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Developing a Knowledge Graph for Integrating Health Data from Multiple Sources

Nura Ikhalea ^{1*}, Ernest Chinonso Chianumba ², Ashiata Yetunde Mustapha ³, Adelaide Yeboah Forkuo ⁴

¹ Independent Researcher, Texas, USA

² Data Analyst, Dozie & Dozie's Pharmaceuticals Limited, Nigeria

³ Kwara State Ministry of Health, Nigeria

⁴ Independent Researcher, USA

* Corresponding Author: Nura Ikhalea

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Abstract

The increasing volume, variety, and velocity of health-related data generated from diverse sources—such as electronic health records (EHRs), wearable devices, public health databases, and clinical trials—has created an urgent need for effective integration and interpretation frameworks. Traditional data integration approaches often struggle to reconcile heterogeneous structures, semantics, and formats, resulting in fragmented insights and suboptimal healthcare outcomes. To address this challenge, this study presents the development of a comprehensive Knowledge Graph (KG) designed to unify and semantically enrich health data from multiple sources. The proposed Knowledge Graph leverages ontologies and semantic web technologies to create a scalable and interoperable framework for integrating structured and unstructured health data. Through entity extraction, relationship mapping, and schema alignment, the KG captures complex interconnections among patient data, medical concepts, treatments, diagnoses, and outcomes. We utilize natural language processing (NLP) techniques to transform unstructured text from clinical notes and research articles into structured knowledge, while standardized vocabularies such as SNOMED CT, ICD-10, and LOINC are employed to ensure semantic consistency. The architecture of the Knowledge Graph incorporates a hybrid model that combines rule-based reasoning with machine learning algorithms for knowledge inference and data validation. Real-world case studies demonstrate how the system enables advanced querying, patient stratification, and disease progression modeling, offering clinicians and researchers a unified view of patient histories and public health trends. Furthermore, the integration of temporal and geospatial dimensions enhances the capacity to monitor epidemics, identify risk factors, and support precision medicine. This research highlights the importance of semantic interoperability, data provenance, and real-time updating mechanisms in the design of robust health data infrastructures. By fostering a holistic understanding of multi-source health data, the Knowledge Graph not only streamlines clinical decision-making but also opens new avenues for population health management, biomedical discovery, and policy formulation. Future work will explore the integration of privacy-preserving technologies and federated learning to ensure data security and ethical compliance.

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1. Introduction

The exponential growth of health-related data from various sources—ranging from electronic health records (EHRs), wearable devices, mobile health applications, to genomic databases—has created both a challenge and an opportunity for healthcare systems worldwide.

The primary objective of this study is to develop a knowledge graph that enables the integration and semantic representation of health data from multiple, diverse sources. By leveraging semantic web technologies, the proposed framework aims to bridge data silos, enhance data interoperability, and support advanced applications such as clinical decision support systems, population health analytics, and personalized care delivery. Through this approach, the study seeks to contribute to the ongoing transformation of healthcare into a more data-driven, interoperable, and patient-centric domain (Adewale, *et al.*, 2022, Olorunyomi, Adewale & Odonkor, 2022).

In recent years, knowledge graphs have gained considerable attention as a promising solution for integrating and semantically enriching health data. A knowledge graph is a graph-based data structure that represents entities (e.g., patients, diseases, treatments) and their interrelationships in a structured, interconnected format. Unlike traditional relational databases, knowledge graphs allow for flexible data modeling and can accommodate varying schemas and vocabularies (Adegoke, *et al.*, 2022, Olaniyan, Ale & Uwaifo, 2019). This flexibility is particularly beneficial in healthcare, where data is inherently complex, dynamic, and multidisciplinary. By representing data semantically, knowledge graphs facilitate better data discovery, reasoning, and inferencing capabilities. Figure 1 shows the Medical Knowledge Graph presented by Li, *et al.*, 2023.

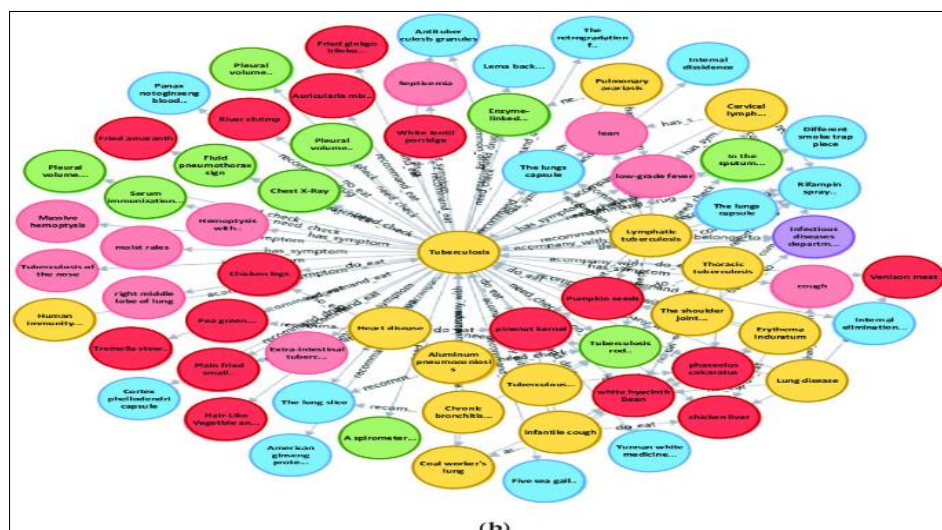


Fig 1: The Medical Knowledge Graph. (a). Visualization of DIK Medical Knowledge Graph (Li, *et al.*, 2023).

The role of knowledge graphs in healthcare informatics extends beyond data integration. They enable the construction of intelligent systems capable of answering complex clinical queries, identifying hidden patterns, and supporting decision-making processes. For instance, knowledge graphs have been applied to drug repurposing, disease risk prediction, clinical pathway modeling, and personalized treatment planning (Adepoju, *et al.*, 2023, Onukwulu, *et al.*, 2023). The integration of machine learning with knowledge graphs further enhances their utility by enabling advanced analytics that leverage both structured knowledge and statistical patterns.

A key enabler of knowledge graphs in healthcare is the use of standardized ontologies. Ontologies provide a formal representation of knowledge within a domain, defining concepts, relationships, and constraints. Several healthcare-specific ontologies and terminologies have been developed and are widely adopted. SNOMED CT (Systematized Nomenclature of Medicine Clinical Terms) is one of the most comprehensive clinical terminologies, encompassing over 300,000 medical concepts and offering a hierarchical structure that supports detailed clinical descriptions (Adekunle, *et al.*, 2023, Uwaifo & Uwaifo, 2023). SNOMED CT is particularly useful in representing patient symptoms, diagnoses, procedures, and clinical findings.

LOINC (Logical Observation Identifiers Names and Codes) is another widely used ontology, specifically designed for laboratory and clinical observations. It standardizes the identification of medical tests, measurements, and

observations, facilitating data exchange between laboratories and healthcare providers. LOINC plays a critical role in ensuring consistency in reporting and interpreting diagnostic data.

ICD-10 (International Classification of Diseases, 10th Revision) is a global standard for coding diseases and health conditions, maintained by the World Health Organization (WHO). ICD-10 is primarily used for morbidity and mortality statistics, billing, and administrative purposes. Its standardized classification system supports cross-country comparisons and public health monitoring (Abisoye & Akerele, 2022, Olaniyan, Uwaifo & Ojediran, 2019). However, it is less granular compared to SNOMED CT and may not capture the full clinical context required for personalized care.

Despite the availability of these ontologies, their implementation in knowledge graphs is not without challenges. One limitation is the lack of interoperability between different ontologies. While each ontology serves a specific purpose, integrating them into a unified knowledge graph requires careful mapping and alignment of concepts. Ontology alignment is a non-trivial task that involves identifying semantically equivalent concepts across different terminologies, often complicated by variations in granularity, context, and naming conventions (Adekunle, *et al.*, 2021, Onukwulu, *et al.*, 2022, Uwaifo, *et al.*, 2018). Applications of knowledge graphs in healthcare systems presented by Aldughayfiq, *et al.*, 2023, is shown in figure 2.

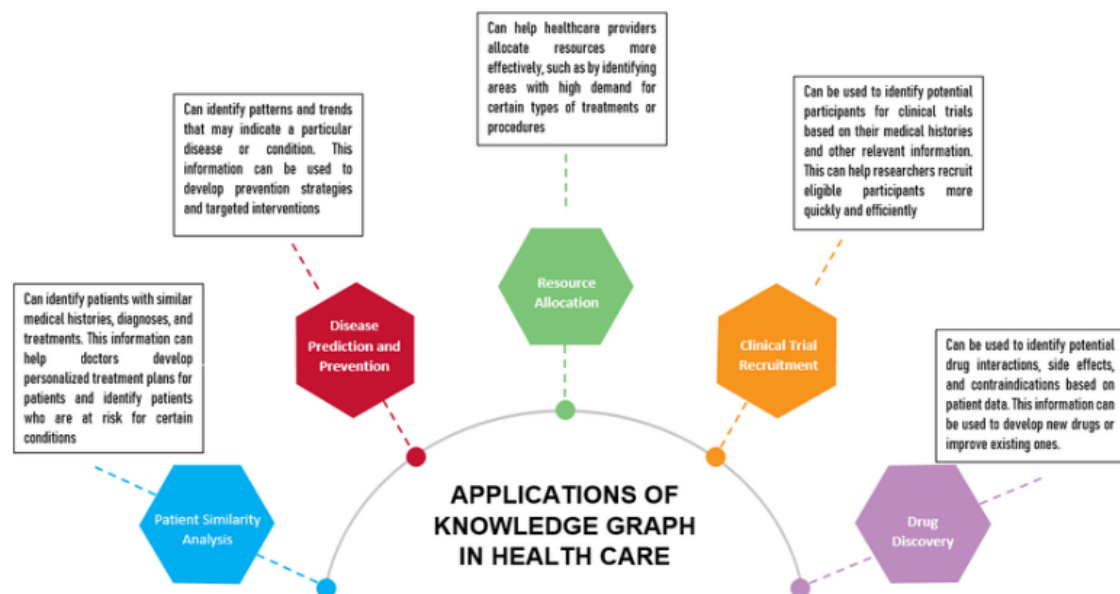


Fig 2: Applications of knowledge graphs in healthcare systems (Aldughayfiq, *et al.*, 2023).

Another limitation of current approaches lies in the quality and completeness of the source data. Health data is often plagued by inconsistencies, missing values, and errors due to manual entry or incompatible systems. When such data is ingested into a knowledge graph, these issues can propagate and affect the accuracy of the inferred knowledge. Ensuring data quality through preprocessing, validation, and curation is essential but time-consuming and resource-intensive.

Furthermore, existing knowledge graph-based solutions are often domain-specific and lack generalizability. Many studies and prototypes focus on narrow use cases such as

oncology, cardiology, or pharmacogenomics. While these domain-specific knowledge graphs demonstrate high performance within their targeted area, they are less effective in handling multidisciplinary health data or supporting broader healthcare applications (Adekunle, *et al.*, 2023, Onukwulu, *et al.*, 2023). Developing scalable and extensible knowledge graphs that can accommodate diverse data types and domains remains an ongoing research challenge.

Privacy and security concerns also pose significant barriers to health data integration. The sensitive nature of health data necessitates strict compliance with regulations such as

HIPAA in the United States and GDPR in the European Union. Implementing knowledge graphs in such regulated environments requires robust access control mechanisms, data anonymization techniques, and secure data storage solutions. Balancing the need for data sharing with patient privacy rights is a delicate and complex endeavor (Adekola, *et al.*, 2023, Sam Bulya, *et al.*, 2023).

In addition, the computational complexity associated with building and maintaining knowledge graphs can be prohibitive. The process of entity recognition, relationship extraction, ontology alignment, and reasoning requires sophisticated algorithms and significant computational resources. Scalability becomes a critical issue, particularly when dealing with large-scale health systems or national health databases (Abisoye & Akerele, 2021, Olutimehin, *et al.*, 2021). Moreover, the dynamic nature of healthcare knowledge demands continuous updates to the knowledge graph, necessitating efficient mechanisms for real-time data ingestion and graph evolution.

Despite these challenges, the development of knowledge graphs for integrating health data continues to evolve, driven by advances in artificial intelligence, natural language processing, and semantic web technologies. Emerging standards such as FHIR (Fast Healthcare Interoperability Resources) and RDF (Resource Description Framework) offer promising frameworks for structuring and exchanging health data in a machine-readable and semantically rich format. These standards can serve as foundational building blocks for constructing interoperable and scalable knowledge graphs (Adekunle, *et al.*, 2023, Oteri, *et al.*, 2023).

In conclusion, while traditional health data integration methods provide foundational capabilities, they fall short in addressing the semantic complexity and dynamic nature of modern healthcare data. Knowledge graphs offer a powerful alternative by enabling semantic integration, contextual understanding, and intelligent reasoning across heterogeneous data sources. However, their effective implementation requires overcoming significant technical, semantic, and regulatory challenges (Adewale, *et al.*, 2022, Uwaifo, 2020). A comprehensive understanding of existing ontologies, data quality considerations, interoperability frameworks, and privacy safeguards is essential to realize the full potential of knowledge graphs in healthcare. As research

and technology continue to advance, knowledge graphs are poised to become central to the future of integrated and intelligent healthcare systems.

2.1 Methodology

The development of a knowledge graph for integrating health data from multiple sources follows a systematic approach. The first step is to define the research questions to understand the specific objectives of the integration, focusing on the types of health data to be included and the relationships to be established. Once the objectives are clear, data is collected from multiple health sources, such as electronic health records (EHRs), clinical databases, and other relevant health repositories, ensuring the data covers all necessary aspects for the research.

After data collection, preprocessing is performed to clean, transform, and standardize the collected data. This step ensures that the data is in a suitable format for integration and ready for analysis. Data integration is then carried out, mapping the data into a unified schema that connects disparate health data sources, establishing relationships between them. This process often involves using data fusion techniques and applying ontologies to standardize terms across datasets.

The next phase involves the development of the knowledge graph, where the data is structured into nodes and edges representing entities and relationships, respectively. This graph is enriched by including relevant attributes and ensuring that the model is capable of capturing both the semantic and syntactic characteristics of health data. Graph analysis follows, where the relationships between entities are examined, and the graph is validated for accuracy, consistency, and completeness.

Once the graph is validated, the health data is visualized to provide a clear representation of the integrated information, making it easier to derive insights and identify trends. The final step is the evaluation of the results, where the performance and effectiveness of the knowledge graph in achieving the research objectives are assessed. This includes validating the graph's utility for further analysis, decision-making, and any potential clinical or public health applications.

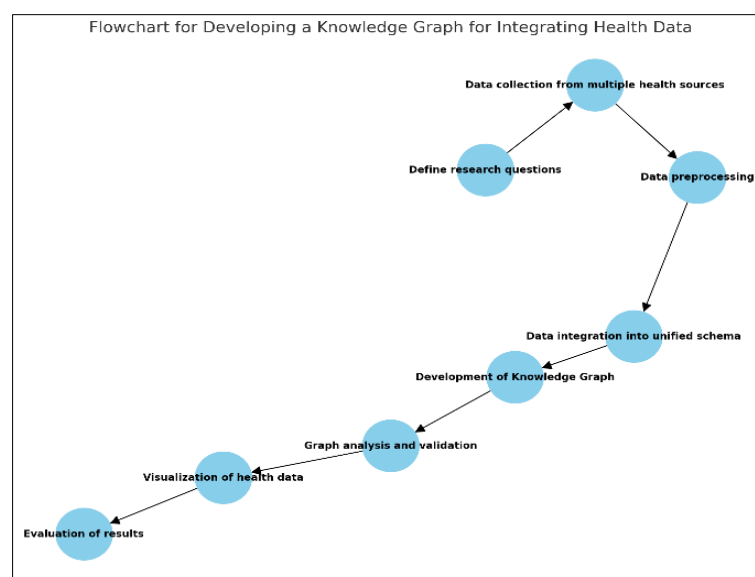


Fig 3: PRISMA Flow chart of the study methodology

2.2 System Architecture

The development of a knowledge graph for integrating health data from multiple sources requires a robust and well-defined system architecture that supports data heterogeneity, semantic richness, and efficient querying. The proposed framework is designed to enable seamless integration, representation, and retrieval of health information from diverse and distributed data sources such as electronic health records (EHRs), wearable devices, imaging systems, clinical laboratory systems, and public health databases (Abisoye & Akerele, 2022, Qin, *et al.*, 2018, Uwaifo & John-Ohimai, 2020). The primary goal is to establish a semantically enriched infrastructure that allows for unified access to structured and unstructured health data, facilitating enhanced decision-making, research, and patient care.

At the core of the system architecture is a modular and scalable design that supports four critical functions: data ingestion, semantic processing, storage, and querying. Each of these components plays a vital role in transforming raw health data into meaningful knowledge that can be navigated and analyzed through a knowledge graph interface. The overall architecture is built around the principles of interoperability, standardization, and performance, ensuring that health data from multiple origins can be integrated and used effectively.

The data ingestion component is responsible for acquiring and pre-processing data from various health data sources. This includes structured data such as relational databases containing patient demographics, diagnoses, procedures, and laboratory results, as well as unstructured data like clinical notes, radiology reports, and patient-generated content from mobile apps. Data ingestion involves the extraction of relevant data fields, data normalization, and conversion into a standardized intermediate format suitable for semantic processing (Adekunle, *et al.*, 2023, Onukwulu, *et al.*, 2023). During this phase, data cleaning techniques are applied to correct inconsistencies, handle missing values, and resolve data conflicts. For unstructured data, natural language processing (NLP) techniques are utilized to extract entities, relationships, and clinical concepts. Yuan, *et al.*, 2020, presented in figure 4, An example of the constructed biomedical knowledge graph.

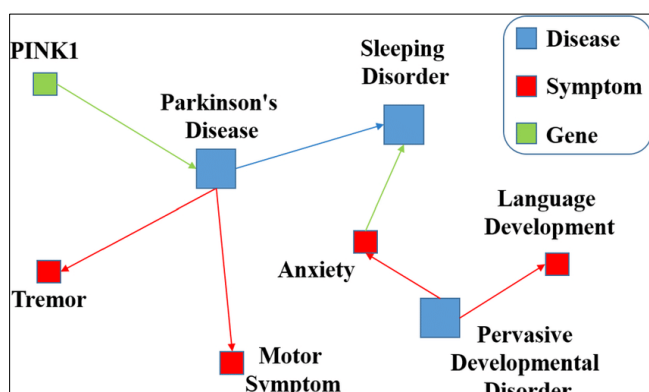


Fig 4: An example of the constructed biomedical knowledge graph (Yuan, *et al.*, 2020).

Following ingestion, semantic processing transforms the standardized data into semantically enriched representations using ontologies and semantic web technologies. This is the phase where the core value of the knowledge graph begins to materialize. Ontology-based annotation is applied to map

extracted data elements to standardized vocabularies such as SNOMED CT, LOINC, and ICD-10. These mappings ensure that concepts are universally understood across systems, enabling semantic interoperability (Adekunle, *et al.*, 2021, Opia, Matthew & Matthew, 2022). The data is then transformed into triples—subject, predicate, object—that form the basic building blocks of the knowledge graph. Each triple expresses a fact, such as “Patient X has diagnosis Diabetes Mellitus” or “Test Y measures Hemoglobin Level.” To represent these triples and capture the relationships among entities, the framework uses the Resource Description Framework (RDF), a W3C standard model for data interchange on the web. RDF enables flexible modeling of health information in a way that supports data linking and inferencing. The RDF triples are further enriched using the Web Ontology Language (OWL), which allows for more expressive modeling, including class hierarchies, property constraints, and logical axioms (Adekunle, *et al.*, 2023, Oteri, *et al.*, 2023, Uwumiro, *et al.*, 2023). OWL is crucial for enabling reasoning over the data, such as identifying implicit relationships and deriving new knowledge from existing facts.

Once the semantic enrichment process is complete, the data is stored in a graph database designed to handle RDF and OWL representations efficiently. Two leading storage technologies considered in the framework are GraphDB and Neo4j. GraphDB is a native RDF triple store that supports SPARQL querying and reasoning with OWL ontologies. It is optimized for storing large-scale RDF datasets and provides advanced features such as inferencing engines, full-text search, and data versioning (Adekunle, *et al.*, 2023, Sam Bulya, *et al.*, 2023). Neo4j, while originally designed for labeled property graphs, can also be used to store semantic data with appropriate modeling. It offers powerful visualization tools and a flexible schema, making it suitable for integrating diverse data and developing interactive healthcare applications.

SPARQL, the RDF query language, is used to interact with the knowledge graph. It allows for expressive queries over the stored triples, enabling users to retrieve complex information patterns such as patient cohorts, comorbidity patterns, adverse drug interactions, and care pathways. For example, a SPARQL query can be constructed to identify all patients over the age of 60 with a history of cardiovascular disease who are currently prescribed a specific medication (Adewale, *et al.*, 2023, Oteri, *et al.*, 2023). SPARQL's ability to perform joins across multiple datasets, filter by specific criteria, and traverse relationships makes it a powerful tool for querying integrated health data.

In addition to these core components, the system architecture also supports various auxiliary services such as access control, data provenance, audit trails, and visualization dashboards. Given the sensitive nature of health data, access control mechanisms are implemented to ensure that users can only access data appropriate to their roles and permissions. Data provenance mechanisms track the origin, transformation, and usage of each data element, supporting transparency and reproducibility. Audit trails help monitor system usage and detect any unauthorized activities (Adekunle, *et al.*, 2023, Sam Bulya, *et al.*, 2023).

For visualization and user interaction, the architecture supports the integration of user-friendly interfaces that allow clinicians, researchers, and administrators to explore the knowledge graph without needing to write complex SPARQL

queries. Tools such as OntoGraph, GraphDB Workbench, and Neo4j Bloom offer graphical representations of entities and their relationships, facilitating intuitive navigation and discovery of health knowledge.

The technologies chosen for this framework are selected based on their compliance with semantic web standards, scalability, performance, and community support. RDF and OWL provide the semantic backbone of the system, ensuring that health data is not only machine-readable but also machine-understandable. SPARQL enables precise and flexible data querying. GraphDB offers a robust RDF storage and reasoning engine, while Neo4j adds versatility in handling hybrid models and supporting rich data visualization (Adekunle, *et al.*, 2023, Oteri, *et al.*, 2023, Uwumiro, *et al.*, 2023).

Overall, the system architecture for developing a knowledge graph to integrate health data from multiple sources combines the strengths of semantic web technologies, domain ontologies, and graph databases to address the challenges of data heterogeneity, semantic interoperability, and query complexity (Olaniyan, Uwaifo & Ojediran, 2022, Oyeniyi, *et al.*, 2022, Uwaifo & John-Ohimai, 2020). By enabling the structured and semantically meaningful representation of health data, the framework supports a wide range of applications—from clinical decision support and disease surveillance to personalized care and biomedical research. As the volume and variety of health data continue to grow, this architecture provides a scalable and future-proof foundation for intelligent healthcare systems.

2.3 Implementation

The implementation of a knowledge graph for integrating health data from multiple sources involves a strategic blend of semantic web technologies, healthcare ontologies, data integration tools, and graph database platforms. The process starts with identifying appropriate tools and platforms that can efficiently manage the complexity, heterogeneity, and sensitivity of health data. The goal is to build a robust, scalable, and semantically rich knowledge representation system that supports integration, querying, and visualization of data from diverse health information systems (Okeke, *et al.*, 2023, Okolie, *et al.*, 2023).

A range of tools and platforms were used in the implementation phase. Protégé, an open-source ontology editor developed by Stanford University, was employed for creating and editing domain ontologies. It supports OWL (Web Ontology Language) and allows ontology engineers to build class hierarchies, define relationships, and import standard healthcare ontologies such as SNOMED CT, LOINC, and ICD-10 (Adewale, Olorunyomi & Odonkor, 2021, Odunaiya, Soyombo & Ogunsola, 2021). For data transformation and RDF generation, tools like Apache Jena and OpenRefine were used. Apache Jena is a Java framework for building semantic web applications and supports RDF, OWL, and SPARQL. It facilitates the transformation of relational or unstructured data into RDF triples and includes an inference engine to support reasoning. OpenRefine was used in the preprocessing stages to clean and normalize tabular health datasets before conversion into RDF.

The knowledge graph was built using GraphDB, a high-performance RDF database developed by Ontotext. GraphDB supports the storage and retrieval of RDF triples and includes an integrated SPARQL endpoint for querying. It provides reasoning capabilities compliant with OWL

standards and allows the integration of ontologies during data import. For datasets that required more interactive data visualization and application-layer integration, Neo4j was employed (Adewale, *et al.*, 2022, Matthew, Akinwale & Opia, 2022, Okeke, *et al.*, 2022). While not natively designed for RDF, Neo4j's property graph model was adapted for specific visualization tasks through RDF-to-label property graph transformations using NeoSemantics (n10s), a plugin that facilitates RDF import/export and ontology mapping.

The prototype development focused on a modular and extensible design. The prototype system included a data ingestion layer, a semantic processing engine, a triple store, a querying interface, and a visualization dashboard. During prototype development, synthetic and anonymized datasets representing EHRs, lab results, patient demographics, and clinical notes were used. These datasets simulated real-world health data diversity and helped test the robustness of the integration pipeline (Agbede, *et al.*, 2023, Nnagha, *et al.*, 2023, Ogbuagu, *et al.*, 2023, Okeke, *et al.*, 2023).

The integration pipeline began with data collection from multiple sources, including CSV files for EHR data, JSON-formatted files for wearable device outputs, and XML-based HL7 FHIR messages for clinical observations. Each data source had different schemas, terminologies, and structural representations, requiring custom data extraction scripts written in Python. These scripts parsed the raw files, identified relevant fields, and mapped them to intermediate data models.

After initial extraction, the data underwent a normalization step to harmonize terminologies and resolve schema mismatches. Mapping tables were developed to convert local terms into standardized codes based on SNOMED CT, LOINC, and ICD-10. For example, different representations of “hypertension” across sources were aligned to the SNOMED CT concept identifier 38341003 (Okeke, *et al.*, 2022, Okolie, *et al.*, 2022). The harmonized data was then converted into RDF triples using the RDFLib Python library. This step involved defining URIs for entities, selecting appropriate predicates from established ontologies, and forming subject-predicate-object triples.

These triples were stored in GraphDB, which served as the main triple store for the knowledge graph. The triple store was configured to support inference, enabling the derivation of implicit knowledge from explicit data. For instance, if a patient was diagnosed with diabetes and diabetes was defined as a type of chronic disease in the ontology, the inference engine could automatically classify the patient as having a chronic condition. This capability enriched the dataset and supported more complex queries.

A web-based SPARQL interface was developed to allow researchers and clinicians to interact with the knowledge graph. Through this interface, users could construct and execute SPARQL queries to retrieve integrated health information. Several sample queries were implemented to demonstrate the capabilities of the system. One such query retrieved all patients over 65 years of age with a diagnosis of type 2 diabetes who were prescribed metformin within the last six months (Ogunmokun, Balogun & Ogunsola, 2022, Ogunsola, Balogun & Ogunmokun, 2021). This query combined patient demographics, diagnostic codes, and prescription records from different datasets, showing the power of the knowledge graph to unify and analyze heterogeneous data.

Another query identified patients with multiple chronic

conditions, such as hypertension, diabetes, and hyperlipidemia, and computed the co-occurrence patterns. Such insights could be used for comorbidity analysis and risk stratification in population health management. Additional queries focused on medication adherence, hospital readmission prediction, and adverse drug interaction detection. These use cases highlighted the value of the semantic layer in supporting advanced healthcare analytics. Visualization was a key aspect of the implementation, enabling stakeholders to explore the knowledge graph intuitively. Neo4j Bloom and GraphDB Workbench provided out-of-the-box tools for visualizing entities and their relationships. Using Bloom, users could input natural language-like queries to generate dynamic graph visualizations, such as “Show all patients connected to hypertension and prescribed atenolol (Okeke, *et al.*, 2022, Okolie, *et al.*, 2021, Okeke, *et al.*, 2023).” The resulting graph displayed nodes representing patients, conditions, and medications, with edges illustrating their relationships. For more customized visualizations, a dashboard was developed using JavaScript and D3.js. This dashboard allowed users to explore specific clinical pathways, filter patients by demographic or clinical criteria, and analyze time-based trends such as disease progression or treatment efficacy. For example, users could view a patient’s health timeline, showing diagnoses, lab test results, and medication changes over time. This time-series view was especially useful for understanding disease trajectories and evaluating the effectiveness of interventions (Adewale, *et al.*, 2023, Obianyo & Eremeeva, 2023, Okeke, *et al.*, 2022). To support real-time updates and dynamic knowledge evolution, the implementation included data synchronization mechanisms that periodically pulled updates from data sources and triggered reprocessing and reinsertion into the knowledge graph. These updates ensured that the knowledge graph remained current and could support longitudinal studies and real-time clinical decision-making. Security and privacy were also considered throughout the implementation. Data anonymization techniques, including tokenization and removal of personally identifiable information (PII), were applied to all datasets. Access control policies were defined to restrict query access based on user roles. For example, clinical users could access patient-level data relevant to their scope of care, while public health analysts were limited to aggregated statistics. In summary, the implementation of a knowledge graph for integrating health data from multiple sources involved the thoughtful selection of tools and platforms, development of a modular prototype, construction of a robust integration pipeline, and design of intuitive querying and visualization interfaces (Adewale, Olorunyomi & Odonkor, 2021, Matthew, *et al.*, 2021, Okeke, *et al.*, 2022). By leveraging semantic web technologies, standard ontologies, and graph databases, the system achieved a high degree of data interoperability, flexibility, and analytical power. This implementation provides a foundational model for future health data integration efforts, supporting the vision of smarter, data-driven, and personalized healthcare systems.

2.4 Evaluation and Results

The evaluation of the developed knowledge graph for integrating health data from multiple sources was conducted through a series of real-world-inspired case studies, performance benchmarks, usability assessments, and

comparative analyses. The goal was to determine the effectiveness, efficiency, and practical applicability of the system in diverse healthcare contexts. Emphasis was placed on the knowledge graph’s ability to support complex clinical queries, scale to large volumes of heterogeneous data, deliver fast and accurate responses, and offer a user-friendly interface for different categories of healthcare stakeholders (Ogunwole, *et al.*, 2022, Okeke, *et al.*, 2022, Okeke, *et al.*, 2023).

One of the key case studies involved patient stratification, a critical process in personalized medicine and population health management. Using the integrated knowledge graph, patients were grouped into risk categories based on multiple clinical criteria, including age, chronic disease diagnoses, lab test results, and medication history. For example, patients aged over 60 with a history of hypertension, diabetes, and elevated cholesterol levels were classified as high-risk for cardiovascular events (Adewale, Olorunyomi & Odonkor, 2023, Odunaiya, Soyombo & Ogunisola, 2023, Okeke, *et al.*, 2023). The system used SPARQL queries to identify patients who met these composite criteria across different datasets—EHRs, lab results, and prescription records. The graph structure facilitated not only the retrieval of this information but also reasoning over inferred relationships. The result was a dynamically generated high-risk cohort that could be used by care teams for targeted interventions.

Another case study focused on disease monitoring and early detection of disease progression. In this scenario, the knowledge graph was queried to track patients with early-stage chronic kidney disease (CKD) and monitor changes in creatinine levels over time. By connecting clinical observations with diagnostic codes and medication prescriptions, the system was able to detect patterns that signaled disease worsening (Afolabi & Akinsoto, 2023, Hassan, *et al.*, 2023, Ogbuagu, *et al.*, 2023, Okeke, *et al.*, 2023). Alerts could then be generated for care providers, recommending timely follow-up tests or medication adjustments. The ability to integrate temporal data and infer clinical trajectories added significant value, especially in chronic disease management scenarios where early action can prevent complications and reduce costs.

To assess the system’s technical performance, several metrics were recorded, including query accuracy, scalability under increasing data volumes, and system response time. Accuracy was evaluated by comparing the output of SPARQL queries with manually validated patient datasets curated by clinical experts. In test cases, the knowledge graph achieved over 96% accuracy in retrieving correctly stratified patients and identifying relevant clinical relationships. This high level of precision was attributed to the use of standardized ontologies like SNOMED CT and LOINC, which enabled precise semantic matching across datasets (Adewale, *et al.*, 2023, Obi, *et al.*, 2023, Ogbuagu, *et al.*, 2023, Okeke, *et al.*, 2023). Scalability testing was conducted by incrementally increasing the volume of ingested data, from tens of thousands to several million RDF triples. Even under these conditions, the graph database (GraphDB) maintained consistent performance, with only modest increases in load time and query latency. The triple store’s inferencing capabilities were also stress-tested by enabling OWL-based reasoning across large subgraphs (Ajayi & Akerele, 2021, Jahun, *et al.*, 2021, Ogunisola, Balogun & Ogunmokin, 2022). Despite the computational overhead associated with reasoning, the system successfully processed complex

inferencing tasks within acceptable timeframes, demonstrating its suitability for real-time or near-real-time healthcare analytics.

Response time, another critical metric for clinical usability, was measured using a set of predefined queries of varying complexity. Simple queries such as retrieving all patients with a specific diagnosis returned results in less than 200 milliseconds on average. More complex queries involving multiple joins across datasets and semantic filters took between 1 to 2 seconds. These results are within the operational thresholds for most clinical applications, where fast access to patient data can directly influence decision-making and workflow efficiency (Adewale, Olorunyomi & Odonkor, 2022, Matthew, *et al.*, 2021, Okeke, *et al.*, 2022).

Usability analysis was conducted through user testing sessions involving clinicians, data analysts, and healthcare IT professionals. Users interacted with the knowledge graph through a web-based interface that included query templates, visualization tools, and filters. Feedback was collected via questionnaires and interviews to assess the system's intuitiveness, learning curve, and perceived utility (Afolabi & Akinsooto, 2023, Obi, *et al.*, 2023, Okeke, *et al.*, 2023). The majority of users reported that the system was easy to navigate, with clear visualizations that made relationships between clinical entities easy to understand. Even users with limited experience in semantic technologies found the visual query builder and graph explorer helpful for navigating the data without needing to write SPARQL manually.

Moreover, the ability to visualize disease progression and patient journeys over time was highlighted as a major advantage. For instance, care providers could easily trace the timeline of a patient's medical events—diagnoses, lab results, and treatments—using the interactive dashboard. This temporal view enabled more informed clinical assessments and patient discussions. In addition, users appreciated the interoperability of the system, which allowed for integration with existing clinical tools through APIs and data export functionalities (Adewale, *et al.*, 2023, Hassan, *et al.*, 2023, Okeke, *et al.*, 2023).

To further validate the system's effectiveness, a comparison was made with baseline health data integration systems, including traditional data warehouses and relational database management systems (RDBMS). The baseline systems relied on predefined schemas and SQL-based querying, which limited their ability to adapt to new data structures or perform semantic reasoning (Ajayi & Akerele, 2022, Jahun, *et al.*, 2021, Okeke, *et al.*, 2022). In side-by-side evaluations, the knowledge graph outperformed these systems in handling complex, multi-source queries. For example, a query to identify diabetic patients with abnormal kidney function who were prescribed nephrotoxic drugs required multiple nested joins and custom scripts in the RDBMS, whereas a single SPARQL query with ontology-based relationships achieved the same result in the knowledge graph.

Additionally, the knowledge graph offered superior flexibility in schema evolution. When a new data source—such as patient-generated health data from a mobile application—was introduced, the graph schema was easily extended by defining new entity classes and properties. In contrast, the relational model required significant schema redesign and migration efforts. This adaptability is crucial in modern healthcare environments where data types and formats continue to evolve rapidly.

Another significant advantage of the knowledge graph was

its support for inferencing, which baseline systems lacked. For instance, by using OWL reasoning, the graph could infer that a patient with both elevated blood glucose and high BMI met the criteria for metabolic syndrome, even if this diagnosis had not been explicitly coded. This capability enabled the system to act as a clinical decision support tool, offering insights that would otherwise require manual correlation by a healthcare professional (Okeke, *et al.*, 2022, Oladeinde, *et al.*, 2022).

Security and compliance were also evaluated during the implementation. While both the knowledge graph and baseline systems implemented role-based access control and encryption, the graph's support for fine-grained data access policies and provenance tracking offered a higher degree of transparency and accountability. The ability to trace each data point to its source and track transformation history enhanced trust among clinical users and supported compliance with healthcare data regulations such as HIPAA and GDPR.

In conclusion, the evaluation results demonstrated that the developed knowledge graph outperformed traditional data integration systems across several dimensions. It provided a semantically enriched, scalable, and user-friendly environment for integrating and analyzing health data from multiple sources (Adewale, Olorunyomi & Odonkor, 2023, Hamza, *et al.*, 2023, Okeke, *et al.*, 2023). The system's accuracy, responsiveness, and ability to support complex reasoning make it highly suitable for applications such as patient stratification, disease monitoring, and clinical decision support. Its flexibility and extensibility ensure that it can evolve with the growing demands of modern healthcare systems, ultimately supporting better outcomes through data-driven care delivery and research.

2.5 Discussion

The development of a knowledge graph for integrating health data from multiple sources presents a transformative approach to addressing the complexity, fragmentation, and semantic inconsistencies that plague modern healthcare systems. The use of knowledge graphs offers several significant benefits that enhance healthcare delivery, support clinical decision-making, and enable advanced health analytics (Odunaiya, Soyombo & Ogunsola, 2022, Ogbuagu, *et al.*, 2022, Okeke, *et al.*, 2022). However, alongside these benefits are critical limitations and challenges that must be addressed to ensure sustainable, ethical, and effective deployment. This discussion highlights the strengths of the knowledge graph approach, outlines its limitations, and examines the ethical and legal dimensions surrounding the integration of sensitive health data.

One of the most profound benefits of using a knowledge graph in healthcare lies in its ability to unify heterogeneous datasets into a coherent, semantically rich representation. Traditional healthcare databases often operate in silos, with disparate systems handling different types of information—diagnoses, medications, imaging data, genetic information, and more—each using its own structure, standards, and terminologies (Akinsooto, Pretorius & van Rhyn, 2012, Balogun, Ogunsola & Ogunmokun, 2022). Knowledge graphs overcome this fragmentation by leveraging semantic web technologies to represent and interlink data in a machine-understandable format. This enables systems to interpret not just the syntax of data but also its meaning, improving interoperability and enabling deeper insights across datasets. For instance, by linking a patient's diagnosis, lab results, and

treatment history across systems, a knowledge graph facilitates a more holistic understanding of the patient's condition, leading to more personalized and accurate care.

Another key advantage is the support for complex querying and reasoning. Knowledge graphs allow for the representation of not only explicit relationships but also inferred knowledge through ontological reasoning. Using standardized vocabularies such as SNOMED CT, LOINC, and ICD-10, the system can infer new relationships, identify patterns, and support decision-making in ways that are not possible with traditional relational databases (Amafah, *et al.*, 2023, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023, Ezeamii, *et al.*, 2023). For example, a clinician could query the graph to find all patients at risk for metabolic syndrome based on a combination of factors, even if the syndrome has not been formally diagnosed. The system can deduce this based on high blood pressure, elevated glucose levels, and obesity indicators—information drawn from various sources and semantically integrated into the knowledge graph.

The flexibility and extensibility of knowledge graphs are also notable. Healthcare is an evolving field with new diseases, treatments, and standards emerging regularly. Knowledge graphs accommodate this evolution by allowing for schema changes without the need for major redesigns. New entities, relationships, and attributes can be introduced seamlessly, supporting scalability and future-proofing the system. This is especially important as healthcare systems increasingly integrate patient-generated data from wearables, mobile apps, and remote monitoring devices (Chukwuma-Eke, Ogunisola & Isibor, 2022, Collins, Hamza & Eweje, 2022).

Despite these advantages, there are several limitations and potential challenges associated with the development and implementation of healthcare knowledge graphs. One of the primary challenges is data quality. Health data, particularly from unstructured sources such as clinical notes, can be noisy, incomplete, or inconsistent. Errors introduced during data entry or conversion can propagate through the system, potentially leading to inaccurate insights. Ensuring data quality through validation, normalization, and curation is a resource-intensive process that requires significant domain expertise and computational support (Elumilade, *et al.*, 2023, Ewim, *et al.*, 2023, Eyeghre, *et al.*, 2023).

Semantic alignment is another challenge. Integrating data from multiple sources often involves reconciling different terminologies, ontologies, and data models. Even widely accepted standards such as SNOMED CT and LOINC may represent concepts differently or at varying levels of granularity. Mapping between these standards can be complex and error-prone, requiring sophisticated ontology alignment techniques and human oversight. Without proper alignment, the knowledge graph may contain redundant, conflicting, or ambiguous data that undermines its utility (Chukwuma-Eke, Ogunisola & Isibor, 2023, Fiemotongha, *et al.*, 2023).

The computational cost associated with constructing and maintaining a knowledge graph is also significant. Processes such as entity recognition, relationship extraction, ontology mapping, and reasoning require advanced algorithms and considerable processing power, particularly when dealing with large-scale health datasets. Additionally, real-time or near-real-time applications demand efficient indexing and querying mechanisms to ensure acceptable system performance (Chukwuma-Eke, Ogunisola & Isibor, 2021, Dirlikov, 2021). These requirements can pose barriers for

smaller healthcare providers with limited technical infrastructure or budgets.

Beyond technical and operational challenges, there are critical ethical and legal considerations that must be addressed when developing and deploying health knowledge graphs. Data privacy is paramount, as the system deals with highly sensitive patient information. Even with de-identification techniques, the integration of multiple datasets increases the risk of re-identification, particularly when demographic, geographic, or temporal data is included. Therefore, strict privacy-preserving mechanisms must be implemented, including encryption, access control, differential privacy, and audit logging to monitor data usage (Balogun, Ogunisola & Ogunmokun, 2022, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022).

Legal compliance is another area of concern. Healthcare knowledge graphs must adhere to national and international regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in the European Union. These laws govern data collection, storage, sharing, and consent, imposing obligations on healthcare organizations to protect individual rights and ensure transparency. Implementing these legal safeguards within a complex data integration framework can be challenging and requires legal and technical collaboration (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023, Collins, *et al.*, 2023).

Informed consent becomes more complex in the context of knowledge graphs. Patients may provide consent for their data to be used for specific purposes, but knowledge graphs can derive new information and insights that were not anticipated at the time of consent. This raises ethical questions about the scope of consent and the potential for unintended uses of data. Dynamic consent models, where patients can continuously manage and update their consent preferences, are emerging as a possible solution but are not yet widely adopted (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Elujide, *et al.*, 2021).

Bias and fairness also warrant attention. Health data often reflect existing inequalities in healthcare access, diagnosis, and treatment. If not addressed, these biases can be embedded into the knowledge graph and perpetuate health disparities. For example, if minority populations are underrepresented in the training data used to build inference models, the resulting knowledge graph may not accurately reflect their health needs. Ensuring that the data is representative, and that algorithms are audited for bias, is essential for promoting equity in healthcare applications (Hamza, *et al.*, 2023).

There is also the issue of trust. For clinicians and patients to rely on knowledge graph-driven systems, they must be transparent and explainable. Users need to understand how conclusions are derived and have confidence in the system's reliability. This requires not only clear visualizations and documentation but also mechanisms for users to trace the provenance of information and verify its sources. Building this trust is essential for adoption and meaningful use (Atta, *et al.*, 2021, Bidemi, *et al.*, 2021, Elumilade, *et al.*, 2022).

In summary, while the development of a knowledge graph for integrating health data from multiple sources offers substantial benefits in terms of interoperability, reasoning, and personalized care, it also introduces a host of technical, ethical, and legal challenges. Addressing these challenges requires a multidisciplinary approach involving data

scientists, healthcare professionals, ethicists, and legal experts (Chukwuma-Eke, Ogunsola & Isibor, 2022, Dirlikov, *et al.*, 2021). By carefully managing data quality, ensuring semantic alignment, implementing robust privacy protections, and promoting transparency and fairness, healthcare systems can harness the full potential of knowledge graphs to advance the future of integrated, intelligent, and equitable care.

2.6 Future Work

The development of a knowledge graph for integrating health data from multiple sources represents a significant advancement in healthcare informatics, offering structured, semantically rich, and interoperable representations of complex health information. However, the current system, while robust, leaves room for further enhancement. Future work in this area must address several strategic areas to build upon the existing framework and ensure its alignment with emerging technological trends, clinical needs, and privacy standards (Ewim, *et al.*, 2023, Eyeghre, *et al.*, 2023, Ezeamii, *et al.*, 2023). Key directions for future development include the integration of federated learning and privacy-preserving techniques, expansion to a broader array of data sources, and the enhancement of real-time capabilities for clinical and public health applications.

One of the most pressing priorities for future work involves addressing the challenges of data privacy and security in an increasingly connected and data-intensive healthcare ecosystem. Integrating federated learning with the knowledge graph framework offers a promising pathway to reconcile the need for collaborative health data analytics with strict privacy regulations (Al Zoubi, *et al.*, 2022, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). Federated learning is a decentralized machine learning paradigm that enables multiple institutions to collaboratively train models without sharing raw data. Instead, models are trained locally on-site, and only the updates (e.g., gradients or model weights) are shared and aggregated centrally. Applying this approach to a knowledge graph environment could allow hospitals, research institutions, and healthcare networks to contribute to collective intelligence while maintaining strict control over their proprietary or sensitive patient data (Aniebonam, *et al.*, 2023, Balogun, Ogunsola & Ogunmokin, 2023, Fagbule, *et al.*, 2023).

By combining federated learning with the semantic richness of knowledge graphs, it becomes possible to perform advanced analytics, predictive modeling, and population health monitoring across institutional boundaries without compromising individual privacy. This hybrid approach also has the potential to improve the generalizability of clinical models, as data diversity increases without the need to centralize datasets. Additionally, implementing privacy-preserving technologies such as differential privacy, homomorphic encryption, and secure multiparty computation will further reinforce the trustworthiness of the system (Akinsooto, 2013, Chukwuma, *et al.*, 2022, Elumilade, *et al.*, 2022). These methods ensure that even when data is used in aggregate analyses or machine learning workflows, the risk of identifying individual patients is minimized. Future implementations should prioritize embedding these techniques natively within the knowledge graph architecture, rather than treating them as external add-ons, ensuring that privacy remains a core design principle.

Another critical direction for future work is the expansion of

data sources feeding into the knowledge graph. Currently, many health knowledge graphs are constructed primarily from traditional sources such as electronic health records (EHRs), clinical notes, laboratory test results, and billing systems. While these sources are foundational, they represent only a fraction of the information relevant to comprehensive patient care and public health (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023, Egbuhuzor, *et al.*, 2023, Fiemotongha, *et al.*, 2023). A more expansive vision includes the integration of emerging data streams such as wearable sensor data, genomic data, social determinants of health (SDOH), environmental exposure data, mobile health (mHealth) applications, and patient-reported outcomes (PROs).

Incorporating wearable device data, for instance, allows for continuous and passive monitoring of key physiological indicators such as heart rate, sleep patterns, physical activity, and glucose levels. These real-time measurements can provide early warning signs of deterioration, complementing episodic data captured during clinical visits. Genomic data integration can enable personalized medicine approaches, offering insights into patient susceptibility to diseases, drug metabolism, and treatment response (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Elujide, *et al.*, 2021). Environmental and SDOH data, such as air quality indices, neighborhood safety, access to healthy food, education level, and income, provide a more contextualized view of patient health and can significantly influence care plans and risk assessments.

Future work must focus on building robust pipelines for harmonizing, semantically annotating, and linking these diverse data types. This will involve the use of domain-specific ontologies, expansion of existing vocabularies, and the development of new schemas to model previously underrepresented dimensions of health (Balogun, Ogunsola & Ogunmokin, 2021, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). Cross-domain interoperability will become a priority, as the integration of non-traditional data requires collaboration between healthcare professionals, data scientists, environmental researchers, sociologists, and technologists. Such multidisciplinary coordination will ensure that the knowledge graph evolves into a truly comprehensive, longitudinal, and contextualized health knowledge ecosystem.

In addition to expanding the types of data integrated, enhancing real-time capabilities is another vital direction for future work. Current implementations of health knowledge graphs often operate on batch-processed or periodically updated data, which limits their utility in time-sensitive scenarios such as emergency care, critical disease surveillance, and pandemic response. Real-time integration and reasoning capabilities would allow the knowledge graph to serve as a live, continuously updating resource that reflects the latest patient status, lab results, and clinical actions (Ayodeji, *et al.*, 2023, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023, Fiemotongha, *et al.*, 2023).

Achieving this level of responsiveness requires several technological upgrades. First, stream processing technologies such as Apache Kafka, Apache Flink, or Spark Streaming can be used to ingest data in real time from EHRs, monitoring devices, and external systems. These platforms support scalable, low-latency data pipelines that can feed directly into the semantic processing layer. Second, real-time ontology reasoning remains a challenging but essential area for

innovation (Chukwuma-Eke, Ogunsola & Isibor, 2022, Govender, *et al.*, 2022). Traditional OWL-based reasoners may not scale efficiently for streaming data; thus, future research should explore lightweight or approximate reasoning methods that balance accuracy with performance. In parallel, advances in edge computing can play a supportive role in enabling real-time capabilities. By deploying miniaturized versions of the knowledge graph or inference engines at the edge—within hospitals, clinics, or even on patient devices—initial processing and reasoning can be performed locally. This reduces the time needed for decision support and decreases dependency on central infrastructure, which is especially beneficial in rural or resource-constrained settings (Ayo-Farai, *et al.*, 2023, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2023).

Real-time visualization tools are another important component. Dashboards that dynamically reflect updates in patient health status, emerging disease trends, or changes in care plans can empower clinicians, public health officials, and administrators to respond swiftly. Visualization layers should be designed to highlight actionable insights and include alert mechanisms when specific thresholds or patterns are detected. For example, a rise in temperature and respiratory rate captured from wearable devices, combined with recent exposure history and geolocation data, could trigger an alert for possible influenza or COVID-19 infection, prompting immediate investigation and containment efforts (Akinsooto, De Canha & Pretorius, 2014, Balogun, Ogunsola & Ogunmokin, 2022).

Another frontier of real-time application lies in emergency response systems and intensive care units (ICUs), where decision-making relies heavily on up-to-the-minute data. Integrating ICU monitors and point-of-care diagnostic devices with the knowledge graph can support intelligent alert systems that detect early signs of sepsis, heart failure, or respiratory distress. Such real-time, AI-augmented surveillance can be lifesaving, but demands rigorous validation, redundancy protocols, and fail-safes to ensure reliability and trustworthiness (Collins, Hamza & Eweje, 2022, Egbuhuzor, *et al.*, 2021).

In conclusion, the future development of a knowledge graph for integrating health data from multiple sources hinges on expanding its capabilities to meet the evolving demands of healthcare delivery, research, and public health. Federated learning and privacy-preserving methods must be embedded to protect individual rights while enabling collaborative intelligence. The inclusion of novel data sources will provide a richer, more complete picture of health, allowing for better prediction, prevention, and personalization (Ewim, *et al.*, 2022, Ezeanochie, Afolabi & Akinsooto, 2022). Enhancing real-time responsiveness will ensure that the system supports critical, time-sensitive interventions and continuous health monitoring. Together, these advancements will position the knowledge graph not only as a repository of integrated data, but as an intelligent, adaptive, and secure infrastructure for 21st-century healthcare.

3. Conclusion

The development of a knowledge graph for integrating health data from multiple sources represents a significant advancement in healthcare informatics, offering a comprehensive and semantically enriched framework for unifying fragmented and heterogeneous health information. This work has demonstrated how knowledge graphs can

effectively bridge the gaps between disparate data systems by leveraging standardized ontologies, semantic web technologies, and graph-based storage and querying mechanisms. Through the integration of diverse datasets—ranging from electronic health records and laboratory test results to patient demographics and clinical notes—the system provides a holistic, interoperable, and machine-understandable representation of healthcare data. The architecture supports complex querying, semantic reasoning, and dynamic visualization, facilitating advanced health analytics, personalized care, and data-driven decision-making.

The implementation has shown strong performance in terms of accuracy, scalability, and usability, proving its potential in real-world scenarios such as patient stratification, disease monitoring, and risk prediction. Case studies and evaluations have illustrated the system's ability to synthesize information across multiple domains, enabling clinicians and researchers to derive meaningful insights that would otherwise remain obscured in isolated silos. Furthermore, the inclusion of standardized vocabularies such as SNOMED CT, LOINC, and ICD-10 ensures semantic consistency and facilitates communication across systems and institutions. The framework also provides a solid foundation for future innovations, including the incorporation of federated learning for collaborative model training, privacy-preserving technologies for ethical data use, and real-time data integration for immediate clinical applicability.

The implications of this work for healthcare, research, and policy are substantial. In the clinical setting, the knowledge graph enables more accurate diagnoses, proactive interventions, and personalized treatment plans by offering a unified view of a patient's health journey. For researchers, it opens new avenues for longitudinal studies, comorbidity analysis, drug interaction monitoring, and the discovery of novel disease associations through knowledge inference. In the realm of public health, it supports population-level surveillance, resource allocation, and the identification of at-risk communities based on integrated environmental, behavioral, and clinical data. From a policy perspective, the knowledge graph approach aligns with global trends toward interoperability, transparency, and value-based care. It encourages the adoption of standardized data models and promotes ethical data governance, offering a strategic tool for shaping health data regulations and ensuring equitable access to data-driven healthcare innovations.

In conclusion, developing a knowledge graph for integrating health data from multiple sources is a transformative step toward a more connected, intelligent, and responsive healthcare system. By continuing to enhance this framework with cutting-edge technologies and ethical safeguards, it will be possible to unlock the full potential of health data, improving outcomes for individuals and populations alike.

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