

# Generative AI as a Catalyst for Interoperability and Data-Driven Decision Support in Healthcare Systems of Developing Countries

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**Abstract**—Interoperability across heterogeneous information systems remains a persistent challenge, particularly in resource constrained contexts where infrastructures are fragmented and data formats remain incompatible. This study introduces a novel methodology that integrates generative Artificial Intelligence (AI) with the urbanization of information systems to enable scalable and seamless interoperability. The approach employs AutoGen AI, an open-source orchestration framework powered by Large Language Models (LLMs), specifically GPT-4o, to coordinate task-specific intelligent agents for data extraction, transformation, and harmonization. By converting disparate data into a standardized JSON representation, the architecture resolves both syntactic and semantic inconsistencies while simultaneously emphasizing multi-agent concurrency, distributed orchestration, and computational scalability, resulting in improved throughput, reduced latency, and enhanced robustness. A real-world healthcare case study is presented to illustrate the framework's effectiveness: heterogeneous clinical datasets were unified into a coherent JSON structure, enabling accurate health indicator generation and reliable decision support. Experimental results demonstrate substantial improvements in system connectivity, processing efficiency, and integration reliability, with potential to generalize far beyond the medical sector. Moreover, the methodology incorporates advanced prompt engineering and context-aware dialogue design, minimizing model hallucinations and ensuring trustworthy outputs in LLM-driven processes. Overall, the study positions generative AI not only as a promising solution for interoperability in health informatics, but also as a transformative paradigm for intelligent system integration across diverse domains characterized by distributed, heterogeneous environments.

**Keywords**—Decision support systems; interoperability; generative Artificial Intelligence; Large Language Model (LLM); heterogeneous data sources; information system

## I. INTRODUCTION

The integration and interoperability of Health Information Systems (HIS) remain pressing challenges, particularly in developing countries where infrastructures are fragmented and data ecosystems are heterogeneous. As healthcare organizations increasingly adopt diverse digital platforms, the demand for seamless system communication and reliable data exchange becomes more urgent. Effective interoperability is not only important for consistent and accurate information sharing, but also for enhancing patient care, optimizing clinical workflows, and strengthening evidence-based decision-making [1]. How-

ever, the prevalence of autonomous, distributed, and technologically diverse data sources exacerbates these challenges, often resulting in inconsistent health indicators, organizational misalignments, and limited decision-making capacity [2].

To address these limitations, innovative and flexible approaches are required that can connect fragmented infrastructures while adapting to evolving requirements. In this study, we propose a novel methodology that leverages generative AI, specifically LLMs, to achieve interoperability across distributed medical data sources. Central to this approach is the concept of urbanization of information systems, a strategic framework for modernizing legacy infrastructures incrementally. By reducing the reliance on costly system replacements, this strategy supports the sustainable integration of cutting-edge AI-driven technologies into existing health ecosystems.

The proposed solution is operationalized through AutoGen AI, an open-source orchestration framework for LLM powered applications, implemented via AutoGen Studio and GPT-4o. It employs a network of intelligent agents to collect, transform, and harmonize heterogeneous datasets, thereby constructing a unified and machine-compatible platform. The normalized data is integrated into a central repository, enabling real-time analytics, computationally efficient processing, and reliable decision support.

This study proposes a scalable generative AI-driven interoperability methodology for fragmented healthcare information systems in developing countries, grounded in an urbanization information system strategy and implemented through AutoGen AI and GPT-4o. The contributions include a modular multi-agent harmonization workflow, a canonical JSON standardization layer for KPI-oriented decision support, and a real-world validation using precision, recall, and record-consistency metrics.

This methodology has been validated through a comprehensive real-world healthcare case study, which demonstrates its effectiveness in addressing interoperability challenges at scale. The findings highlight the role of generative AI as a catalyst for dynamic, scalable, and adaptive integration, yielding substantial improvements in data exchange, analytics efficiency, and healthcare service delivery. More broadly, this work underscores the potential of intelligent multi-agent orchestration as a generalizable paradigm for system interoperability in heterogeneous and distributed environments.

The remainder of this study is structured as follows: Section II provides a literature review covering heterogeneous data interoperability, generative AI in healthcare, and urbanization strategies for HIS. Section III details the proposed architectural framework and its technical components. Section IV discusses the results of the case study, presenting validation outcomes and key insights. Finally, Section V concludes by summarizing the contributions and outlining directions for future research.

## II. LITERATURE REVIEW

This section presents related studies in the literature on interoperability approaches for heterogeneous data sources, the interoperability of medical data sources, and the urbanization of information systems.

### A. Interoperability of Data Sources

With the rise of the Internet and Intranet, the exchange and sharing of information from distributed, autonomous, and heterogeneous data sources have become a fundamental requirement [2]. In such scenario, simultaneous access to multiple sources is often necessary, as they contain relevant and complementary information, emphasizing the importance of interoperability among these systems. Consequently, achieving interoperability and integrating data sources to provide users with a unified access interface is a significant challenge. This challenge encompasses three main aspects: data heterogeneity, source autonomy, and the evolving nature of sources [3].

Integrating disparate information systems requires addressing interoperability issues stemming from various forms of heterogeneity, including hardware platforms, software systems, and especially semantic differences. According to [4], interoperability entails collaboration between applications, specifically referring to the ability of independently developed tools to cooperate and function together. Interoperability means that source A can request and receive services from source B and use their features, thereby establishing interoperability between sources A and B. Data exchange represents a limited form of interoperation, where system A periodically transfers data to system B. Generally, two information systems are considered interoperable if they meet certain criteria: the ability to exchange messages and requests or the ability to work together as a single unit to accomplish a common task [4].

As noted by [5], two information systems are interoperable if: 1) they can exchange messages and requests; 2) they can function as a unit to achieve a shared task. These conditions imply that interoperable systems can leverage each other's functions, act as both clients and servers, and communicate effectively even if their internal components are incompatible. In [4], the authors outline several levels of interoperability:

- The most internal level within the architecture of data management systems, facilitated by specialized gateways programs that establish connections between systems, enabling one system (A) to access data from another (B). Such gateways are already available for many database management systems (DBMS).
- The intermediate level, which involves deploying a multi-database system. This software layer allows users to define their persistent views or perspectives

on a set of databases. These systems ensure appropriate connections based on defined views, enabling distributed data access but not managing consistency constraints across different data sources.

- The highest level, where a global system is developed atop existing systems, ensuring overall coherence among them and providing the desired level of integration for a set of data sources.

Interoperability aims to enable effective communication between heterogeneous data models, ensure the integration of functionalities from distinct applications, and support coordination, data dissemination, training, and process validation. However, achieving interoperability is often hindered by three core challenges: conceptual, technological, and organizational barriers. To address these challenges and establish interoperability across multiple data sources, three main strategies can be utilized: the integrated approach, the unified approach, and the federated approach (see Fig. 1).

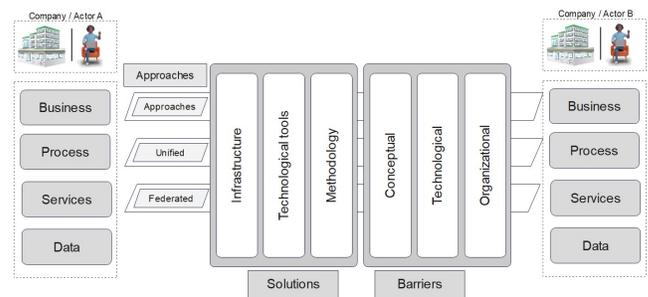


Fig. 1. Interoperability: Levels, barriers, approaches, and solutions.

### B. Interoperability and Decision Support

Decision support information systems are a solution to the problems of integration and interoperability of heterogeneous information systems [6]. A decision support system is a truly integrated system that leverages a wide range of tools from various origins, such as specialized software, powerful machines, query tools, DBMS, etc., [7]. It is an information system dedicated to decision-making applications. These applications provide a set of information and tools made available to decision-makers to effectively support the decision-making process. Thus, it is a decision support system aimed at facilitating decision-making based on a wealth of heterogeneous data sources. Implementing such a system is a complex task that involves numerous challenges [8]. Its rigorous design is complicated by the multiplicity of data sources and the so-called complex data that may appear in non-numerical or non-symbolic [9].

A decision support system cannot be built independently of existing systems. Its development process requires a comprehensive vision of operational information systems. Two major phases characterize this process: the information extraction phase and the exploitation phase of the aggregated data from the warehouse.

The first phase involves extracting information from the original data sources, which are often heterogeneous and even distributed. This phase culminates in the construction of a data

warehouse. The integration module addresses the heterogeneity issues of various sources by incorporating them into a global source (GS). This global source is virtual, as the data used for decision-making remains stored in the original data sources and is only extracted during the warehouse update process. The construction module extracts relevant decision-making data and transfers it to the data warehouse while retaining, if necessary, changes in data states. The data warehouse consolidates extracts from source databases that are useful to decision-makers. It serves as a centralized collection of data, a specifically designed database, or a repository for Decision Support Information System (DSIS) applications.

The exploitation phase is handled by database experts. Their role involves restructuring the data in the warehouse to meet the needs of decision-makers. The reorganization module produces data marts. This reorganization aims to efficiently support data query and/or analysis processes. These data marts can be used by online analytical processing (OLAP) applications. To achieve this, the data imported into the marts is organized in a multidimensional manner. Data marts are derived from the warehouse and are tailored to specific analytical needs. The query module manipulates multidimensional data to analyse past trends and support decision-making. The data is represented in forms that facilitate comprehension and manipulation by non-technical decision-makers (tables, charts, maps, etc.).

A viable decision support system requires a specific and scalable data model. Its architecture demonstrates the management of two distinct configurations: the data repository (DW and DM) on the storage side (server), which allows access to all information, and the transactional side (client), which comprises analytical tools that ensure document presentation via graphical interfaces.

### C. Generative AI and LLMs for Interoperability

Interoperability across heterogeneous data sources remains a major challenge, especially when information is embedded in unstructured formats or spread across distributed environments. Traditional approaches, ETL pipelines, ontology-based mappings, middleware, and decision support tools, require substantial human effort and often deliver limited scalability. Generative AI, and more specifically LLMs, has emerged as a promising solution to simplify multi-step processes, harmonize diverse inputs, and enable semantic alignment across systems.

Recent literature highlights the growing role of LLMs in data integration. In [10], the authors demonstrate their ability to facilitate entity extraction and resolution from heterogeneous sources by combining automation with human expertise in semi-autonomous pipelines. Similarly, [11] and [12] underline that, despite contextualization and reformulation capabilities, LLMs still struggle with private data access, discrimination between multiple sources, and scalability challenges. In the field of system interoperability, [13] investigates the translation of API calls into natural language.

Schema alignment and ontology matching also benefit from LLMs. In [14], the authors employ LLMs combined with Retrieval-Augmented Generation (RAG) to semi-automate schema harmonization, while [15] introduce Harmonia, an

interactive framework integrating LLM reasoning with harmonization primitives. More recently, [16] evaluated LLMs4OM for ontology matching, showing mixed performance compared to traditional methods. In [17], the authors highlight that LLMs can generate Common Data Elements (CDEs) for biomedical research, though with modest interoperability scores. Additionally, [18] present TeabERT, a knowledge-infused model improving medical entity normalization in multilingual contexts.

In healthcare, several studies demonstrate the effectiveness of LLMs for transforming clinical texts into standardized formats such as HL7 FHIR. In [19], [20], and [21], the authors show that, by using prompts, annotations, clustering, or RAG, LLMs can achieve high accuracy in generating structured FHIR resources, sometimes surpassing traditional NLP. Complementary work by [22] illustrates their potential for transforming laboratory results and mapping diagnostic codes, while [23] show how they can analyze echocardiogram reports to support natural language querying. These applications demonstrate the potential of LLMs to simplify data exchange, improve decision-making, and reduce the need for overly complex standardization.

Beyond clinical texts, [24] and [25] emphasize the importance of common type systems and ontologies to ensure semantic interoperability across biomedical terminologies. In [26], the authors propose retrieval architectures combining NLP with database technologies, while [27] show how ETL, NLP, and semantic web methods can achieve technical, syntactic, and semantic integration across healthcare institutions. Challenges remain in multilingual interoperability and ontology alignment, requiring closer collaboration between NLP and applied ontology [25].

Practical implementations further confirm these insights. In [28], the authors explore FHIR-enabled machine learning systems for improved interoperability and analysis, while [29] proposes a middleware to integrate structured sensor data with unstructured indigenous knowledge for environmental monitoring. Generative AI also shows strong potential in automating workflows and improving patient care [30][31], creating new data forms including text, images, and music [32], and advancing areas such as medical imaging, protein prediction, clinical documentation, and drug design [33][34].

Noteworthy generative models include GPT-4 [35], Claude [36], and PaLM2 [37], which have significantly advanced natural language processing and interoperability applications. Research by [38] shows the widespread adoption of ChatGPT among medical students in Nigeria, underscoring its accessibility and perceived utility. Furthermore, [39] highlight its ability to improve patient understanding and adherence to treatment.

Finally, new AI-driven methods are extending beyond data integration into clinical applications. In [40], the authors propose a privacy-preserving system for abnormal gait detection using encrypted video capture and ML classification. In [41], the authors develop a gait-based analysis model for Parkinson's disease with high accuracy, while [42] survey intelligent models combining NLP, deep learning, and speech recognition for neurological disease interpretation.

Overall, LLMs and generative AI represent a transformative force. They address computational challenges of interoperability in heterogeneous data environments and demonstrate

strong potential in healthcare applications, from clinical documentation to advanced diagnostics. The remaining challenges include prompt dependency, token limits, privacy preservation, and standardization, but evidence consistently shows their ability to bridge gaps between complex informatics infrastructures and practical use of healthcare.

*1) Critical synthesis and research gap:* Overall, the literature shows that interoperability is commonly addressed through three major directions: i) engineering-based solutions such as ETL pipelines and middleware, ii) semantic approaches relying on ontologies and mapping rules, and iii) decision support architectures built on data warehouses. These methods can be effective in stable and well resourced environments, yet they often require substantial manual effort, rigid schema assumptions, and continuous maintenance, which limits their scalability in rapidly evolving and resource constrained settings. More recently, LLM-based approaches have introduced promising flexibility by enabling semantic reasoning and dynamic transformation; however, they remain sensitive to prompt quality, context limitations, privacy constraints, and the risk of hallucinated outputs. Taken together, these limitations motivate the need for a framework that combines the adaptability of generative AI with a structured modernization strategy, enabling scalable harmonization without requiring disruptive infrastructure replacement.

#### *D. The Urbanization Approach in Health Information Systems*

The Urbanization of Health Information Systems is a strategic method designed to enhance the interoperability, agility, and efficiency of health information systems, particularly in developing countries such as Cameroon. According to the World Health Organization (WHO), health information systems must align with public health strategies to ensure their effectiveness. However, the systems currently deployed in contexts like Cameroon are often inadequate, poorly adapted to strategic goals, and suffer from limited interoperability [43]. These systems are fragmented, unstable in the face of organizational and regulatory changes, and difficult to use in collaborative processes [2].

Health systems in developing countries lack coherent digitization. They are characterized by the absence of reliable and accessible data, as well as fragmented and unsecured information systems [44]. These challenges hinder coordination among healthcare institutions, thus impeding the effective implementation of public health policies.

Inspired by urban city planning, the urbanization of information systems aims to modernize existing systems by aligning organizational objectives with technological opportunities while adhering to common rules to ensure quality and consistency [45]. This approach promotes an open, scalable, and adaptable architecture, avoiding costly system overhauls [46].

In the context of health information systems, urbanization entails the development of a national urbanization strategy, supported by general rules for interoperability, accessibility, and security. Such a strategy facilitates information exchange and collaboration among public, private, and non-governmental actors [43]. It also supports the integration of technological

innovations such as the Internet of Medical Things (IoMT) and cyber-physical systems [47].

By combining top-down and bottom-up approaches, the urbanization of health systems can improve the quality of care, enhance professional practices, and foster patient engagement in managing their health. Achieving this requires an open architecture, semantic data management, and the integration of decision-support tools [48].

*1) Positioning of the proposed approach:* The urbanization of information systems offers a well-established strategy for incrementally modernizing healthcare infrastructures, particularly in developing countries. However, existing studies provide limited operational mechanisms for automating semantic harmonization across heterogeneous and autonomous data sources. In this work, generative AI is introduced as the enabling layer that translates urbanization principles into practice through intelligent multi-agent orchestration, thereby connecting strategic modernization goals with concrete interoperability execution.

#### *E. Comprehensive Summary of Key Articles on Interoperability with Generative AI*

To make the comparison across existing studies more explicit, Table I synthesizes representative works and highlights not only their contributions, but also recurring limitations, particularly in terms of scalability, semantic consistency, and feasibility in low-resource environments.

The main goal of this study is to design an intelligent tool based on AutoGen AI and GPT-4o, capable of producing reliable outputs with high accuracy and reduced error rates in interoperability driven tasks. Achieving this performance relies on optimized prompts, structured multi-agent workflows, and validation mechanisms designed to mitigate hallucinations and ensure consistent transformations.

### III. PROPOSED ARCHITECTURAL FRAMEWORK

The methodology presented in this study leverages generative Artificial Intelligence, particularly large language models, to address challenges related to the interoperability and integration of heterogeneous and distributed medical data sources in developing countries.

AutoGen AI, an open-source framework by Microsoft, enables collaborative multi-agent systems using large language models to solve complex tasks. It integrates customizable agents, tools, and human input, supporting scalable deployment and research innovation.

The main goal of this study is to demonstrate how generative AI, specifically through Microsoft's Autogen AI, can be applied to overcome interoperability issues associated with disparate medical data. This approach facilitates the seamless integration of information from diverse sources into a centralized environment while ensuring the consistency and quality of processed data.

The methodology is primarily based on generative AI technologies, notably Autogen AI, structured around an agent-based approach for each phase of data processing. These agents are specifically configured to perform various tasks, ranging

TABLE I. COMPREHENSIVE SUMMARY OF KEY ARTICLES ON INTEROPERABILITY WITH GENERATIVE AI

Citation Key	Description	Limitations
[26]	Proposes architectures that integrate NLP with databases for querying heterogeneous clinical data sources.	Limited adaptability to evolving data formats and semantic inconsistencies.
[25]	Discusses linguistic challenges in biomedical ontologies and emphasizes semantic alignment.	Persistent misconceptions in ontologies and difficulty in integrating multiple terminologies.
[27]	Uses ETL, NLP, and semantic web technologies to improve syntactic and semantic interoperability.	Lack of standard clinical representation and issues with multi-language support.
[28]	Explores machine learning systems leveraging FHIR for clinical interoperability.	Challenges include scalability and lack of robust clinical validation.
[29]	Proposes middleware architecture to unify structured and unstructured environmental data using semantic tools.	Limited scalability and potential domain specificity.
[22]	LLMs used to extract structured insights from unstructured clinical records like lab results and diagnosis codes.	Complexity in mapping across coding systems.
[23]	Uses LLMs to query echocardiogram histories with natural language.	Focused on specific report types.
[10]	Applied LLMs for entity extraction and resolution from heterogeneous sources in higher education; designed semi-autonomous pipelines combining automation and human expertise.	Manual integration remains time-consuming; success highly dependent on prior modeling decisions.
[11]	Drew lessons from data integration research; explored LLMs for contextualization and reformulation in multi-source access.	Difficulty handling private data, discriminating between multiple sources, and achieving scalability.
[19][20]	Used multiple prompts and manual annotations (3,671 clinical text excerpts) to transform clinical texts into FHIR resources with GPT-4, Llama-2-70B, and Falcon-180B; compared with existing NLP tools.	High dependency on prompt design; token limitations; incomplete medical terminologies; risk of hallucinations.
[21]	Employed clustering, prompt engineering, and RAG to transform structured clinical data into HL7 FHIR format.	Difficulty linking complex resources; limited scalability; lack of user-friendly interfaces.
[14]	Applied LLMs and RAG to semi-automate schema alignment in healthcare data integration.	Preliminary research; limited efficiency and scalability.
[15]	Proposed an interactive harmonization system combining LLM reasoning, harmonization primitives, and a user interface.	Process remains complex and time-intensive; further research required.
[16]	Developed an ontology matching framework using RAG + LLM, including confidence filtering and post-processing.	Limited context length; risk of hallucinations; underperformed traditional methods on Bio-ML tasks.
[17]	Leveraged LLMs with human-in-the-loop (HITL) to generate Common Data Elements (CDEs) from biomedical ontologies and corpora.	Low mapping efficiency (32.4%); modest interoperability score (53.8/100); manual revisions still required.

from converting data into uniform formats to managing interoperability within a data warehouse. This structure not only optimizes the flow of information but also ensures efficient data harmonization, thereby enabling in-depth analyses and informed decision-making.

By integrating these advanced technologies, our methodology aims to establish an interoperable data ecosystem that meets the specific needs of healthcare systems in developing countries. It also provides a framework for continuous innovation and the improvement of medical care practices, thereby contributing to enhanced healthcare quality and better patient outcomes.

*A. An Approach Based on the Urbanization of Information Systems*

The aim of medical data interoperability is to federate data sources for effective decision-making. To achieve this, the Urbanization of Information Systems methodology is adopted, focusing on four levels of concern: business, functional, application, and technical. It balances organizational strategy implementation, system consistency, efficiency, and cost-effective integration of new technologies.

This structured approach involves key steps, including study planning, strategic axis review, current situation analysis, strategy definition, convergence planning, strategy publication, and updates. Applied to medical data interoperability, this methodology results in a framework (Fig. 2) tailored to the integration of distributed and heterogeneous data sources.

The proposed model consolidates consistent medical data into a decision-support-oriented data warehouse. It features: i) Environmentally Open Architecture (Facilitates sharing and integration of distributed data across healthcare stakeholders), ii) Integrated Architecture (Unifies data from autonomous sources into a flexible ecosystem), and iii) Decision-Support Architecture (Provides tools like indicators and statistical analysis for informed decision-making). This system serves as a monitoring tool, offering valuable insights into medical phenomena while supporting strategic healthcare programs.

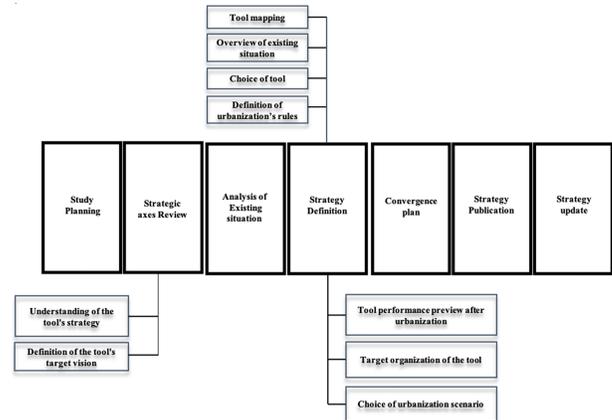


Fig. 2. Implementation of the proposed methodology for information system urbanization, supporting interoperability across heterogeneous data sources.

## B. Proposed Architectural Framework

This section addresses the overall architecture of the interoperability methodology for medical data sources, applicable in urban areas of developing countries. Fig. 3 given below provides an overview of our methodological approach.

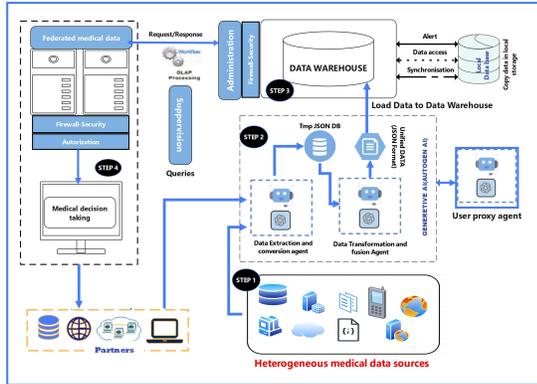


Fig. 3. Interoperability architecture for medical data sources based on the use of generative AI (AutoGen AI framework).

This architecture outlines a complex and structured process to manage the interoperability of heterogeneous medical data, ensuring its transformation, unification, and security with the help of generative AI. The ultimate goal is to create a federated and secure system capable of supporting precise and rapid medical decision-making by using unified and reliable data.

AutoGen AI, an open-source framework developed by Microsoft, streamlines the development of applications leveraging large language models through a multi-agent approach designed to collaboratively tackle complex tasks. These customizable agents, inspired by human teamwork dynamics, integrate LLMs, diverse tools, and human contributions to optimize their performance. AutoGen supports local development of multi-agent systems before deploying them in distributed cloud environments. This innovative platform establishes a synergistic framework where the collective capabilities of agents surpass those of any individual agent, thereby facilitating advanced research and development in artificial intelligence.

The AutoGen AI Framework leverages specialized agents and GPT-4o language models to automate the extraction, transformation, and integration of heterogeneous medical data into a unified platform. These agents perform specific tasks, such as data normalization, semantic mapping, and error correction, while the LLMs ensure contextual understanding and conversion of diverse formats. The system operates through orchestrated workflows with real-time feedback, enabling scalable and efficient data harmonization. This approach ensures compliance with regulatory standards and supports decision-making in healthcare systems.

*1) Architectural design rationale:* The architecture adopts a multi-agent design because interoperability is inherently a multi-step process that benefits from task specialization (extraction, normalization, semantic alignment, and validation). AutoGen AI was selected as it natively supports agent

orchestration, tool integration, and human supervision, which are essential for controlled execution in sensitive healthcare contexts. A canonical JSON representation was chosen as the primary interoperability layer due to its lightweight structure, ease of validation, and direct compatibility with downstream decision-support pipelines. Finally, the data warehouse component ensures long-term consistency and enables systematic KPI computation without disrupting operational source systems, in line with information-system urbanization principles.

*a) Step 1. Data extraction and conversion:* In this initial step, data is extracted from multiple heterogeneous and distributed medical sources. These sources may include databases, medical records management systems, connected devices, or even local files. The extracted data can be in various formats (e.g., XML, CSV).

The Data Extraction and conversion Agent is responsible for collecting the necessary and relevant data for interoperability. It verifies the formats of the extracted data and converts non-JSON formats into a standardized JSON format. The converted data is stored in a temporary database, TMP JSON DB, for further processing. The conversions are performed without any data loss or alteration.

*b) Step 2. Data transformation and fusion:* This phase is managed by the Data Transformation and Fusion Agent, which is responsible for data transformation, the handling of heterogeneity issues, and the fusion of multiple JSON files into a single coherent JSON file. The agent reads all JSON files stored in the TMP JSON DB and applies transformation rules provided via the prompt and the tool, including: i) identifying inconsistencies across files (e.g., variations in keys, data types, structures, etc.); ii) resolving these inconsistencies to ensure uniform, consistent, and interoperable outputs; iii) performing any additional operations required by the transformation rules.

Once the transformation is complete, the agent merges all files into a single JSON file, removing redundancies, null values, and non-pertinent data to produce a clear and unambiguous result. Owing to the quality of the preceding transformation, the fusion process is seamless and coherent. The merged file is stored in the Unified Data database and subsequently transferred to the Data Warehouse, which may be performed using a dedicated data-loading tool.

*c) Step 3. Storage and administration:* The unified data is transferred to a Data Warehouse for centralized and secure storage. Additionally, some data is saved in a local database for faster access or specific processing needs. This step also includes: Data Security (Access to the data is controlled through firewalls and authorization mechanisms); Monitoring (Continuous supervision ensures data integrity); Administration (Administrators manage data, configure access rules, and address user requests);

*d) Step 4. Data utilization for decision-making:* In this step, federated data is leveraged to support medical decision-making. ETL (Extraction, Transformation, Loading) tools are employed to extract the necessary indicators and convert them into actionable insights for clinical decisions. Health partners can also access the data for analysis or to offer additional services.

AutoGen AI plays a central role in steps 1, 2, and 3

by orchestrating the agents responsible for data extraction, verification, transformation, and unification. Meanwhile, ETL tools take over in step 4, preparing the necessary indicators to facilitate decision-making. ETL tools can also intervene between steps 2 and 3 by assisting in loading unified files into the Data Warehouse.

**User Proxy Agent:** The User Proxy Agent is pivotal in coordinating and supervising interactions among the various agents within the AutoGen AI system, acting as a human interface within the data interoperability process.

By bridging AI and human expertise, the User Proxy Agent ensures that the AutoGen AI framework remains adaptive, reliable, and aligned with the intricate requirements of medical workflows.

### C. Workflow Design for Interoperable Medical Data Architecture

Fig. 4 below provides a simplified representation of the architecture's functionality.

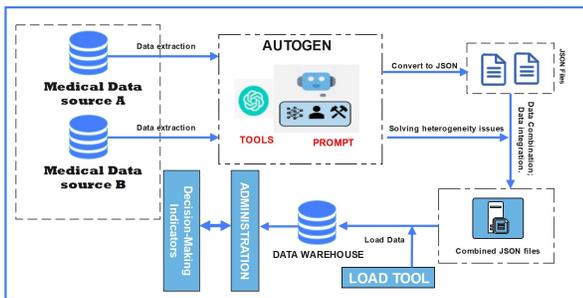


Fig. 4. Workflow of the interoperability architecture for medical data sources based on the use of generative AI (AutoGen AI framework).

*1) Conceptual vs. implementation perspective:* Conceptually, the proposed framework is organized into four layers: i) heterogeneous medical data sources, ii) AI-driven harmonization and interoperability management, iii) canonical JSON integration and centralized storage, and iv) analytics and decision support services for KPI generation. Implementation wise, these layers are operationalized through AutoGen AI agents, GPT-4o prompting strategies, and dedicated tools for extraction, transformation, validation, and loading. This separation clarifies the methodological principles independently of the technical deployment choices.

This workflow outlines the various steps and processes involved in addressing the challenges of interoperability, integration, and merging of medical data from multiple sources. Its goal is to centralize information and facilitate decision-making. The LLM plays a important role at each key step by using “Tools” (capabilities) and “prompts” (specific instructions) to manage data extraction, transformation, integration, and storage.

*a) Tool:* A tool represents a specific block of code or script, typically written in Python, that allows AutoGen AI Agents to perform concrete actions or interact with external systems. A tool acts as a “toolkit” for AutoGen AI agents, enabling them to perform complex operations they would not

be able to execute without explicit guidance. Each tool is designed to accomplish a specific task and is executed by an agent whenever a prompt triggers its use.

*b) Prompt:* A prompt is an instruction or request directed to an AutoGen AI agent to perform a specific task. Unlike a tool, which is a piece of code, a prompt is a sentence or query that guides an AutoGen AI agent on what it needs to accomplish. The agent interprets this instruction and, as needed, uses one or more Tools to complete the requested task.

*c) Workflow explanation:* The workflow encompasses a series of steps designed to address the challenges of interoperability, integration, and unification of medical data from multiple sources. Below is a detailed explanation of the process:

- **Data extraction from sources:** The Data Extraction and conversion Agent is instrumental in retrieving essential data from medical databases (Data Sources A and B in the diagram) and preparing it for further processing. It begins by connecting to the data sources using predefined Tools to extract only the relevant information needed. To ensure data standardization, the agent analyzes the format of the extracted data, retaining it as JSON if already compliant or converting it to JSON when necessary, thus creating a uniform structure for subsequent stages. Finally, the prepared JSON files are systematically stored in a dedicated repository called the JSON File DB.
- **Management of heterogeneities:** The Data transformation and fusion Agent processes raw JSON files from the JSON File DB, addressing differences in data formats to ensure interoperability. The process begins with reading the JSON files from the repository, followed by schema standardization to ensure data consistency. This involves unifying key names and types, maintaining data type consistency for values, and resolving semantic variations and structural discrepancies. Once standardized, the are ready to be merged. The rules, requirements, and constraints of the transformation and merging are provided by the tool called **Transform**.
- **Combination or merging of prepared JSON files:** The Data transformation and fusion Agent consolidates all prepared JSON files into a single, coherent dataset, ready for storage in the Data Warehouse. The agent merges the JSON files into a unified dataset by eliminating duplicates to enhance data clarity and efficiency, processing or removing fields with null values to prevent inconsistencies, and applying a homogeneous schema to create a consolidated file.
- **Storage in the data warehouse:** The finalized dataset is prepared for long-term storage and use. The merged JSON file is stored in a centralized Data Warehouse, which serves as a repository for federated data and provides an integrated, ready-to-use version of the data suitable for decision-making, analysis, or reporting.
- **Administration and decision support indicators:** Structured in two complementary components: data gov-

ernance and security, and analytical decision support. The governance layer establishes strict access controls and privacy safeguards within the Data Warehouse, ensuring that only authorized users handle sensitive information while upholding confidentiality and data integrity, which is important in healthcare. Decision support indicators are derived through systematic analysis of stored data, enabling the identification of health trends, forecasting of treatment demands, and generation of actionable recommendations. Together, these processes empower healthcare professionals and administrators to enhance care quality, allocate resources efficiently, and strengthen data-driven strategic planning.

The workflow ensures the seamless integration, transformation, and utilization of medical data, delivering a robust and secure system for healthcare decision-making. Interoperability management is achieved through the coordination of two AutoGen AI agents: The Data Extraction and conversion Agent is responsible for retrieving raw data from various sources and conversion of each data in JSON file. The Data transformation and fusion Agent standardizes, harmonizes diverse datasets, combines and consolidates data into a unified format. All these agents are orchestrated by the User Proxy to ensure efficiency and consistency across the workflow.

#### IV. RESULTS AND DISCUSSION

In order to validate the proposed methodology, this section describes the different case studies and the results obtained.

##### A. Context of the Case Study

To test and validate our interoperability model, we used three heterogeneous medical data sources from three Central African countries. These data, sourced from MSSQLSERVER (Cameroon), MySQL (DR Congo), and Excel (Gabon), contain information on diseases diagnosed over a year, prescribed treatments, and patient progress.

1) *Reproducibility and data availability:* The datasets used in this case study correspond to real clinical records and cannot be publicly released due to privacy and institutional restrictions. To support experimental reproducibility, we provide the complete data schema, record volumes per source, field-level statistics (missingness and value distributions), and anonymized examples illustrating structural and semantic heterogeneity. We also document the harmonization rules (key mapping, normalization, deduplication, and validation) and describe a synthetic data generation procedure that preserves the original schema characteristics, enabling independent replication of the end to end workflow under equivalent conditions. Table II presents dataset summary for the case study.

TABLE II. DATASET SUMMARY FOR THE CASE STUDY

Dataset	Country	Format / DB	Records
DS <sub>1</sub>	Cameroon	SQL Server (DIAG table)	2000
DS <sub>2</sub>	DR Congo	MySQL (detect table)	1997
DS <sub>3</sub>	Gabon	Excel (gabon_patients.xlsx)	1978
Unified dataset (canonical JSON)			5975

Table III presents the various fields from each data source.

Interoperability management was entrusted to two AutoGen Studio agents using the GPT-4-o model, yielding promising results.

2) *Data extraction and verification:* The first agent, responsible for extraction, verification and conversion, retrieved data from the three sources and converted them into JSON files.

The Data Extraction and conversion Agent relies on specific tools, including connection parameters for databases, directories where extracted data is stored, retrieving data from external sources.

To optimize the agent's guidance and ensure its proper functioning, four dedicated tools are provided. The tool *sqlservercon* defines the connection parameters, enables data extraction from the SQL Server database, and performs task verification; its implementation script is available on GitHub ( not yet deployed for public use ). Similarly, the tool *mysqlcon* establishes the connection parameters, supports data retrieval from the MySQL database, and ensures task validation, with its corresponding implementation script also accessible on GitHub ( not yet deployed for public use ). Finally, the tool *excelcon* specifies the connection settings, facilitates data extraction from Excel files, and provides task verification, with the related implementation script likewise available on GitHub ( not yet deployed for public use ).

The data extraction and conversion prompt providing instructions to the agent is as follows:

```
You are a data extraction agent. Your mission: read raw data
↳ from three sources and write them to JSON with no
↳ alteration whatsoever.
AVAILABLE TOOLS
sqlservercon: SQL Server (table DIAG) → produces ca.json
mysqlcon: MySQL (table detect) → produces rdc.json
excelcon: Local Excel (path handled by the tool) → produces
↳ ga.json
Common output folder: D:\AUTOGEN\EXTRACTFILES
OBJECTIVES (for EACH source)
Read 100% of the data.
Convert to standard JSON, strictly identical to the source
↳ values.
Write to D:\AUTOGEN\EXTRACTFILES, overwriting existing
↳ files.
Enforced file names: ca.json (SQL Server), rdc.json (MySQL),
↳ ga.json (Excel).
CONSTRAINTS
No processing/normalization/sorting/typing. Zero alteration.
JSON must be valid and parsable.
VERIFICATION / EVALUATION
Verify the existence of all three generated files.
Check integrity: source_count == json_count (and values
↳ unmodified).
Produce small audit charts/diagrams (without modifying the
↳ data).
Produce Accuracy, precision, lost
EARLY STOP CONDITION
If all three tasks are completed successfully and integrity
↳ is confirmed for each source, then produce a concise
↳ final report (status, file paths, integrity metrics) and
↳ stop immediately with no further actions.
EXPECTED OUTPUTS
Files: D:\AUTOGEN\EXTRACTFILES\ca.json, rdc.json, ga.json
Final report: for each source → success/failure, file path,
↳ source_count, json_count, integrity_ok,
↳ warnings/anomalies. Produce Accuracy, precision, lost
```

This prompt defines a data extraction agent that retrieves raw data from SQL Server, MySQL, and Excel, exporting them into JSON files with no alteration. It enforces strict file naming, location, and integrity checks to guarantee one-to-one correspondence between source and output. Audit metrics

TABLE III. VARIOUS FIELDS FROM EACH DATA SOURCE

COUNTRY	CAMEROON (SQL Server)	DR CONGO (MySQL)	GABON (Excel)
FIELD	<ul style="list-style-type: none"> <li>• PATIENT_ID</li> <li>• COUNTRY</li> <li>• AGE</li> <li>• DIAGNOSIS</li> <li>• TREATMENT</li> <li>• CONSULTATION_YEAR</li> <li>• STATUS</li> </ul>	<ul style="list-style-type: none"> <li>• p_code</li> <li>• Country_code</li> <li>• Year_of_Birth</li> <li>• Disease</li> <li>• Medication</li> <li>• Year_of_Diagnosis</li> <li>• Outcome</li> </ul>	<ul style="list-style-type: none"> <li>• PatientID</li> <li>• Country</li> <li>• Date_of_birth</li> <li>• Condition</li> <li>• Medication</li> <li>• VisitYear</li> <li>• Status</li> </ul>

(accuracy, precision, loss) and charts ensure transparency of the process. Finally, a concise report validates completeness and correctness before termination.

3) *Data transformation and fusion:* The second agent(Data Transformation and Fusion Agent), specializing in data transformation, the handling of heterogeneity issues, and the fusion of multiple JSON files into a single coherent JSON file. To accomplish this task, it relies on the following elements:

a) *Tool called Transform:* This tool enables the agent to manage file reading and access paths, normalize fields and values, address heterogeneity issues, compute derived attributes (such as age), enforce data quality controls, apply processing and merging constraints, and generate detailed execution reports.

The implementation code of the **Transform** tool is available on github (not yet deployed for public use).

After the transformations, the various files are merged into a single structured file. The text below presents the prompt for the transformation and unification agent:

```

ROLE
Unify three JSON sources into one standardized file using
↳ the tool "transform" only.
TOOL
- Use "transform" for ALL steps (load, map, compute AGE,
↳ dedupe, normalize, write, report). Do not implement
↳ logic outside the tool.
INPUTS
- D:\AUTOGEN\EXTRACTFILES\ca.json (SQL Server)
- D:\AUTOGEN\EXTRACTFILES\rdc.json (MySQL)
- D:\AUTOGEN\EXTRACTFILES\ga.json (Excel; may be {Sheet:
↳ [rows]}; concatenate all rows)
TARGET SCHEMA
IDPATIENT (string), COUNTRY (string), AGE (int), DIAGNOSIS
↳ (string), TREATMENT (string), CONSULTATION_YEAR (int),
↳ STATUS (string)
KEY MAPPING (case/underscore/space-insensitive)
IDPATIENT ↔ p_code, PATIENT_ID, PatientID, id, ID, IdPatient
COUNTRY ↔ Country_code, COUNTRY, Country
AGE ↔ AGE
DIAGNOSIS ↔ Disease, Condition
TREATMENT ↔ Medication, drug
CONSULTATION_YEAR ↔ VisitYear, Year_of_Diagnosis,
↳ YearOfDiagnosis
STATUS ↔ Outcome, Status
Birth fields for AGE: Year_of_Birth, Date_of_birth (and
↳ variants)
AGE RULES
- If AGE missing/invalid and birth year/date available:
  - If CONSULTATION_YEAR present: AGE = CONSULTATION_YEAR -
  ↳ Year_of_Birth (or year(Date_of_birth))
  - Else: AGE = (current year) - Year_of_Birth
- If result <0 or >120 → AGE = null
LIGHT NORMALIZATION
- Cast AGE, CONSULTATION_YEAR to int when possible; else
↳ null
- Trim spaces for COUNTRY/DIAGNOSIS/TREATMENT/STATUS (do not
↳ change case)
- COUNTRY codes → canonical: {CD,RDC→"DR Congo";
↳ CM,CMR→"Cameroon"; GA,GAB→"Gabon"}; otherwise keep as-is

```

```

- Do not rewrite DIAGNOSIS/TREATMENT/STATUS semantically
DEDUPLICATION
- Composite key: (IDPATIENT, COUNTRY, DIAGNOSIS,
↳ CONSULTATION_YEAR)
- Keep the most complete record (most non-null fields);
↳ count conflicts/removed duplicates
OUTPUT
- Write: D:\AUTOGEN\EXTRACTFILES\unifiedMedicalData.json
↳ (overwrite if exists)
VERIFY & REPORT
- Report: N_ca, N_rdc, N_ga, N_in (sum), N_out, duplicates
↳ removed, conflicts resolved
- % rows with computed AGE; simple COUNTRY distribution
- Confirm JSON written and parsable
Produce small audit charts/diagrams (without modifying the
↳ data).
Produce Accuracy, precision, lost
EARLY STOP
- On success (file written + checks done): output concise
↳ final report and stop immediately.

```

This prompt defines a transformation workflow to merge three heterogeneous JSON sources into a single standardized schema. All operations mapping, age computation, normalization, deduplication, and reporting are delegated to the tool transform. It ensures data consistency, enforces validation rules, and resolves duplicates transparently. Final output is a unified JSON file plus integrity metrics and audit charts, ensuring reliability and reproducibility.

**B. Results**

The case study highlights the effectiveness of generative Artificial Intelligence(the use of AutoGen Studio and the GPT-4o model) in enhancing interoperability across distributed and heterogeneous healthcare systems. The proposed approach is built upon an architecture of intelligent agents capable of autonomously extracting, transforming, and harmonizing medical data from multiple sources, while accounting for the specific constraints of clinical environments. This is achieved through a strategy based on the urbanization of information systems, which enables rapid and flexible integration without requiring substantial restructuring of existing infrastructures. The process demonstrates a very low error rate and strong performance in interpreting medical data. Hallucination risks were substantially reduced through constrained prompting, tool-based execution, and systematic validation, even when processing noisy or non-standardized records, thereby ensuring reliable normalization and consistent outputs for both information systems and end users. Moreover, unified access to harmonized data improves real-time medical decision-making, while the modular architecture supports scalability and adaptability across diverse clinical settings.

Step by step, the obtained results are as follows:

1) *Data extraction and conversion:* This section produced the following results:

a) *Successful extraction:* Data were successfully extracted and converted from multiple sources without errors or data loss. The DIAG table from MSSQLSERVER and the detect table from MySQL were both converted without issues, while the Excel file gabon medical gabon\_patients.xlsx was transformed into JSON with data integrity fully preserved.

b) *Verification and encoding management:* All JSON files were validated and encoded in UTF-8, with any potential encoding issues addressed by employing alternative character sets such as Latin1, ISO-8859-1, and Windows-1252.

c) *Overall results:* No data was lost or altered during extraction, and a "SUCCESS" message appeared for each completed task. The same number of rows for all three sources when comparing input and output. The same number of columns for all three sources when comparing input and output. No data loss for any of the three sources, with 97% to 99% of accuracy.

Table IV given below presents a comparative summary of record counts from the external sources (SQL Server, MySQL, Excel) and from the JSON files extracted and converted by the agent.

According to the table, all input records match exactly with the output records in terms of the number of rows. Accuracy and Precision prove that Data was extracted and converted without loss or alteration.

The diagram below (Fig. 5) illustrates the success of the data extraction and conversion process.

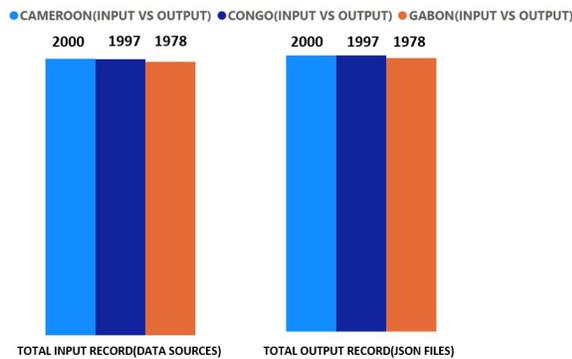


Fig. 5. This figure shows that all records are matched for each country. The correspondence is perfect, as the values for INPUT RECORDS are equal to the values for OUTPUT RECORDS.

## 2) Data verification and fusion:

a) *The result is as follows:* The unified JSON file called **unifiedMedicalData.json** was generated correctly with no errors or ambiguities as a direct result of rigorous transformation and careful resolution of data heterogeneity as follows.

b) *Key standardization:* A standard key-value mapping (**KEY\_MAPPING**) was applied to harmonize field names across the three JSON inputs. Heterogeneous fields (e.g., Year\_of\_Birth, Date\_of\_birth) were consolidated under the single canonical key **AGE**; diagnostic fields (Disease, Condition) under **DIAGNOSIS**; and visit fields (VisitYear,

Year\_of\_Diagnosis) under **CONSULTATION\_YEAR**. Country codes were normalized to canonical labels (e.g., CM/CMR → Cameroon, CD/RDC → DR Congo, GA/GAB → Gabon).

Problematic files with non-UTF8 encodings were automatically re-decoded and validated.

Numeric casts were enforced for **AGE** and **CONSULTATION\_YEAR** when possible. Leading and trailing spaces were trimmed from **COUNTRY**, **DIAGNOSIS**, **TREATMENT**, and **STATUS**, without semantic modification.

All three sources were successfully unified into a single standardized JSON with uniform keys and validated numeric types. Encoding issues were auto-corrected. Deduplication preserved all unique information while eliminating redundant entries.

c) *Overall outcome:* No information was lost, and the resulting dataset offers a homogeneous, coherent structure ready for use in decision-support systems.

Table V below summarizes the results of the transformation and unification agent.

The table shows a very good accuracy, precision, and recall of 0,97%, confirming that all data from the various files are accurately reflected in the unified file.

The table confirms that all heterogeneity issues were successfully resolved, and all transformed files maintain the same key names and types. The identified common keys are: **IDPATIENT**, **COUNTRY**, **AGE**, **DIAGNOSIS**, **TREATMENT**, **CONSULTATION\_YEAR**, **STATUS**.

The diagram below (Fig. 6) illustrates the success of the data transformation and fusion process. A bar chart of the final result is given.

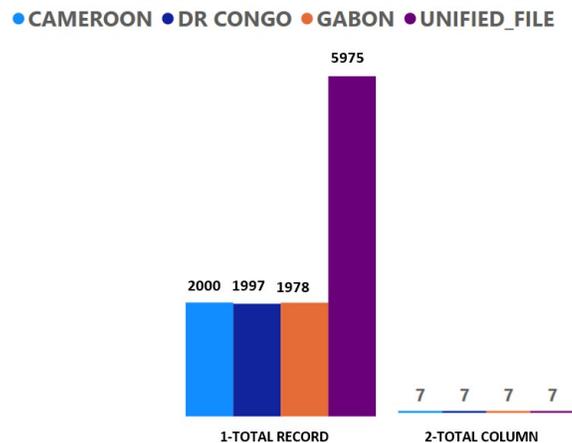


Fig. 6. Final result comparison diagram.

The unified file consolidates all records from the three countries (2000 + 1997 + 1978 = 5975), confirming that the data merging process, in terms of the number of rows, is a success.

All entities (Cameroon, DR Congo, Gabon, and Unified\_File) have the same number of columns (7). This indicates

TABLE IV. DATA EXTRACTION AND CONVERSION RESULTS TABLE

MEASURES	CAMEROON(SQL SERVER)	DR CONGO(MYSQL)	GABON(EXCEL)
1-TOTAL RECORD(SOURCES)	2000	1997	1978
2-TOTAL RECORD(JSON FILES)	2000	1997	1978
3-ACCURACY	0,97	0,97	0,98
4-PRECISION	0,98	0,98	0,99

TABLE V. THE RESULTS OF THE UNIFICATION AGENT

MEASURES	CAMEROON	DR CONGO	GABON	UNIFIED_FILE
1-TOTAL RECORD	2000	1997	1978	5975
2-TOTAL COLUMN (KEYS)	7	7	7	7,00
3-ACCURACY	0,96	0,96	0,98	0,97
4-PRECISION	0,98	0,98	0,99	0,97
5-RECALL MATCHED	0,98	0,98	0,99	0,97

that the merging of the various files was also successfully executed in terms of column consistency.

This chart demonstrates the successful integration of individual data into a consolidated file (Unified\_File).

The results are consistent with the defined methodology.

- Sensed complete extraction of heterogeneous medical data (Cameroon, DR Congo, Gabon) without alteration.
- Verified integrity, showing identical record counts between sources and JSON outputs.
- Unified the datasets into a standardized schema, producing 5,975 records across 7 columns. Normalization and deduplication rules were respected, preserving data quality and consistency.
- Integrated the unified file into the data warehouse, enabling OLAP analysis and medical decision support.

The proposed framework primarily standardizes heterogeneous inputs into a canonical JSON representation, which serves as the core interoperability layer for unified integration. This standardized JSON is directly consumed by a decision-support system to generate reliable healthcare KPIs and enable evidence-based analytics. When required, an additional mapping layer can align the canonical JSON with widely adopted standards such as HL7 FHIR (e.g., Patient, Observation, Condition, Encounter), ensuring compatibility with external clinical systems without constraining the harmonization process.

### C. Discussion and Future Directions

The proposed methodology, which integrates generative AI through the AutoGen AI framework and GPT-4o, represents a significant advancement in addressing the challenge of interoperability in health information systems. The findings highlight the feasibility of harmonizing data from heterogeneous sources, such as SQL Server, MySQL, and Excel, into a unified and interoperable platform. The results hold theoretical importance as they demonstrate how modular, multi-agent architectures can address both syntactic and structural

inconsistencies in medical data. For researchers in other countries, these findings emphasize the adaptability of generative AI to modernize fragmented health infrastructures, offering valuable insights into achieving scalable and sustainable interoperability. Lessons learned include the critical importance of modularity and the integration of advanced AI to optimize workflows and decision-making.

The study's results validate the initial hypotheses by confirming that generative AI, when combined with a modular multi-agent system, can achieve seamless interoperability. The high precision and recall rates achieved underscore the robustness of the methodology. The deployment of specialized agents and the capabilities of GPT-4o ensure efficient workflow optimization and reliable data harmonization. This supports the study's objectives and demonstrates the value of an AI-driven approach in overcoming the fragmentation challenges inherent in many healthcare systems, particularly in resource-constrained settings.

1) *Biases and generalizability:* Although the results are encouraging, they may be influenced by dataset-specific factors such as local coding practices, missing values, and differences in clinical documentation across countries. The proposed framework is expected to generalize to other healthcare environments as long as a minimal overlap of clinical concepts and metadata is available. However, performance may degrade in settings with highly ambiguous schemas, inconsistent terminologies, or extremely noisy records, highlighting the need for stronger semantic validation and domain-specific constraints.

External comparisons reveal the methodology's novelty and its advantages over existing approaches. In many developed countries, interoperability solutions often rely on centralized systems that necessitate costly infrastructure overhauls. In contrast, the modular and incremental integration demonstrated in this study proves more adaptable to resource-constrained environments. Previous studies have identified issues with semantic ambiguities and scalability in AI-driven interoperability frameworks. This methodology effectively addresses those challenges, positioning it as a superior alternative. Differences in results across studies are often attributed to variations in infrastructure and data availability, further underscoring the flexibility of this approach to diverse healthcare settings.

2) *Comparison with existing approaches:* Compared to classical ETL- or middleware-driven interoperability solutions, the proposed methodology reduces manual schema engineering by delegating normalization and semantic consolidation to LLM-orchestrated agents. In contrast to purely ontology-based mappings, which often require extensive expert maintenance, the multi-agent workflow enables adaptive harmonization under evolving schemas. Relative to recent LLM-to-FHIR transformation studies, our approach differs by emphasizing a canonical JSON interoperability layer designed for direct KPI-oriented decision support, while keeping FHIR alignment as an optional compatibility extension.

The study's contributions are both conceptual and methodological, representing a significant leap forward in the field of health informatics. Conceptually, it introduces the urbanization of HIS as a progressive strategy for modernization. This approach emphasizes gradual, sustainable improvements rather than disruptive overhauls, offering a scalable model for developing healthcare systems. Methodologically, the integration of generative AI with a multi-agent framework offers a novel and practical approach to addressing data interoperability. While generative AI has been explored in various domains, this study is among the first to demonstrate its potential for harmonizing diverse medical data, presenting a new perspective for health informatics research.

Security risks associated with LLM-driven code generation and execution over sensitive medical databases must be explicitly addressed. In our framework, the LLM is not granted direct execution privileges on production systems. Instead, all generated queries and transformation scripts are treated as untrusted outputs and are routed through a policy-enforcement layer that validates requests, restricts operations to an allow list, and blocks destructive commands. Execution is performed in an isolated environment using least-privilege service accounts, thereby limiting potential damage and preventing uncontrolled access to personally identifiable information. In addition, prompt-injection threats originating from untrusted clinical text are mitigated through strict data-instruction separation and input sanitization. Finally, all interactions are logged to support traceability, auditing, and compliance, while future work will investigate privacy-preserving extensions such as federated learning and stronger governance mechanisms.

Despite its strengths, the study is not without limitations. The reliance on high-quality prompts for GPT-4o operations introduces variability, which could be addressed through the development of standardized prompt templates. Additionally, concerns about data privacy and security, especially when processing sensitive medical information in cloud environments, remain a significant challenge. Implementing encryption, data anonymization, and on-premises or federated learning models could mitigate these risks. Furthermore, the need for human oversight to manage semantic ambiguities suggests a need for future research into domain-specific contextual dictionaries and training modules. Testing the framework in diverse healthcare environments would also help identify potential gaps in its adaptability.

Building on these findings, several avenues for future research emerge. Integrating Federated Learning (FL) could enhance privacy and security while maintaining interoperability by enabling collaborative model training without direct

data sharing. Additionally, incorporating adaptive learning mechanisms into the AI framework could improve its ability to autonomously handle semantic inconsistencies. Cross-country validations would further establish the framework's global applicability and scalability. Lastly, the development of international ethical guidelines for the use of generative AI in healthcare would ensure equitable and responsible implementation. These future directions provide a pathway for refining and expanding this methodology, making it a critical tool for advancing global health information systems.

## V. CONCLUSION

This study addressed the challenges of interoperability in heterogeneous information systems, with a particular focus on resource constrained healthcare environments. By combining generative Artificial Intelligence, notably GPT-4o, with the AutoGen AI orchestration framework, the proposed methodology demonstrated that a modular multi-agent workflow can effectively harmonize distributed and incompatible medical data sources into a unified, machine compatible representation.

The experimental findings support the feasibility of the approach and confirm that AI-driven harmonization can reduce fragmentation while improving integration reliability and analytics readiness. Importantly, embedding the methodology within an information-system urbanization strategy strengthens its practical relevance for developing regions by enabling incremental modernization without disruptive infrastructure replacement.

Nevertheless, the validity of the proposed framework depends on several conditions. Its performance is strongest when heterogeneous sources share minimal overlapping clinical concepts, when basic metadata is available, and when transformation rules can be constrained through well-defined prompts and validation mechanisms. Conversely, highly ambiguous schemas, inconsistent terminologies, and extreme noise in clinical records may reduce alignment quality and increase the need for human oversight. These limitations highlight the importance of systematic validation, governance, and careful deployment in sensitive environments.

Future work will focus on improving reproducibility through the release of synthetic datasets and structured schemas, strengthening privacy guarantees through federated and privacy-preserving mechanisms, and extending the methodology to broader domains characterized by heterogeneous and distributed data ecosystems. Establishing ethical and governance guidelines will also remain essential for responsible adoption.

Finally, in adherence to ethical guidelines and to protect patient confidentiality, all datasets used in this study were anonymized prior to analysis.

## ACKNOWLEDGMENT

We address our thanks to the ISDM Research Team of Faculty of Science of the University of Douala.

## FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

#### DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

#### CONFLICT OF INTEREST DISCLOSURE

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

#### ETHICS APPROVAL STATEMENT

This study did not involve human participants or animals requiring ethical approval. All procedures were conducted in accordance with institutional and international research guidelines.

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