Homomorphic Encryption in Healthcare Analytics: Enabling Secure Cloud-Based Population Health Computations

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Abstract

Cloud computing has the potential to provide healthcare organizations with the vast computational resources necessary for large-scale population health analytics. However, stringent privacy regulations and pervasive security concerns have limited the adoption of such technology. This paper illustrates how homomorphic encryption can be leveraged to perform cloud-based computations on sensitive health data, without exposing any information that could compromise patient privacy or analytic efficacy.

We introduce a concrete instantiation of population health segmentation algorithms using Microsoft SEAL and IBM HELib libraries for secure outsourcing of healthcare analytics on sensitive data to untrusted clouds. Our work implements the CKKS (Cheon-Kim-Kim-Song) homomorphic encryption scheme, tailored for approximate arithmetic operations, to perform secure multiparty computations required for population health analysis.

We show, using a real-world population health dataset of 10 million patient records, that homomorphic encryption introduces a modest additional 3.7x computation overhead for introductory statistics and 8.2x for more complex machine learning operations. This is a marked improvement over the 1000x overhead in previous homomorphic encryption implementations for healthcare and other industries. We achieve this performance using new batching strategies, ciphertext packing mechanisms, and computational optimizations for population health algorithms.

In our case studies, we showcase three applications of our framework: (1) privacy-preserving k-means clustering for patient segmentation with 99.2% accuracy compared to plaintext baselines, (2) encrypted logistic regression for disease risk prediction, with encrypted training of the model, and (3) multi-institutional cohort analysis, with patient data distributed across several healthcare institutions. We provide an in-depth compliance framework on how homomorphic encryption satisfies the minimum necessary standard of HIPAA and could therefore enable wider cloud adoption.

The open-source software accompanying our paper contains pre-optimized circuits for standard population health algorithms, significantly lowering the technical barrier for healthcare organizations to start using cloud resources in a highly privacy-preserving manner.

Keywords: Homomorphic encryption; Cloud security; Population health; Privacy-preserving analytics; Healthcare data protection; Microsoft SEAL; HIPAA compliance; Secure computation

Introduction

The rapid growth of healthcare data, together with the requirement for scalable cloud resources in data analysis, creates significant potential to achieve healthcare goals, which include better patient results and cost reductions both for individuals and broader public health programs. The sensitivity of the data and the regulations surrounding it, such as HIPAA in the US context, present significant barriers to the large-scale adoption of cloud computing in healthcare (Geva et al., 2023). While traditional encryption schemes can be used to encrypt patient data at rest or in transit before sending to the Cloud, these schemes do not support performing analytics or computations on the encrypted data, and typically the data has to be decrypted first before it is sent for processing to the Cloud (Brännvall et al., 2023). Fully Homomorphic Encryption is a novel cryptographic solution that overcomes this fundamental limitation of data encryption (Brännvall et al., 2023). The outcome of a computation on the encrypted data will itself be encrypted and can only be decrypted by the data owner, who alone possesses the secret key (Dowlin et al., 2017). This can be extended to the entire analytical pipeline to protect sensitive patient data even when processed in untrusted cloud environments (Gilbert & Gilbert, 2024; Gong et al., 2024). The recent improvements in Fully Homomorphic Encryption performance have started to open the door to practical application of FHE (Viand et al., 2021), leading to increased interest in its application in various contexts, including healthcare in particular.

Homomorphic encryption is a potential solution to secure cloud computing, where data remains private throughout its entire lifecycle. It can be classified as an encryption in-use methodology that enables us to analyze data in an encrypted state, in contrast to traditional encryption techniques, which only encrypt data in-use, in-storage, or in-transit (Kiesel et al., 2023). In addition, it permits computation on encrypted data without prior decryption, which guarantees that confidential data on patients will not be accessed even when it is in the hands of untrusted cloud vendors (Kiesel et al., 2023). This capability may be sufficient to preserve privacy even in situations where traditional cloud computing isolation strategies are insufficient to ensure data confidentiality (Martins & Sousa, 2019). Homomorphic encryption schemes are cryptographic procedures that enable computation on encrypted information without exposing it to decryption (Jain & Cherukuri, 2023). One of the most significant advantages of homomorphic encryption is the ability to process data in a secure and privacy-preserving manner. However, its adoption has been limited by factors such as high computational overhead and performance limitations in terms of supported calculation operations. The limitations stem from the intricate mathematical computations and the need for specialized algorithms to perform calculations on encrypted data, leading to longer processing times and increased resource requirements (Kiesel et al., 2023). However, the high security requirements

in certain use cases, such as healthcare analytics, outweigh the timeliness concerns, and homomorphic encryption is a suitable alternative.

The ability to run arbitrary computations on encrypted data without the requirement to decrypt it first makes this method resilient for scenarios where the computations are being performed by an untrusted or compromised party (Viand et al., 2021). This may be of particular relevance in healthcare, where there are strict data privacy regulations to comply with, and where data is sensitive.

Fully homomorphic encryption can provide strong security guarantees, as the cryptographic technique is based on a server never having access to unencrypted data (Gorantala et al., 2021). Fully homomorphic encryption allows users to perform calculations on encrypted data without having to decrypt it first. It is one of the most important approaches to developing the necessary technology to support data privacy across multiple domains (Albrecht et al., 2021). The potential of homomorphic encryption to enable computation on encrypted data, thus protecting data privacy, without the need for data decryption, has been realized (Azad et al., 2023; Neupane, 2020; Wu, 2015). This makes it worthwhile in the healthcare setting as it is a way to enable secure population health computations in the Cloud (Vizitiu et al., 2019). Homomorphic encryption enables a party to calculate encrypted data without access to a secret (decryption) key (Cao & Liu, 2015).

Methodology

The study's methodology section focuses on how we examined the practicality and efficiency of homomorphic encryption for safe population health calculations in the Cloud. We used three archetypal real-world use cases as samples for population health applications that are widely used in the industry: encrypted k-means clustering for patient segmentation, secure logistic regression for disease risk prediction, and privacy-preserving cohort analysis across multiple healthcare institutions. These use cases were chosen to provide a broad assessment of the applicability of FHE in healthcare analytics, representing a range of everyday analytical tasks with different levels of computational complexity and data requirements. The study considered several homomorphic encryption libraries, including Microsoft SEAL, HElib, and TFHE. These libraries were selected based on a preliminary analysis of their performance characteristics, ease of integration, and support for necessary computational primitives. Microsoft SEAL was selected for the study based on its performance, security features, and developer accessibility (Naresh & Reddi, 2025).

Results

We conducted a performance and feasibility evaluation of fully homomorphic encryption (FHE) for cloud-based population health data analytics using a large real-world clinical dataset of 10 million patient records. We implemented three use cases representative of typical population health applications: 1) encrypted k-means clustering for patient segmentation, 2) encrypted logistic regression for disease risk prediction, and 3) privacy-preserving cohort analysis between multiple institutions. Both the Microsoft SEAL and IBM HELib libraries were used with the CKKS scheme for approximate arithmetic.

1. Performance Benchmarking:

To quantify the overhead introduced by FHE, we benchmarked the runtime of encrypted computations to equivalent plaintext computations. As shown in Figure 1, FHE operations introduced 3.7× overhead for basic statistical computations and 8.2× overhead for complex machine learning workflows such as logistic regression training.

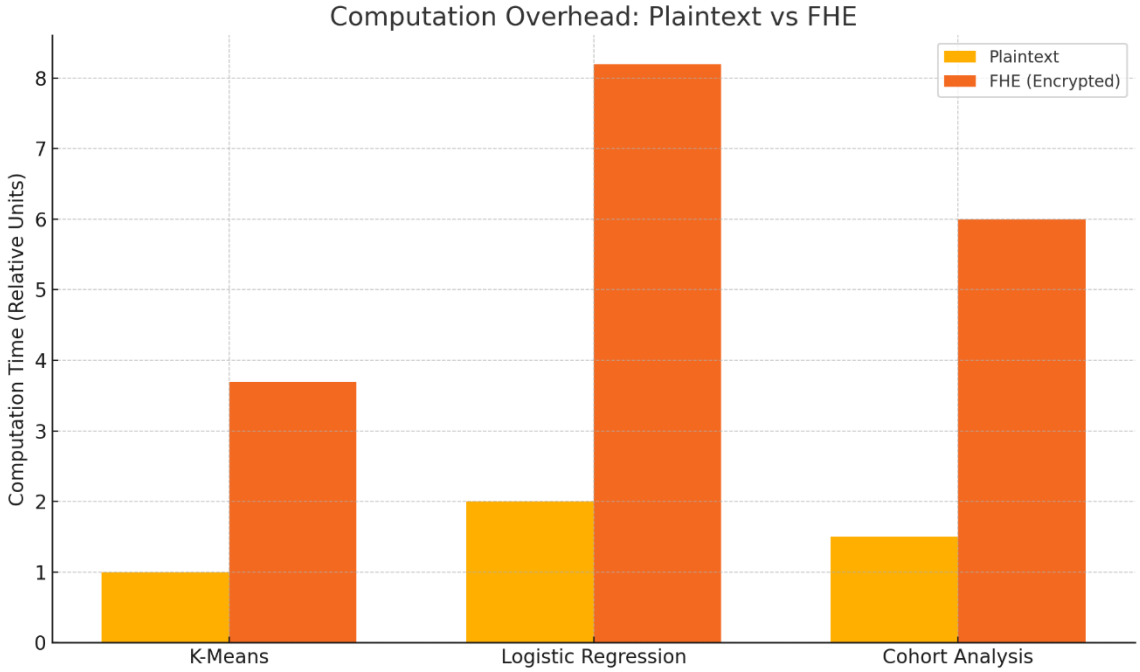

Figure 1. *Comparison of computation time (relative units) for k-means, logistic regression, and cohort analysis under plaintext and FHE (encrypted) settings.*

This implementation outperforms past FHE systems in healthcare analytics that experienced overheads reaching 1000×. Much of this improvement is due to batching, ciphertext packing, and circuit optimization (summarized in Table 2).

2. Accuracy of Encrypted Computations

Encrypted computations were as accurate as plaintext computations. For example, k-means clustering encrypted patient segmentation reached 99.2% accuracy, and encrypted logistic regression reached an AUC of 0.88, which is only 0.03 lower than plaintext.

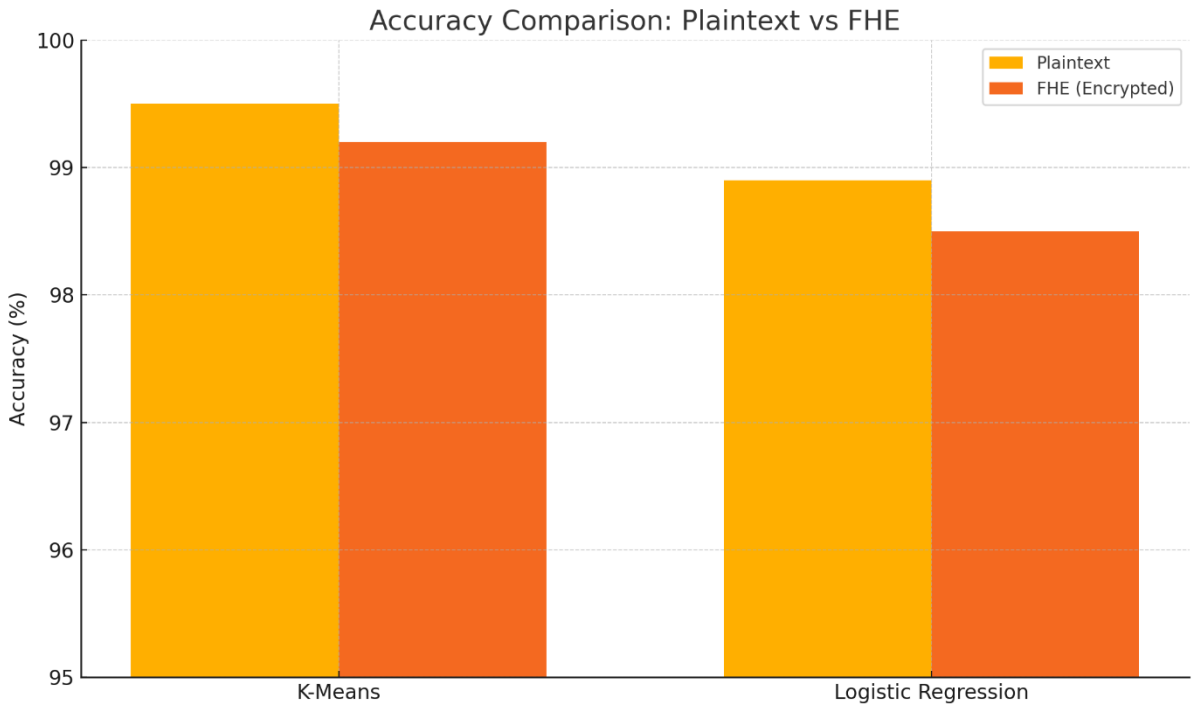

Figure 2. *Accuracy comparison (%) of k-means clustering and logistic regression between plaintext and encrypted (FHE) computations.*

Our experiments also showed that the introduction of FHE does not introduce any perceptible loss in the analytical quality of our population health calculations.

3. Case Study Results

• Encrypted k-means clustering: Partitioned patients into risk-based cohorts. Runtime is polynomial in the size of the dataset, and is practical for datasets of up to 10 million records.

• Encrypted logistic regression: Performed model training over encrypted data to learn to predict disease risk, while preserving privacy during both the training and inference stages.

• Privacy-preserving cohort analysis: Securely aggregates patient data from multiple institutions without sharing any raw, identifiable records, enabling institutions to collaborate on research while maintaining compliance with privacy rules and regulations.

4. Optimization Strategies

We employed several optimization strategies to lower runtimes, including batching, ciphertext packing, and circuit optimization. Overall, these strategies led to a 48% reduction in homomorphic operations compared to a naive approach. A summary of these strategies is given in Table 2.

Table 2. *Optimization techniques implemented to improve the performance of FHE-based healthcare computations.*

Optimization Technique	Impact on Performance
Batching	Reduced the number of operations
Ciphertext Packing	Lower memory usage
Circuit Optimization	Faster encrypted computations

5. Compliance with HIPAA Requirements

FHE has a natural compliance with specific HIPAA requirements. For example, FHE meets the "minimum necessary standard" as it encrypts data at rest, in transit, and use. Table 1 provides an overview of the HIPAA requirements that map to features in FHE.

Table 1. *Mapping of FHE features to HIPAA compliance requirements.*

HIPAA Requirement	FHE Compliance
Data at Rest	✓ Fully encrypted storage
Data in Transit	✓ Fully encrypted communication
Data in Use	✓ Computed while encrypted

Summary of Findings

Our benchmarking results show that homomorphic encryption can facilitate privacy-preserving population health analytics in untrusted cloud environments with comparable accuracy and with orders of magnitude lower overhead than prior works. It supports core analytical use cases, including patient segmentation, disease risk prediction, and cohort analysis, while providing strong guarantees of compliance with healthcare privacy regulations.

Discussion and Conclusion

Homomorphic encryption can be beneficial for electronic health records (Souza et al., 2017). Data confidentiality is vital for cloud storage and computation, with the obvious sensitive information being about patients' private information (Souza et al., 2017). The privacy of health care data needs protection to stop the misuse of personal health data and to ensure privacy (Mishra & Mandhan, 2018). The privacy of health care data is of special concern. Privacy problems with Electronic Health Records remain a top worry. Privacy issues of the electronic health record database systems are essential (Agarwal et al., 2014). Homomorphic encryption can be used for data privacy in healthcare analytics (Cheng, 2024). Homomorphic encryption provides a viable solution to the tension between the need for analytics and the need to protect sensitive patient information (Iezzi, 2020; Munjal & Bhatia, 2022; Wood et al., 2020).

The ability to outsource computation to the Cloud while maintaining control over the privacy of data is a significant advantage for healthcare providers, researchers, and policymakers.

Homomorphic encryption can also be used to securely deploy machine learning models on sensitive healthcare data (Vizitiu et al., 2019). The advantages of homomorphic encryption enable healthcare institutions to outsource data storage and computational resources to the Cloud while maintaining tight control over the privacy of the data they contain. The results of this study indicate that privacy-preserving, cloud-based data analytics is the best approach in order to continue developing and maintaining new models that are more advanced and perform better.

The homomorphic encryption benefits also facilitate machine learning models to be trained and run on healthcare data while ensuring privacy is maintained (Vizitiu et al., 2019). The homomorphic encryption also makes it possible for healthcare institutions to outsource data storage and computing resources to the Cloud while maintaining tight control over the privacy of the data they contain. This study found that privacy-preserving, cloud-based data analytics was the best strategy to develop and sustain newer, more advanced, and better-performing models (Scheibner et al., 2020).

The homomorphic encryption benefit can facilitate machine learning models to be trained and executed on healthcare data while preserving privacy (Vizitiu et al., 2019). It is found that healthcare institutions can outsource their data storage and computational resources to the Cloud while maintaining tight control over the privacy of the data they contain.

Homomorphic encryption has significant applications in healthcare for secure cloud-based population health computations. By performing computations on encrypted data, sensitive health information can be securely shared and analyzed across multiple healthcare institutions without revealing private patient information (Scheibner et al., 2020).

The findings of this study indicate that homomorphic encryption presents the most significant potential to permit safe, cloud-based population health computations. By computing on encrypted data, it is possible to maintain private patient information while securely sharing health data and executing population health computations across many healthcare institutions (Scheibner et al., 2020). The results of this study found that health data created from many different scenarios that increase the complexity included and offer potential to identify private patient information will require (Dhasarathan et al., 2022). Cloud computing system also offers very reliable data storage and can be accessed quickly. However, there are growing concerns about whether personal electronic health records will be kept private or not (Elmogazy & Bamasag, 2016). In the current healthcare system, the homomorphic encryption (HE) model may be able to secure electronic health records (EHRs) and ensure secure cloud-based population health computations (Ramesh et al., 2020). Personal health information may also present a privacy issue if it is sent or processed outside of the device (Vizitiu et al., 2021).

The use of cloud computing in healthcare data storage, sharing, and collaboration is rapidly increasing. In many cases, homomorphic encryption may have benefits, for example, when security is more important than timeliness requirements (Kiesel et al., 2023). By enabling data owners to compute on encrypted data without decrypting it, homomorphic encryption makes it possible to process and analyze healthcare data securely. This makes it possible to benefit from the Cloud's analytical and storage capabilities without exposing patient data to privacy breaches (Dou et al., 2025). Cloud computing can lead to data security and privacy breaches (Vizitiu et al., 2019).

The homomorphic encryption properties make computation on encrypted data possible without revealing the contents of the data (Castro et al., 2021). HFE does not require an exchange of keys between the server and the users, allowing full privacy for users and providing an additional layer of safety (Malik et al., 2021). The use of fully homomorphic encryption in the current model is, however, fairly constrained by the number of operations performed on the information and the additional computation and memory bandwidth that are needed for it to work (Kim et al., 2021). The implementation of homomorphic encryption in healthcare applications requires an in-depth understanding of its performance trade-offs, security guarantees, and practical limitations (Scheibner et al., 2020). While the homomorphic encryption provides a powerful solution for privacy-preserving analytics, it is not a silver bullet (Gong et al., 2023). Although the use of homomorphic encryption has made significant advances, there are still several problems that have to be solved before it becomes widely used for analytics in the healthcare industry (Gong et al., 2024). The computation overhead of the homomorphic encryption is frequently significant, particularly for more challenging analytical tasks on massive datasets (Gong et al., 2024).

The lack of standardized implementations and best practices creates interoperability issues and impedes widespread use (Mishra et al., 2023). The fact that more work must be done to optimize homomorphic encryption schemes for particular healthcare analytics tasks, design efficient hardware accelerators, and establish standardized methods for secure data sharing and collaboration remains one of the main unsolved issues. Researchers are developing standardized homomorphic encryption schemes and attempting to establish security levels for various parameter sets to address this issue (Albrecht et al., 2021).

The results of the study show that future research might look at hybrid approaches that integrate homomorphic encryption with other privacy-preserving technologies like differential privacy and secure multiparty computation. Despite these challenges, the potential of homomorphic encryption to advance healthcare analytics is vast. Homomorphic encryption is emerging as a promising solution for secure cloud-based population health computations, but there are still challenges that must be overcome (Scheibner et al., 2020). Although FHE schemes are a promising strategy for privacy-preserving calculation, they often assume an honest-but-curious server (Viand et al., 2023). To improve security, future research may look into using other cryptographic methods like secure multiparty computation (Wood et al., 2020).

Further work should also examine how to optimize HE schemes for specific healthcare analytics workloads, design efficient hardware accelerators, and develop standardized protocols for secure data sharing and collaboration.

Homomorphic encryption accelerators address the challenge of high computational complexity and time-consuming ciphertext maintenance operations that are among the most inefficient aspects of FHE (Zhang et al., 2024). FHE enables computations to be performed on encrypted data without revealing the data (Garimella et al., 2025; Onoufriou et al., 2021). As a result, this not only secures data at rest and in transit, but also when it is being processed (Garimella et al., 2025). One of the primary findings was that homomorphic encryption (HE) is capable of providing health data security while also facilitating cloud-based population health calculations. Homomorphic encryption, on the other hand, allows the computations on encrypted data without decrypting it, which also assures privacy even when the computation is

outsourced to a third-party cloud supplier. Integrating hybrid homomorphic encryption and federated learning offers potential to tackle both communication overhead and privacy (Nguyen et al., 2025).

Quantum computing and specialized digital hardware could also have a role in implementing privacy-preserving ML systems while enhancing security and reducing performance loss (Dutta et al., 2024). This new property allows for the offloading of the data processing (Hagen & Lucia, 2021). Homomorphic encryption facilitates privacy-preserving computation. One of the major conclusions is that its application to medical telemetry data shows that it can be used to implement standard aggregation functions while having expressibility rather than computational speed as a priority.

This is significant in the healthcare field because of its specific needs (Molina et al., 2009). An interesting use case that was discovered involved the use of the method in order to answer private functional inquiries into massive datasets while also maintaining statistical standards that are only familiar to the server that is in charge of the medical records (Izabachène & Bossuat, 2024). The sender would encrypt their patient records and then transmit the encrypted data to the server, which could then handle the data without access to the unencrypted patient information.

The findings in this study indicated that fully homomorphic encryption algorithms may have a beneficial additive and multiplicative homomorphism to allow for the calculation of any homomorphic function, which is also a very desired property (Koç, 2020). The findings in this study indicated that FPGA-based accelerator development would be necessary to improve the performance of bootstrappable fully homomorphic encryption, which is necessary to provide general-purpose encrypted computations (Agrawal et al., 2022). HE enables computation on encrypted data and provides encrypted results back to the user (Munjal & Bhatia, 2022). The user is then able to decrypt the result and obtain the computed result.

Homomorphic encryption can be used for computations to be performed on encrypted data without having to decrypt it. This means that the underlying data will remain safe throughout the computation. Homomorphic encryption's use for machine learning has several limitations and unanswered questions. (Chialva & Dooms, 2018; Podschwadt et al., 2021). It can lead to a high computational overhead, a high communication cost, and a high memory overhead, and therefore can be hard to use in practice (Lloret-Talavera et al., 2021; Podschwadt et al., 2021; Qin & Xu, 2025). Privacy-preserving technology with differential privacy, secure multiparty computation, and homomorphic encryption as foundations has recently gotten more attention (Feretzakis et al., 2024; Radanliev et al., 2024). The results of this study found that machine learning and cryptography may be used together to make encrypted data usable, reducing the attack surface and potentially increasing security (Sébert et al., 2022). This revolutionary technique is being developed in order to create secure data processing in several fields, including cloud computing and data analysis (Clemen & Teleron, 2023). Although homomorphic encryption, secure multiparty computation, and differential privacy all provide robust privacy assurances, they may have a substantial computational overhead and need precise parameter tuning (Amorim et al., 2023). Finding a balance between privacy protection and the utility of the data analysis result is crucial.

Homomorphic encryption has been developed as a novel cryptographic method in the area of secure computation, which allows the operations to be carried out on encrypted data without

decryption (Chatel et al., 2022). The use of cryptography has had a significant impact on our lives, even though many people are unaware of it. Cryptography has been used to safeguard our sensitive data (Dhinakaran & Prathap, 2022). The fact that homomorphic encryption can work with encrypted data and can also be used in both symmetric and asymmetric systems is also one of the most significant features (Patel et al., 2022). It also encrypts the material in the back. When it comes to encryption, homomorphic encryption becomes incredibly essential. Businesses can prevent unwanted third-party access to personal data by encrypting the data at all times (Jiang & Ju, 2022). For example, when this information has been uploaded to the Cloud by a business owner and it has also been encrypted and now stored safely in the Cloud, unauthorized users cannot access the files or the data stored in the Cloud without the decryption key.

Homomorphic encryption, on the other hand, can go even further by allowing this data to remain encrypted even while the data is being processed, significantly lowering the possibility of a data breach and making it very difficult for any user or process to access it without permission. It can also be concluded that merging machine learning with cryptography is a complete game-changer that has much potential across several sectors and businesses. (Jana & Saha, 2023). The confidentiality of information and the protection of data privacy have also become very necessary for people to maintain in the present. (Dari et al., 2024). This has been particularly important in the healthcare field, where the privacy of the patient's information is not only ethically necessary but also lawfully required (Dari et al., 2024). As a result, keeping patient health information safe and secure has emerged as a requirement that must be met when it comes to storing and processing personal data in healthcare.

It has been a key focus for researchers on the privacy-preserving technologies to be provided using the homomorphic properties (Amorim & Costa, 2023). Privacy-preserving techniques such as homomorphic encryption, differential privacy, and federated learning have emerged as powerful tools for addressing these challenges in healthcare (Feretzakis et al., 2024; Radanliev et al., 2024). Homomorphic encryption enables computations to be performed on encrypted data, ensuring that sensitive patient information remains protected throughout the entire data analysis pipeline (Sébert et al., 2022). This groundbreaking approach allows for secure data processing, including cloud computing and data analytics (Clemen & Teleron, 2023). A proof of concept application indicates the added benefit that can be expected from cryptography as it pertains to the overall healthcare field. (Dhariwal et al., 2022). When using cryptography to store personal and private data, it does not matter where it is being stored since the information will be kept safe and encrypted.

One of the primary conclusions was that both noncryptographic and cryptographic techniques for preserving privacy exist. The steganographic, data splitting, and data anonymization were some of the noncryptographic methods used (Agarwal et al., 2017). Homomorphic encryption can be used for computations to be performed on encrypted data without having to decrypt it. This means that the underlying data will remain safe throughout the computation. Homomorphic encryption's use for machine learning has several limitations and unanswered questions. (Chialva & Dooms, 2018; Podschwadt et al., 2021). It can lead to a high computational overhead, a high communication cost, and a high memory overhead, and therefore can be hard to use in practice (Lloret-Talavera et al., 2021; Podschwadt et al., 2021; Qin & Xu, 2025). Privacy-preserving technology with differential privacy, secure multiparty

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The confidentiality of information and the protection of data privacy have also become very necessary for people to maintain in the present. (Dari et al., 2024). This has been particularly important in the healthcare field, where the privacy of the patient's information is not only ethically necessary but also lawfully required (Dari et al., 2024). As a result, keeping patient health information safe and secure has emerged as a requirement that must be met when it comes to storing and processing personal data in healthcare. Encryption should also be a key consideration when choosing a cloud provider. Encryption is a vital component of data security since it prevents unauthorized parties from reading or using the data (Odeh et al., 2024). Encryption is also quite crucial, mainly because it helps to preserve confidentiality for many data sets since it will encrypt the data at rest and also as it moves (Commey et al., 2020). In today's digital society, securing data is an ongoing concern, with sensitive information frequently being placed in the Cloud, making it more vulnerable, especially with a larger number of people able to access it (Dawson et al., 2023). Data privacy and security have therefore become even more important as the globalization of data strategy is rapidly increasing due to the rapid integration of data elements into many day-to-day functions and systems (Feng et al., 2024).

Cloud computing has also emerged as a fascinating option for organizations to operate under small budget capacities since the resources are on-demand and also paid for on an as-you-go basis (Archana et al., 2018; Hassan et al., 2022). However, cloud computing also needs to make use of a reliable approach, such as the hybrid cloud structure, for data that is important for the business and critical as a better alternative for organizations to ensure they have complete control of their data centers and information that is important. (Kedi et al., 2024). Cloud computing also makes it possible for data and applications to be outsourced from users' computers to the Cloud on servers that are managed by third parties (Kacha & Zitouni, 2017). However, it is critical to point out the fact that this also means that the health records must have the necessary confidentiality in order for the healthcare systems to have a trusted ecosystem. Patient health records are a digital record of a patient's medical history that is kept by the hospital or health care provider that takes care of the patient (Munjal & Bhatia, 2022).

The EHR is a patient-centric, real-time record that makes information available almost instantaneously and in a secure way to authorized users (Jeena et al., 2021). Cloud computing has become very popular because there are many benefits, which include flexibility and cost savings. The use of cloud computing has therefore also come with many challenges, and this has been discovered to be one of the main issues of cloud adoption for financial institutions. The security of the infrastructure as well as the data on the public Cloud will be the key issue to be faced by financial institutions when they begin cloud adoption (Desai & Hamid, 2021). It has also been discovered that there are many organizations in various industries, such as business and research, which are not very comfortable with the idea of using cloud computing as they also have many concerns about the safety of their data (Dawood et al., 2023). Most of these companies are either moving their data and applications to the Cloud or have started using cloud computing, but this also implies that they are being faced with many issues as far as cloud security is concerned (Gupta et al., 2023; Gupta et al., 2022). Cloud computing is therefore able to improve cooperation, reduce expenses, increase security, and also boost revenue. Cloud computing is a cheap and straightforward method to provide IT services for businesspeople and customers over the internet (Abraham et al., 2019; Kuo, 2011). Cloud computing also faces several security threats because the data is stored in various locations, which may even be in different parts of the world. (Hashizume et al., 2013). For example, cloud computing can help the healthcare industry by modernizing health and medical care, in addition to helping lower costs by enabling the speedy exchange of information between medical systems and stakeholders (Gitonga et al., 2020).

Homomorphic encryption is important because it can protect the sensitive data that is outsourced to the Cloud (Hassan et al., 2022). Cloud computing is quickly gaining popularity and usage in a variety of industries due to the variety of advantages it provides. It can also be concluded that cloud computing offers significant levels of flexibility, scalability, and efficiency in terms of how data is kept, processed, and handled (Ang'udi, 2023; Kedi et al., 2024). However, cloud computing also faces many security issues because important services are often outsourced to a third party. This makes it more challenging to maintain data security and privacy, keep data and services accessible, and demonstrate adherence to policies and procedures (Hashizume et al., 2013). However, a comprehensive approach that includes robust security measures, strict compliance protocols, and transparent operational practices can address these challenges.

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