays and quick compliance checks for normal tasks like patient monitoring and emergency care are possible as a result of this.

In federated learning patient privacy is protected by training LLMs on separate datasets without requiring them to share their sensitive data. It helps the models to be accurate, and also, it enables believing the model will comply with regulations such as HIPAA or GDPR.

Future models that can continuously learn will not need to have a complete retraining process in the case of FHIR standards becoming outdated. It makes them more useful and reduces maintenance costs in time. Also, the combinations of LLMs that can parse a bunch of different types of data including text, images or audio will help in compliance check by providing a much more detailed validation. Furthermore, the setup of data sharing rules around the world beyond FHIR will be necessary when healthcare systems interconnect. It will allow the smooth transfer and compliance checks against different regions despite disparate local laws and data formats.

With these new technologies and even more research, healthcare providers will have secure, simple, and effective ways of providing compliance for future healthcare data management.

XI. CONCLUSION

The way Large Language Models (LLMs) are being utilized in the FHIR compliance checks represents a significant advancement in handling healthcare data. LLM automates key tasks such as data validation, spotting errors and generating reports and solves long standing data sharing, accuracy and scaling problems. This ability to deal with both structured and unstructured data make sure that they can easily keep to modifying FHIR standards and regulatory requirements. Real time monitoring makes efficiency stronger, mistakes less, and fines of the regulatory order decrease.

But the use of them is needed to be regulated carefully to meet the concerns such as bias, transparency, and accountability. Automated processes need to be fair, explanation for decisions should be transparent, and error account responsibility. Furthermore, LLMs work together with technologies like blockchain, edge computing and federated learning to enhance data security, mitigate processing times to instant, and protect patient's privacy. Together these solutions provide a strong base for secure and flexible compliance systems.

This evolution of healthcare will assist in promoting global data sharing and improve innovation when LLMs are utilized in conjunction with these new technologies. Although LLMs can be used to ensure compliance, LLMs also provide opportunities to improve patient care, streamline administrative tasks, and facilitate data driven decisions. These developments lead healthcare providers to adopt such advancements, thereby building the systems that are not only more secure but also more efficient and patient oriented.

The future of healthcare is holding great potential with the LLMs and the emerging technology. The contribution of this research is to point out the requirement to apply of AI in an appropriate manner to resolve challenges in healthcare data management. In order to move towards a more connected and automated healthcare system, the industry should focus on ethics and play with new solutions so that data sharing, compliance & patient care becomes better.

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