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# Interoperable electronic medical record Framework based on Microservice architecture

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**Abstract**: Electronic health records are a multi-stakeholder-driven ecosystem that serves different e-health services. For blurring borders between different electronic health records (EHRs), healthcare interoperability standards are needed to exchange information between different levels of healthcare. Healthcare interoperability standards ensure different healthcare systems can exchange, interpret, and use data seamlessly. These standards enable effective communication between healthcare providers and improve patient care. Interoperability issues usually pass the interoperability of localized hospital information systems. Consequently, there is a need for a universal health system that manages shared stakeholders' objectives. On the other hand, microservices architecture can enable communication between various EHRs and strengthen the continuity of care, which is one of the main justifications for interoperability in EHRs. A primary contribution of this work is the development of a unified, multipurpose microservice-based health information system framework aimed at improving the provision of healthcare services. This adaptable architectural framework, which is based on Couchbase, delivers a range of services that can be effectively tailored to different application demands and the specific needs of healthcare participants.

**Keywords**: Electronic Health Records, microservice, NoSQL, Health Information System, interoperability.

## 1. Introduction

EHRs are considered the core part of any healthcare information ecosystem (HIS). These systems maintain long-term patient health data, which can be used by clinical decision support (CDS) tools to guide treatment and predict future health trends [1]. This data includes demographics, treatment plans, medications, tests, lab results, imaging reports, and others.

Interoperability between EHR data refers to the ability to exchange information between different levels of health care [2]. EHR interoperability could be categorized according to level and standards as shown in Figure (1). Healthcare interoperability standards [3] ensure different healthcare systems can exchange and use data seamlessly.

The HL7 FHIR (Fast Healthcare Interoperability Resources) standard is one of the cornerstones of healthcare data exchange. FHIR was designed to streamline data sharing between systems in a more flexible and modern way, addressing interoperability issues that have traditionally plagued the healthcare industry. By adopting FHIR, healthcare organizations can ensure that their systems communicate seamlessly with one another, reducing the risk of data silos and improving overall care coordination. Compliance with FHIR standards ensures that data can be exchanged securely, efficiently, and accurately, promoting real-time decision-making and enhancing patient outcomes.

However, data interoperability and ease of access come with the need for robust privacy and security measures, which is where compliance with regulations such as GDPR and HIPAA comes into play. The General Data Protection Regulation (GDPR) is a comprehensive set of rules enforced in the European Union to protect individuals' personal data and privacy. Under GDPR, healthcare providers must ensure that patient data is processed lawfully, transparently, and for specific purposes. Furthermore, patients must be informed of

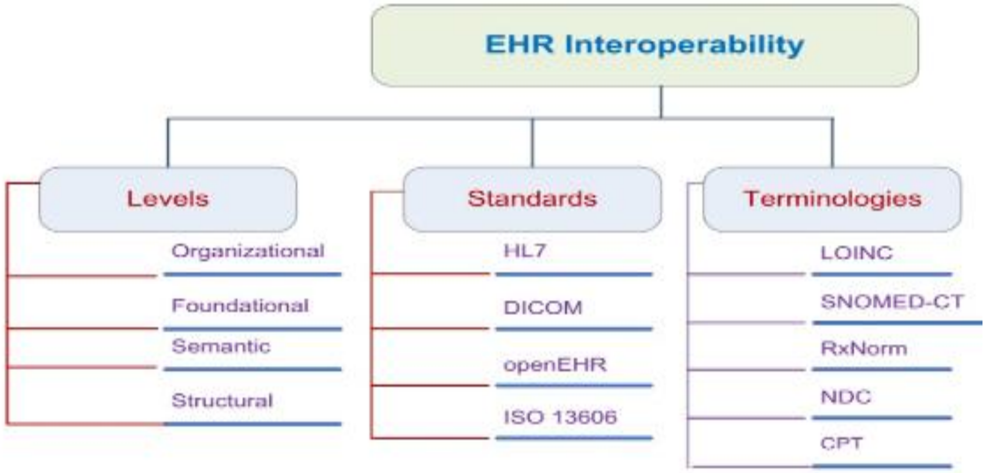


Figure1:EHR Interoperability levels and standards

their rights, including the right to access, rectify, and erase their data. Healthcare organizations that fail to comply with GDPR risk hefty fines and damage to their reputation, which can deter patients from trusting their systems.

On the other side of the Atlantic, the Health Insurance Portability and Accountability Act (HIPAA) sets forth a series of standards in the United States aimed at ensuring the privacy and security of healthcare information. HIPAA applies to healthcare providers, insurers, and clearinghouses, and it regulates how patient information is handled, stored, and shared. HIPAA compliance requires healthcare organizations to implement strict safeguards, such as encryption, access controls, and audit trails, to prevent unauthorized access to sensitive health data.

Violations of HIPAA can lead to severe penalties, including fines and potential criminal charges.

The importance of adhering to these healthcare regulations and standards cannot be overstated. With the increasing digitization of healthcare, from EHRs to telemedicine and mobile health apps, patient data is more accessible and vulnerable than ever before. Ensuring compliance with FHIR, GDPR, and HIPAA standards creates a framework for data exchange that protects patient confidentiality while supporting innovation in healthcare technology. This, in turn, facilitates the real-world adoption of new tools and systems that can enhance patient care, improve operational efficiency, and reduce costs.

Furthermore, achieving compliance with these regulations promotes a culture of accountability and transparency in healthcare organizations. It demonstrates to patients that their privacy is a top priority and that the systems in place have been thoroughly vetted to ensure data security. It also builds trust among other stakeholders, such as insurers and regulators, who rely on these standards to safeguard the integrity of the healthcare ecosystem.

These standards ensure the secure and efficient exchange of patient data while protecting privacy and maintaining interoperability across systems. Adhering to FHIR enhances data sharing, while GDPR and HIPAA safeguard patient information by enforcing strict privacy and security measures. Compliance builds trust with patients, healthcare providers, and other stakeholders, reduces legal risks, and supports innovation in healthcare. Ultimately, meeting these regulations fosters improved patient care, operational efficiency, and long-term success in the digital health landscape.

Therefore, there are several advantages to using standardization in EHR data, which are declared in Figure (2)[4]. This classification system helps in understanding the different aspects of standardization and how they contribute to interoperability, data quality, and overall system efficiency [5].

HL7 is the most popular standard that is used in digital healthcare ecosystems [6,7]. HL7's Fast Healthcare Interoperability Resources (FHIR) [8] specification is a nextgeneration standard designed to improve EHR data integration, exchange, and retrieval. Using "resources," FHIR enables the exchange of specific data elements, enhancing interoperability and reducing implementation costs.

The microservices architecture is a design approach where a system is built as a collection of small, independent services. Each service operates its own process and communicates with others using lightweight methods like an API or HTTP resources [9]. This architecture can address various challenges in Electronic Health Records (EHR) by improving communication between EHR systems and reinforcing continuity of care, which is a key reason for promoting interoperability in EHRs [10].

NoSQL is a type of database specifically built to manage large volumes of data, enabling efficient storage and retrieval. These stores are distributed and schema-less, which means they are well-suited for handling big medical data [11]. These stores are categorized by data model into four classes: (1) key-value, (2) document, (3) column-family, and (4) graph. This classification is necessary because each architecture offers different solutions for varying application needs [12,13]. MongoDB [14] and Couchbase [15,16] is a leading document-oriented NoSQL databases that are designed to handle high-volume data storage quickly, with minimum cost and real-time data access.

EHRS stores data in various structured or unstructured data formats. Moreover, because of EHR data's unique persistence needs, NoSQL systems offer a more appropriate solution by storing data in a format closer to its actual representation [17,18].

Interoperability issues usually pass the interoperability of localized hospital information systems. Consequently, there is a need for a universal health system that manages shared stakeholders' objectives.

The motivation for this paper is that there is a need for a framework that enables health data integration by utilizing both interoperability standards and microservices architecture for simplifying HIS infrastructure. It examines the appropriateness of a NoSQL for storing and managing distributed EHRs. This hybrid framework could solve various healthcare data problems, such as data silos [19,20]. To achieve this scenario, a prototype that is based on a microservice architectural approach and incorporates the FHIR standard as an interoperability standard is proposed. This framework also utilizes the flexible scalability and flexibility characteristics of NoSQL systems.

The remainder of this paper is structured as follows: Section 2 discusses related research on various methods for storing and managing EHRs using different interoperability standards. Section 3 presents the proposed framework. Section 4 outlines and discusses the experimental results. Section 5 is for discussion and section 6 concludes the presented work.

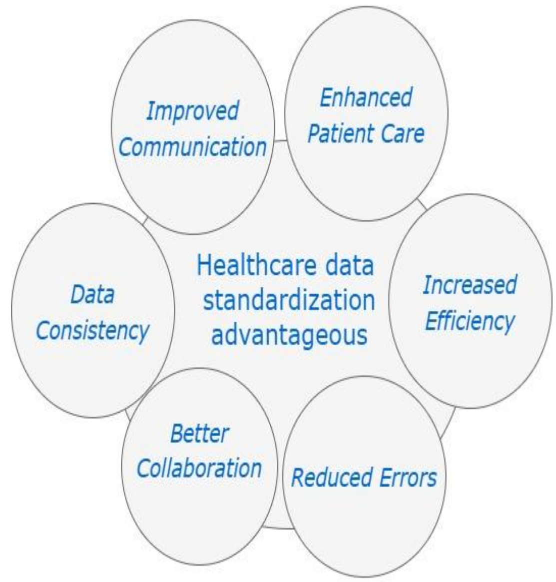


Figure 2: Advantages for using standardization in EHR

## 2. Related works

Due to the difficult and varied nature of healthcare data, and the demanding scale, performance, and flexibility requirements of EHR applications that often exceed basic transactional needs [19,21]. NoSQL databases are better equipped to handle the demands of distributed EHR systems [22]. Various approaches have been presented for persisting EHR data according to different use case scenarios [17, 18, 23–29]. These approaches utilize different interoperability standards such as openEHR other researchers utilize HL7. Owing to the unique characteristics of HL7, various papers have utilized it in their work [7, 30].

Various works suggest utilizing the microservice architecture in healthcare environments. Microservice architecture is based on three separate layers: technology, services, and presentation technology layer to allow seamless use and integration of HL7 messages [31]. Another work proposes an e-healthcare service-oriented architecture (SOA) framework that is based on HL7-FHIR. This framework is based on three key components: FHIR (Gateway) server, Smart Contract Authentication Server, and Client Server. It utilizes the graph-mapping concept to transform each resource variable into an equivalent Graph-Mapped Data Structure (GMS), which is stored in the NoSQL MongoDB database [32]. Another microservices HL7 FHIR architecture is introduced to develop a prototype that acts as a real scenario of Patient Navigation (PN) [10]. It used the scheduling and registration process to simulate communication with current HL7 FHIR-compliant servers. All data that is used to simulate the PN process were stored in MongoDB data in JSON format. Recently, a software architecture based on microservices has been designed to enable the evaluation of the availability and performance of dental medical records [33]. To evaluate this architecture, a prototype was deployed in containers using the Microsoft Azure App Service with predefined features [33].

## 3. Research Methodology

Healthcare systems usually involve two major practices: clinical use and research use which is dedicated to CDS. Though quick data storage is readily achievable; the real difficulty lies in extracting valuable and timely insights from this stored information. Similarly, effective communication between healthcare providers using EHRs necessitates interoperability through adherence to established standards, enabling seamless health information exchange (HIE)[34] A key principle in medical data management is the preservation of data history; instead of overwriting existing entries during modification, new, linked records are created. NoSQL databases appear to offer a viable solution for addressing numerous EHR system requirements.

The major contribution of the study is it proposed a tightly coupled distributed standardized EHR framework by investigating two back-end behaviors for real-time ad hoc queries with different levels of complexity.

This microservice-based architecture is introduced to solve the problems of the layered architecture approach in handling multifunction systems. Queries designed for each database's specific query language were designed and implemented. To highlight performance variations and minimize bias, queries exhibiting potentially divergent behavior were selected. Two NoSQL database management systems, Couchbase and MongoDB, were employed to evaluate their respective capabilities in storing and retrieving EHR objects within a distributed environment.

MongoDB [14] and Couchbase [15,16] are both NoSQL databases, but they are different in the way they handle data [35,36].

Couchbase Server features a multi-dimensional scaling (MDS) architecture, which allows workloads to be scaled independently based on evolving requirements while reducing interference between services [40].

Its goal is to provide a unified, integrated platform capable of handling a wide range of complex operational workloads, along with operational analytics. The adaptable MDS framework allows users to scale their cluster up or down, adjusting data management resources as needed based on changing requirements.

Two different database topologies were implemented for the storage back-ends handling EHRs to assess their performance with varying query complexities. MongoDB was tested using a single, unshared data cluster setup. Meanwhile, Couchbase Server was examined using two topologies: a single-node and a multi-node clusters.

In MongoDB's single-node topology, the pipeline framework for aggregation is utilized to execute queries through multi-stage data processing. All services in it are consolidated within a single zone, with the query service managing different levels of query complexity.

In the multi-node topology, Couchbase services are distributed among many nodes, as opposed to being confined to a single node. This microservices architecture aims to separate the query and analytics services into independent nodes within the cluster. The query service handles many users with less complex operational queries, while the analytics service supports a smaller group of users requiring more complex and resource-demanding analytical queries.

Couchbase Server employs amulti-dimensional scaling (MDS) architecture, designed to facilitate independent workload scaling based on evolving demands and to reduce service conflicts. Its objective is to provide a unified platform suitable for a wide range of operational workloads, including complex tasks and operational analytics. This adaptable MDS structure allows users to adjust their cluster size, adding or removing data management resources as needed. To assess the handling of architectural topologies were implemented for the two storage back-ends used for storing EHRs. MongoDB was tested using a single, unshared data cluster configuration. In contrast, Couchbase Server was evaluated with both single-node and multi-node cluster topologies.

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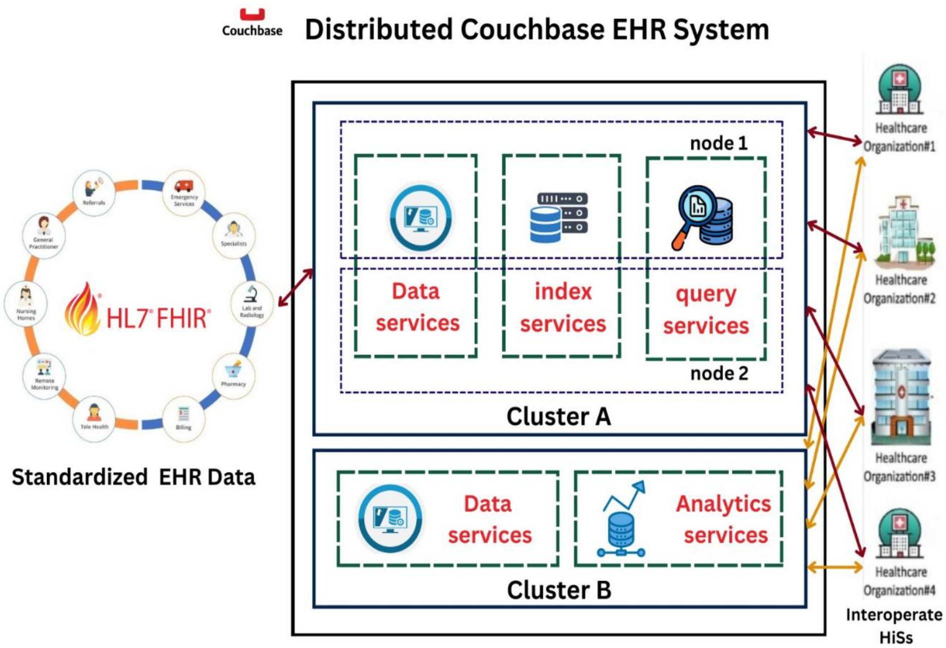


**Figure 3: Proposed microservice-based multifunctional EHRs persistence framework**

the In the MongoDB single-node setup, the aggregation pipeline framework, employing multi-stage data processing pipelines, was utilized for query execution with varying query complexities. In the Couchbase Server single-node cluster, all database functionalities (querying, indexing, and data storage) reside within a single zone. This configuration uses the query service to manage all workload types, regardless of complexity. Conversely, the Couchbase Server multi-node cluster distributes services across multiple nodes. This microservices-based approach aims to separate the query and analytics services—complementary yet having conflicting workload requirements—into distinct nodes within the cluster. The query service is optimized for high-volume, low-cost operational queries, while the analytics service is dedicated to complex, resource-intensive analytical queries typically performed by a smaller user base [36-39].

Figure (3) provides a high-level overview of the deployment of microservice-based distributed EHRs with varied access patterns. This prototype is tested using an interoperable MIMIC-IV (Medical Information Mart for Intensive Care) data set which is a standardized version of MIMIC-IV that is based on FHIR specification.

MIMIC-IV database contains data for 40000 intensive care unit (ICU) stays including patient encounter information, observations, laboratory results, microbiology data, medications, and hospital-level billing codes with size 35 GB.

# 4. Experimental Results

The majority of healthcare operations rely on the retrieval of information from databases. Thus, reduced response time is one of the main factors that enhance the system's performance [41].

To investigate the capability of the proposed framework two data stores are investigated with respect to the same queries respectively. All queries` response times are shown in Table 1.

MongoDB performed better than the Couchbase single-node cluster. By using an analytics service to spread services across multiple nodes instead of relying on a single node, Couchbase server MDS architecture reported better response times than MongoDB.

The proposed EHR system framework offers substantial benefits over loosely coupled systems by using a single, versatile document data model. This eliminates the need for data transformation, enabling fast reporting and real-time analytics on large datasets without data movement or ETL processes. This allows for analytics on the most up-to-date information [42].

*Table 1:queries execution time for the MIMIC dataset*

| | Single node system | Distributed system | |
|---|---|---|---|
| | **Couchbase** | **MongoDB** | **Couchbase analytics** |
| Q1 | 4.6 | 0.42 | 0.07866 |
| Q2 | 4.7 | 0.344 | 0.12234 |
| Q3 | 1.4 | 5.136 | 0.86799 |
| Q4 | 0.9191 | 0.046 | 0.12867 |
| Q5 | 2.8 | 1.796 | 2.21 |
| Q6 | 1.7 | 0.439 | 0.14602 |
| Q7 | 600 | 31.427 | 19.51 |
| Q8 | 5.1 | 0.766 | 0.37029 |
| Q9 | 21.7 | 3.039 | 0.78144 |
| Q10 | 4.6 | 1.169 | 1.5 |
| Q11 | 0.377 | 0.129 | 0.1119 |
| Q12 | 3.9 | 0.899 | 0.32355 |
| Q13 | 4.7 | 12.137 | 1.99 |
| Q14 | 6.6 | 3.142 | 1.83 |
| Q15 | 0.0079 | 15.136 | 3.72 |
| Q16 | 5.2 | 0.447 | 0.11176 |
| Q17 | 4.4 | 0.694 | 0.08631 |
| Q18 | 4.4 | 0.579 | 0.09564 |
| Q19 | 4.3 | 0.864 | 0.09867 |

## 4. Discussion

Couchbase is a NoSQL database known for its scalability, flexibility, and high performance, particularly when handling large amounts of semi-structured or unstructured data. Its multi-model approach (document, key-value, and even full-text search) makes it well-suited for applications that need to manage a wide variety of data types. Couchbase also offers robust features like built-in caching, automatic sharding, and flexible indexing, which can optimize performance and reduce the complexity of data management in healthcare systems. Given its ability to handle high throughput and low-latency access, Couchbase may be an excellent choice for real-time healthcare applications that require quick access to data, such as patient monitoring systems or telemedicine platforms.

However, other NoSQL databases like MongoDB also provide similar features and may be worth considering. MongoDB, for instance, is known for its ease of use and flexible document storage, making it a popular choice for modern applications. While MongoDB is great for handling unstructured data, it doesn't offer the same level of performance optimization (e.g., built-in caching) as Couchbase. On the other hand, MongoDB's rich query capabilities and strong consistency options could be advantageous in scenarios where complex querying and aggregations are needed.
When comparing Couchbase with relational database management systems (RDBMS) like PostgreSQL or MySQL, there are several key differences. RDBMSs are well-suited for structured data and complex transactional systems, offering strong ACID (Atomicity, Consistency, Isolation, Durability) properties. If the healthcare system needs to manage highly structured data (such as patient records or billing information), relational databases may be more appropriate, especially in legacy systems where integrity and consistency are paramount. Moreover, SQL databases are often preferred in scenarios requiring complex joins, detailed reporting, and the use of relational schemas.

However, RDBMSs may struggle to scale horizontally in the same way NoSQL databases can. Couchbase, with its distributed architecture, excels at managing large-scale, high-velocity data in a way that traditional RDBMSs cannot match without significant infrastructure investment. If the healthcare system expects to scale rapidly, handle large volumes of unstructured data, or require high-speed access to dynamic content, Couchbase could be a better fit due to its horizontal scaling and flexible data model.

In conclusion, the decision to use Couchbase as the architectural backbone depends on the specific requirements of the healthcare system. If scalability, flexibility, and real-time performance are top priorities—especially for handling high volumes of semi-structured or unstructured data—Couchbase is an excellent option. However, if the system requires strong relational consistency or complex transactions with highly structured data, a relational database like PostgreSQL or MySQL, or another NoSQL option like MongoDB, might be more appropriate. Ultimately, evaluating the system's scalability needs, data model complexity, and consistency requirements will guide the most suitable database choice. One concern to be addressed in future work is to adapt various data models such as graph and relational models to integrate with proposed architecture model (document model) to introduce a polyglot persistence system architecture.

## 5. Conclusion

As healthcare data grows exponentially, the need for decentralized access and seamless information exchange becomes increasingly crucial. To address this, a large-scale, interoperable, and scalable healthcare system is essential. Interoperability standards ensure the accurate and reliable sharing of Electronic Health Record (EHR) data, enabling smooth data flows across multiple platforms and healthcare providers.

This paper introduces a microservice-based healthcare model designed to manage complex, multi-participant EHR systems typically structured in layered architectures. By using a microservice architecture, the model offers increased flexibility, scalability, and adaptability, which is crucial for managing diverse and dynamic healthcare data. This approach not only enhances system performance but also improves coordination between healthcare providers and systems.

Additionally, the paper highlights Couchbase as an optimal solution for managing unstructured health data across various EHR systems. As a flexible and scalable NoSQL database, Couchbase can efficiently handle the unstructured and semi-structured data that is common in modern healthcare environments. By enabling seamless integration and data exchange, Couchbase helps ensure that healthcare providers have timely access to accurate patient information, ultimately improving patient care and enhancing the overall healthcare delivery process.

**References:**

[1] F. Winter, A., Haux, R., Ammenwerth, E., Brigl, B., Hellrung, N., Jahn, Health Information Systems: Architectures and Strategies, Springer-Verlag London, 2011. https://doi.org/DOI 10.1007/978-1-84996-441-8.

[2] S. Blumenthal, Improving Interoperability between Registries and EHRs, (2018) 20–25.

[3] A. Begoyan, an Overview of Interoperability Standards for Electronic Health Records, Society for Design and Process Science (2007) 1–8. https://pdfs.semanticscholar.org/5ca5/32439868b9fac13bf5a0d6b46365280828d3.pdf?_ga=2.41111780.751753156.1599500483-1005302603.1598205714.

[4] No Title, (n.d.). https://emorphis.health/blogs/healthcare-interoperability-standards-guide/.

[5] N.R. de Oliveira, Y. de R. dos Santos, A.C.R. Mendes, G.N.N. Barbosa, M.T. de Oliveira, R. Valle, D.S.V. Medeiros, D.M.F. Mattos, Storage Standards and Solutions, Data Storage, Sharing, and Structuring in Digital Health: A Brazilian Case Study, Information (Switzerland) 15 (2024) 1–36. https://doi.org/10.3390/info15010020.

[6] R. Gazzarata, J. Almeida, L. Lindsköld, G. Cangioli, E. Gaeta, G. Fico, C.E. Chronaki, HL7 Fast Healthcare Interoperability Resources (HL7 FHIR) in digital healthcare ecosystems for chronic disease management: Scoping review, Int J Med Inform 189 (2024). https://doi.org/10.1016/j.ijmedinf.2024.105507.

[7] J. Nan, L.Q. Xu, Designing Interoperable Health Care Services Based on Fast Healthcare Interoperability Resources: Literature Review, JMIR Med Inform 11 (2023) 1–19. https://doi.org/10.2196/44842.

[8] FHIR, Fast Healthcare Interoperability Resources. https://fhir.org/.

[9] Introduction to Healthcare Microservices Architecture, (n.d.). https://medium.com/@Larisa10/introduction-to-healthcare-microservices-architecture-d81badc0949f.

[10] G.N. Bettoni, T.C. Lobo, C.D. Flores, B.G.T. Dos Santos, F.S. Da Silva, Application of HL7 FHIR in a Microservice Architecture for Patient Navigation on Registration and Appointments, Proceedings - 2021 IEEE/ACM 3rd International Workshop on Software Engineering for Healthcare, SEH 2021 (2021) 44–51. https://doi.org/10.1109/SEH52539.2021.00015.

[11] N. Leavitt, Will NoSQL Databases Live Up to Their Promise?, Computer (Long Beach Calif) 43 (2010) 12–14. https://doi.org/10.1109/mc.2010.58.

[12] V.N. Gudivada, D. Rao, V. V. Raghavan, Renaissance in Database Management: Navigating the Landscape of Candidate Systems, Computer (Long Beach Calif) 49 (2016) 31–42. https://doi.org/10.1109/MC.2016.115.

[13] R. Cattell, Scalable SQL and NoSQL data stores, SIGMOD Rec 39 (2010) 12–27. https://doi.org/10.1145/1978915.1978919.

[14] MongoDB, (2020). https://www.mongodb.com/.

[15] D. Store, Couchbase Document Store, (n.d.).

[16] Couchbase: The Modern Database for Enterprise Applications, (n.d.). https://www.couchbase.com/ (accessed September 3, 2021).

[17] Saber, A., Sakr, M., Abou-Seida, O., & Keshk, A. (2021). A Novel Transfer-Learning Model for Automatic Detection and Classification of Breast Cancer Based Deep CNN. Kafrelsheikh Journal of Information Sciences, 2(1), 1-9.

[18] R. Sánchez-De-Madariaga, A. Muñoz, R. Lozano-Rubí, P. Serrano-Balazote, A.L. Castro, O. Moreno, M. Pascual, Examining database persistence of ISO/EN 13606 standardized electronic health record extracts: Relational vs. NoSQL approaches, BMC Med Inform Decis Mak 17 (2017) 1–14. https://doi.org/10.1186/s12911-017-0515-4.

[19] C.S. Kruse, C. Kristof, B. Jones, E. Mitchell, A. Martinez, Barriers to Electronic Health Record Adoption: a Systematic Literature Review, J Med Syst 40 (2016). https://doi.org/10.1007/s10916-016-0628-9.

[20] Saber, A., Sakr, M., Abo-Seida, O. M., & Keshk, A. (2021, May). Automated Breast Cancer Detection and Classification Techniques–A survey. In 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC) (pp. 200-207). IEEE.

[21] T. Nguyen, Big data system for health care records, Journal of Science: Policy and Management Studies 33 (2017) 146–156. https://doi.org/10.25073/2588-1116/vnupam.4101.

[22] M.Z. Ercan, M. Lane, Evaluation of NoSQL databases for EHR systems, Proceedings of the 25th Australasian Conference on Information Systems, ACIS (2014).

[23] H.M. Kruse, A. Helhorn, L.A. Phan-vogtmann, E. Thomas, A.J. Heidel, K. Saleh, A. Scherag, Modeling a Graph Data Model for FHIR Resources, (2019) 398355.

[24] S. Kalogiannis, K. Deltouzos, E.I. Zacharaki, A. Vasilakis, K. Moustakas, J. Ellul, V. Megalooikonomou, Integrating an openEHR-based personalized virtual model for the ageing population within HBase, BMC Med Inform Decis Mak 19 (2019) 1–15. https://doi.org/10.1186/s12911-019-0745-8.

[25] D. Teodoro, E. Sundvall, M.J. Junior, P. Ruch, S.M. Freire, ORBDA: An openEHR benchmark dataset for performance assessment of electronic health record servers, PLoS One 13 (2018) 1–22. https://doi.org/10.1371/journal.pone.0190028.

[26] S.M. Freire, D. Teodoro, F. Wei-Kleiner, E. Sundvall, D. Karlsson, P. Lambrix, Comparing the performance of NoSQL approaches for managing archetype-based electronic health record data, PLoS One 11 (2016) 1–20. https://doi.org/10.1371/journal.pone.0150069.

[27] S. El Helou, S. Kobayashi, G. Yamamoto, N. Kume, E. Kondoh, S. Hiragi, K. Okamoto, H. Tamura, T. Kuroda, Graph databases for openEHR clinical repositories, International Journal of Computational Science and Engineering 20 (2019) 281–298. https://doi.org/10.1504/IJCSE.2019.103955.

[28] H.Y. Yip, N.A. Taib, H.A. Khan, S.K. Dhillon, Electronic health record integration, Encyclopedia of Bioinformatics and Computational Biology 1–3 (2018)

1063–1076. https://doi.org/10.1016/B978-0-12-809633-8.20306-3.

[29] E. Choi, M.W. Dusenberry, G. Flores, Z. Xu, Y. Li, Y. Xue, A.M. Dai, Learning Graphical Structure of Electronic Health Records with Transformer for Predictive Healthcare, ICML 2019 Workshop on Learning and Reasoning with Graph-Structured Data (2019).

[30] M. Gottumukkala, O. El-Gayar, C. Noteboom, Interoperability in Healthcare using FHIR: A Systematic Literature Review, 28th Americas Conference on Information Systems, AMCIS 2022 21 (2022) 31–38.

[31] J. Guedes, J. Duarte, M. Manuel, C. Quintas, J. Cunha, T. Guimaraes, M.F. Santos, Interoperability Architecture proposal for Adaptive Business Intelligence Systems in Healthcare Environments, Procedia Comput Sci 238 (2024) 920–925. https://doi.org/10.1016/j.procs.2024.06.113.

[32] R. Sreejith, S. Senthil, Smart Contract Authentication assisted GraphMap-Based HL7 FHIR architecture for interoperable e-healthcare system, Heliyon 9 (2023) e15180. https://doi.org/10.1016/j.heliyon.2023.e15180.

[33] J. Arcila-Diaz, C. Valdivia, A Microservice-based Software Architecture for Improving the Availability of Dental Health Records, International Journal of Computing 21 (2022) 475–481. https://doi.org/10.47839/ijc.21.4.2783.

[34] R. Jain, In Search of Database Nirvana:The Challenges of Delivering Hybrid Transaction/Analytical Processing, (2016).

[35] D. Borkar, R. Mayuram, G. Sangudi, M. Carey, Have your data and query it too: From key-value caching to big data management, Proceedings of the ACM SIGMOD International Conference on Management of Data 26-June-20 (2016) 239–251. https://doi.org/10.1145/2882903.2904443.

[36] Hassan, E., Saber, A., & Elbedwehy, S. (2024). Knowledge distillation model for Acute Lymphoblastic Leukemia Detection: Exploring the impact of nesterov-accelerated adaptive moment estimation optimizer. Biomedical Signal Processing and Control, 94, 106246.(DOI: 10.1016/j.bspc.2024.106246

[37] Saber, A., Elbedwehy, S., Awad, W. A., & Hassan, E. (2024). An optimized ensemble model based on meta-heuristic algorithms for effective detection and classification of breast tumors. *Neural Computing and Applications*, 1-14.

[38] Elbedwehy, S., Hassan, E., Saber, A., & Elmonier, R. (2024). Integrating neural networks with advanced optimization techniques for accurate kidney disease diagnosis. *Scientific Reports*, *14*(1), 21740.

[39] Alnowaiser, K., Saber, A., Hassan, E., & Awad, W. A. (2024). An optimized model based on adaptive convolutional neural network and grey wolf algorithm for breast cancer diagnosis. PloS one, 19(8), e0304868.

[40] Hassan, E., El-Rashidy, N., & Talaa, M. (2022). mask R-CNN models. Nile Journal of Communication and Computer Science, 3(1), 17-27.(DOI: 10.21608/njccs.2022.280047

[41] Hussien, A. G., Abualigah, L., Abu Zitar, R., Hashim, F. A., Amin, M., Saber, A., Gandomi, A. H. (2022). Recent Advances in Harris Hawks Optimization: A Comparative Study and Applications. Electronics, 11(12), 1919.

[42] Saber, M. Sakr, O.M. Abo-Seida and A. Keshk, "Tumor detection and classification in breast mammography based on fine-tuned convolutional neural networks," IJCI. International Journal of Computers and Information, 2021.