Novel Approach to De-Identify Relational Healthcare Databases at Rest: A De-Identification of Key Data Approach

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Abstract: Health information systems are widely used in the healthcare sector, and migration to cloud-based applications continues to be prominent in recent practices. Various legislations were issued by different countries to ensure the confidentiality of personal health information, introducing liabilities, and imposing penalties and fines to organizations in violation. This drives organizations to deploy significant investments in information security to safeguard various health information systems. The healthcare industry has experienced the second highest data breaches compared to other industries at 24.5% of the total data breaches in the United States between 2005 and 2023. Database layer vulnerabilities remain one of the most exploited resulting in attacks causing devastating confidentiality breaches for electronic personal health information (ePHI). The framework suggested in this work relied on de-identification using the health insurance portability and accountability act (HIPAA) safe harbor method of removing 18 identifying attributes from the data in its resting state. To achieve this, the work proposes 7 rules that allow the migration of health information system databases to the suggested framework structure to maintain a de-identified state of the database at rest. This is achieved through the segregation of identifying information in different tables based on their identification power and frequency of use while structuring them in a hierarchical manner where tables refer to the next or previous levels through encrypted foreign keys. The paper extends to successfully transform a typical EHR system database schema into a de-identified version of itself abiding to the 7 rules suggested by this work.

1 INTRODUCTION

This To tackle the various issues of ePHI security, the US Congress acted and passed the Health Insurance Portability and Accountability Act (HIPAA) in 1996. The main objective of HIPAA was to establish a uniform set of standards for the disclosure of health data by healthcare providers. The act also sets standards for various other aspects including information security, privacy, fraud prevention, electronic data exchange, healthcare access, revenue, and insurance (Miller and Payne, 2016). HIPAA imposes penalties and fines on organizations in breach of its security and privacy rules reaching up to 1.5M USD per incident. This drives organizations to deploy significant investments in information security to safeguard various health information systems. One way to perform data sharing while abiding by HIPAA regulations is the production of de-identified datasets. De-identified datasets are defined as health information that does not have any reasonable basis to believe that identification of individuals using it is possible (Caplan, 2003). HIPAA requires validation of de-identified datasets through one of two methods: expert determination or safe harbor. Expert determination requires a formal inspection and approval by a qualified subject matter expert, while the safe harbor method requires the removal of 18 personal health information identifiers. Limited datasets are also widely used for research purposes. Limited datasets are limited sets of identifiable patient information that are considered personal health information because of the possibility of re-identification as per the HIPAA privacy rule (Caplan, 2003). Most recent technologies in cloud applications relied on the three-tier approach with an SQL Server as the database server. Three-tier setups improve performance and limit the number of attacks on databases due to their segregation from the application layer (Singh, 2024). Although

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this architecture provides an extra layer of protection for database servers, it is still prone and vulnerable to all common database server attacks through the application layer and directly on the database layer (OWASP, 2024). Piggy-backed queries - where an attacker attempts to piggyback additional statements to the pre-existing SQL queries – are very common and constitute most SQL attacks (Sai Lekshmi and Devipriya, 2017), SQL injections constitute 15% of attacks against cloud-based applications (Unlu and Bicakci, 2010). Such attacks and others directly contribute to risks against information integrity, availability, and confidentiality. In the healthcare context data leaks result in breaches of confidentiality and privacy of electronic personal health information exposing patients and organizations to significant liabilities. Newer DBMS versions support a variety of features to prevent common attacks such as stored procedures that can help prevent SQL injection attacks but only when stored procedures are implemented correctly (Patel et al., 2020). Although such features would increase database security, vulnerabilities are still present and database information is still accessible to internal resources managing them. In the United States, 35,167 known data breaches have been reported from 2005 to 2023 (Rights, 2023).

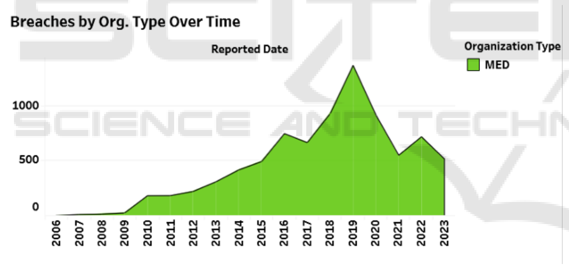


Figure 1: Proposed methodology by (Rights, 2023).

The healthcare industry has experienced the second most data breaches compared to other industries at 24.5% of the total data breaches (Rights, 2023). From 2020 to 2022, the industry suffered from 1,046 data breaches in the United States alone, costing an average of $6.45 million per incident (Enterprise, 2018).

Anonymization and de-identification of data is one solution adopted by the healthcare community to produce datasets for use in the research communities. De-identified datasets enable information sharing for research and public health purposes but cannot be used to protect data at rest for various health information systems. This is due to the integral need for personal health information identification for continuity of care purposes. This work explores a method to de-identify data at rest and allow re-identification at the application layer.

Various security methods, models and new technologies are widely used to protect applications and databases from unauthorized access or data leaks. Mandatory Access Control (MAC) is an access control model enabling access to information based on confidentiality of information and clearance level. Encryption converts information to ciphertext allowing access to authorized users and applications in custody of the key to decipher the code and access the original information. Blockchain is a distributed database composed of blocks accessed through the acquisition of cryptographic hashes to reveal stored information. The framework proposed in this work attempts to utilize MAC, encryption and a blockchain-like structure to de-identfty electronic personal health information in relational databases.

The usage of cloud-based platforms has exponentially increased in the past few years due to the increasing need for medical data available online (Chhabra et al., 2022). Various types of cloud-based platforms were required for a variety of clinical and medical applications such as contact tracing, laboratory test results, travel health declarations, clinical encounters, and other public health tools. This resulted in a significant increase in the amount of electronically identifiable personal health information (ePHI) available online that could be vulnerable to various cloud-based application attacks. Such high availability of health information exposes organizations to significant implications and liabilities due to confidentiality breaches of electronic personal health information (ePHI) resulting in violations of health information privacy policies and laws in various countries.

Four out of the top five vulnerabilities published by the Open-Source Foundation for Application Security (OWASP) can directly impact the database layer and cause unauthorized access to stored information revealing confidential information. Broken access control, injection, insecure design, and security misconfigurations can all lead to privacy and confidentiality breaches with devastating impacts on the healthcare sector. Best practices such as parameterized queries, stored procedures, and other solutions are still vulnerable to a variety of attacks in certain setups (OWASP, 2024).

The emerging needs of big data had rendered non-relational (NoSQL) databases a widely used solution for data storage and retrieval. However, relational (SQL) databases remain the most widely used solution for data storage and retrieval in various applications (Capris et al., 2022). Those databases remain prone to various attacks resulting in confidentiality breaches for electronic personal health information in the healthcare sector.

SQL injections, physical attacks, access control breaches, and other database server attacks could theoretically have less impact if released information is de-identified. Achieving a de-identified storage status using the safe harbor method by eliminating access to the 18 known identifiers of electronic health records in databases at rest would prevent policy violations. This would lessen liabilities for healthcare organizations and help reduce patients' confidentiality breaches while minimally impacting application performance. Such a storage framework is also immune to insider attacks and would offer flexibility in producing limited and de-identified datasets

2 LITERATURE REVIEW

This section explores various modalities designed to increase the immunity of relational databases against common relational database attacks. It covers a variety of solutions that attempt to solve the problem from different angles.

To produce de-identified and limited datasets, (Erdal et al., 2012) discusses an original framework that uses structured data in relational databases-based health information systems. The process performs extract, transform, and load (ETL) to produce a limited dataset that can later be processed into a de-identified dataset.

The objective of this study is to produce datasets that can be used for research purposes that are compliant with HIPAA and the local IRB. The researchers took an interesting approach that relied on the manual removal of HIPAA-protected data attributes through a variety of methods. To isolate patient identifiers, the researchers produced a multi tiered mapping between patient identifiers and pseudo identifiers with a layer of one-way hashing that prevents re-identification through classical SQL queries. For patients more than 90 years of age, the researchers stored their age in a separate table while recording a maximum age of 89 at the level of the limited and de-identified. To produce de-identified datasets, the researchers added a random time increment to disguise dates. The paper later proves the viability of their de-identification framework by running the framework on 20 million records ensuring the efficiency of the framework. The comparison between the original dataset and the produced dataset highlighted a significant increase in CPU processing time (averaging 15 seconds per execution) and a better performance when generating limited datasets in comparison with de-identified datasets. This framework appears to be viable to replace the common manual de-identification processes required to produce limited and de-identified datasets for reporting and research purposes. However, such an approach does not offer any layer of protection to the original datasets, which are still at risk of common relational database vulnerabilities. Furthermore, the model does not offer a real-time reflection of the data available as it would require a significant overhead if deployed in a real-time production environment. The proposed framework in this work offers a solution that would minimally tax the application when protecting health information systems databases.

The work presented in (Lin et al., 2016) attempted to reach k-anonymity in relational databases through an efficient algorithm. To implement this, records go through an anonymization algorithm that would transform data points into a more generic version of themselves to resemble (k) number of rows. The authors suggested an original framework that performed anonymization through three consecutive modules. The pre-processing module was designed to encode transactions to bitmaps that are sorted using the Gray order to approximate similar and classify them into several segments based on similarity for efficient anonymization. The Travelling Salesman Problem (TSP) module was designed to find a cyclical loop between various transactions in each segment rendering the TSP module more efficient to find the cyclical loop between a lesser number of transactions at a time. The anonymization module achieves k-anonymity through the replacement of each class with its center class as calculated by the module. This results in data loss, which is necessary to achieve anonymization.

The paper extended to undergo an experimental evaluation resulting in anonymization for five real-world datasets and one synthetic dataset. Their results showed a significant increase in data loss with an increased (k) value which is consistent with k-anonymization by nature. Although the researchers are presenting a reasonable algorithm that can achieve anonymization, they illustrated significant data loss as anticipated with such an approach. Such data loss can be intolerable in electronic health records or medical records systems.

Authors of (El Emam, 2010) suggested a method to measure the re-identifiability of health information based on a conceptual five-level model of the identifiability continuum as shown in Figure 2. They conceptualize that datasets can reside in gray zones between identifiable and non-identifiable statuses. The authors classified health information datasets into five conceptual categories that are ordinally classified based on the possibility of re-identification. Level 1, which presents datasets that are inclusive of readily identifiable data such as names, social security numbers, and addresses, is at the base of their model with a higher risk of re-identification. Level 2 constitutes datasets with reversibly and irreversibly masked identifiers but accessible quasi-identifiers (i.e. dates, zip codes, date of birth). Exposed data, or level 3 as described by the suggested continuum, is masked data that went through an obfuscation process for quasi-identifiers rendering the dataset more resistant to re-identification but still considered as a high-risk dataset. This is because the custodian did not assess re-identifiability at this level. Level 4 is considered by the authors as the first level to host true de-identified data. Aggregate extracts of the data were marked as level 5, which is the highest form of de-identified data as per the continuum. The paper argues that measuring health data identifiability is possible based on determining the possible risk associated with the data requester. They extended to classify risks into three categories. Prosecutor risk is relevant when an adversary (family member or knowledgeable personnel) is attempting to re-identify data based on previous knowledge of the subject and the fact that the subject exists in the dataset. Journalist risk is relevant when an adversary is attempting to re-identify based on the mere existence of subject knowledge but not its existence in the dataset. Finally, marketer risk, which represents attempts of mass re-identification when comparing datasets with each other such as a comparison between a de-identified health data with a national registry of citizens, which could result in re-identification of a subset of subjects in the dataset. The article argues that by establishing a custodian understanding of the type of risk associated with each type of recipient of the datasets, they would be capable of determining a threshold on the identifiability continuum of types of data at risk of re-identification.

Although the authors' opinion of the existence of re-identification of a dataset on a continuum is valid, the suggestion that the risks are closely associated with target recipients of data is not conclusive. Health information is considered sensitive data with a significant attacker appetite. Therefore, it is prone to residing with an audience that could be of interest in exploiting information when the dataset is not properly de-identified. The framework proposed in this work is designed to enable back-end applications to produce all levels of datasets on the continuum with the capacity to aggregate information into producing level 5 datasets.

The authors of (Omran et al., 2009) discussed the importance of health information exchange and the various recent methods adopted to allow it among various health service providers. The paper also highlights that the higher the availability of healthcare data, the more prone it is to confidentiality and integrity breaches. The Healthcare sector is benefiting from the utilization of web services to promote interoperability, but it significantly increases the possibility of different attacks that would compromise the confidentiality and privacy of patients.

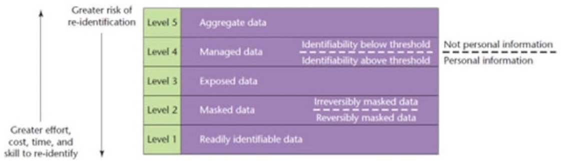


Figure 2: Identifiability Continuum (El Emam, 2010).

The paper discussed security mechanisms and issues in both databases and web services. The first database security measure discussed was access control. The paper compared content-based access control that would only allow access to pre-tabulated views, RBAC model, and System R access control. They later proceed to discuss k-anonymity, aiming to abstract data and release a version that is de-identified. All subjects and attributes that can result in the identification are omitted, leaving a de-identified version of the data that could be shared with minimal confidentiality and privacy risks.

Although there have been successful attempts to re-identify patients from de-identified data, other measures could be taken by policymakers and database architects to minimize such inference. An example of that is changing quantifiable attributes such as age to nominal and ordinal data such as an age group. K-anonymity solves the problem of health information exchange to a great extent, but it does not address security in the case of database vulnerabilities of healthcare cloud applications. It results in significant data loss. The authors also discussed database encryption and Hippocratic databases, both approaches increase the level of security with significant performance impact in database encryption methods.

The study continued to explain web services security and suggested that network security should also be addressed. As the scope of this work focuses on dataset security in relational databases against successful attacks, our focus was to study the different database protection approaches in comparison to the model proposed in this work.

Authors of (Omran et al., 2009) underwent a case study of openEHR security and architecture. openEHR is a widely used open-source electronic health records system. The paper discusses some of the security features of the application such as the segregation of demographics from clinical and administrative data, version control, and access control among others. The openEHR approach to the segregation of data is to achieve anonymity by eliminating any direct clues to identify the patients in the EHR database. The application enforces the storage of an EHR ID (ehr_id) that serves as the foreign key between two databases on different servers. This is stored in a cross-reference database that could be encrypted. This approach attempts to achieve a similar goal to this work. However, the approach presented in this work offers a more efficient and cost-effective solution since the storage of information is done on one database server. It also allows different levels of protection based on the sensitivity of the various data attributes. Due to the hierarchical nature of the proposed framework, software adapting this framework would be capable of producing limited or de-identified datasets on demand without significant overhead. The suggested framework enables security policies and role-based access control due to the multi-tiered classification of sensitive data.

The work presented in (Avireddy et al., 2012) discusses the utilization of randomized encryption for the protection of SQL injection attacks. The paper presented the risks of SQL injection attacks and their common incidence for cloud applications. The paper aimed to develop an algorithm that uses randomized encryption to minimize confidentiality breach risk caused by SQL injection attacks. It extended to develop an application that adapts the algorithm to validate the immunity of this algorithm towards SQL injection attacks.

The authors focused on SQL injection attacks caused by poor validation on the application tier in a three-tier cloud application setup. Such improper validation might cause SQL statements to be passed toward the database server, causing potential extraction of confidential data, taking control, or disturbing data integrity. SQL injection attacks using tautology are very common in applications that do not enforce proper front-end and back-end validation. One example of that would be an attacker passing an SQL statement to extract data or alter the original query designed by development teams. Another example of such attacks is the usage of incorrect queries to return errors from the database server. Attackers usually use this method to infer information about the database structure which could later be used during the construction of malicious SQL statements.

The Random4 algorithm is what the authors propose as their contribution to this paper. It constitutes a method that is based on randomization to convert input into an encrypted salt. The algorithm chooses specific characters that could be used in salting any front-end input before passing it back to the database engine. Each character in the input is later mapped into one of 4 probable characters based on the predefined lookup table relying on the character mapping technique they chose to implement.

The paper suggests that encrypted input should be stored within the database which would significantly decrease the impact of SQL injection attacks. They attempted to develop an application written in C# to encrypt incoming inputs to provide examples. The proposed model would prevent piggy-backed queries since passed input is changed and would not be malicious once received on the SQL server side. The initial explanation of the Random4 algorithm described that user input would be salted before being saved in the database. However, the authors extended to describe that the various database attributes also fall under this technique rendering it harder for attackers to crack the structure of the database.

Random4 algorithm was tested on 5 different applications proving a significant reduction in SQL injection attacks when tautology is used, which is justifiable due to the nature of salting of input. Analyzing the algorithm proposed by the work in [19], it is clear that the encrypted input to SQL databases would result in a significant performance hit due to longer and inconsistent strings as well as the overhead produced by encrypting and decrypting all input and output from and to the database.

The work presented in (Oksuz, 2022) attempted a different approach to achieve a similar goal of database anonymization in electronic health records databases. The proposed model relied on blockchain to store identifiable information. The paper explains a novel approach to anonymize patient records in an EHR database through the storage of medical records by a centralized authority in an off-chain database while referencing a hash accessible in the blockchain. Referentiality of records is lost and all encounters have associated blocks in the chain accessible through a hash provided by the patient. The researchers highlight that although records can only be identified through the presentation of a pseudo-identifier through the patient, institutions are still capable of utilizing anonymized data for analysis and research purposes.

The model in (Oksuz, 2022) allows central providers trusted on a chain to add and create new blocks that can be associated with individual encounters in the chain. Untrusted entities requesting access to clinical encounters would have to use predetermined random hashes to access various blocks associated with the same record or clinical significance to later consume hashes to query off-chain databases. This requires patients to carry specific keys to all their encounters – such as vaccination records – and would not be able to verify the authenticity of the record unless provided with at least two blocks about the same patient pseudo identifier.

This model is the most similar, in terms of functionality and results, to the work proposed in this work. Due to the fact that authors did not introduce solutions to some quasi-identifiers such as encounters dates, it achieves a resting state of the database that is considered a limited dataset by HIPAA definition, with pseudo identifiers available in a blockchain only accessible through the respective block hashes. However, in contrast to the work in this paper, the model proposed by (Oksuz, 2022) requires a resource-intensive setup and a complex integration of off-chain and in-chain records, and due to the nature of blockchain technologies, the performance impact can be significant (Koushik et al., 2019). Furthermore, the model relies heavily on patients presenting access keys for all entities to access their records. This can be counterproductive in an emergency room setting where patients are unconscious, or hashes are lost. The model also did not take into consideration the necessity of case progression and timeline analysis in research applications, which is very crucial in many types of clinical and public health studies and is pivotal to achieving continuity of care.

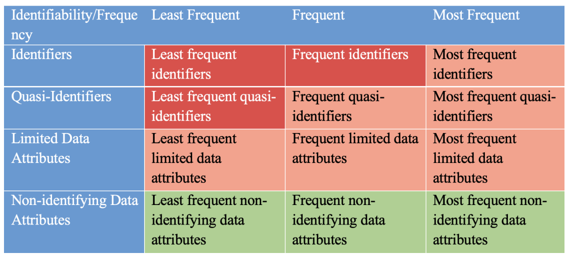
None of the above literature adopts an approach that encrypts foreign keys to de-identify data in a tiered database instance, which is the proposed method in this research. All relevant work focused on using anonymization when data is being extracted for research and statistical analysis.

3 FRAMEWORK DESIGN

This section determines the proposed framework to achieve a secure de-identified databaseenabling the transformation of relational healthcare databases with electronic personal health information into true de-identified databases at rest.

3.1 Determination of Identifiers and Quasi-Identifiers in an EHR Database

This section suggests a categorization matrix for common electronic health records system attributes to determine their protection level. The work scores the sensitivity level of each attribute on the identifiability continuum proposed by (El Emam, 2010) and determines the level of accessibility of each attribute. This is achieved by ranking attributes based on the identifiability continuum and by classifying the frequency of the attribute appearance on various EHR screens. Figure 3 proposes a categorization matrix of the various data attributes based on the potential impact of their confidentiality breach.



Identifiability/Freque ncy	Least Frequent	Frequent	Most Frequent
Identifiers	Least frequent identifiers	Frequent identifiers	Most frequent identifiers
Quasi-Identifiers	Least frequent quasi-identifiers	Frequent quasi-identifiers	Most frequent quasi-identifiers
Limited Data Attributes	Least frequent limited data attributes	Frequent limited data attributes	Most frequent limited data attributes
Non-identifying Data Attributes	Least frequent non-identifying data attributes	Frequent non-identifying data attributes	Most frequent non-identifying data attributes

Figure 3: Proposed categorization of EHR attributes.

As illustrated in 3, all EHR data attributes are classified into 12 categories. Those categories offer a balanced view of their sensitivity and frequency of access. and determine their storage locations and protection policies throughout the framework. The paper aims to classify all attributes encountered in the sample database including personal information, demographics, consultation information, and triage data.

The above categories fall in three protection levels from highest to lowest priority as follows:

- Extremely Protected: this includes least frequent identifiers, frequent identifiers, and least frequent quasi-identifiers.
- Protected: this includes most frequent identifiers, frequent quasi-identifiers, most frequent quasi-identifiers, and all limited data attributes.
- Unprotected: all non-identifying data attributes.

The level of protection governs the level of storage for the associated data attributes in the framework database. The higher the level of storage is the more iterations of foreign key decryptions needed to retrieve the data attribute as illustrated in the next chapters.

3.2 Designing the Hierarchical Structure of the Framework and Determination of Quasi-Identifiers Masking Methods

This section aims to outline the conceptual model of the proposed framework. It suggests the 7 rules governing the design principles based on the protection level of the data attributes. Furthermore, the framework considers the masking of some quasi-identifiers such as dates while preserving the epidemiological and clinical value.

The proposed framework assumes the preservation of the below rules:

3.2.1 Each Searchable Identifiable Attribute Must Be Stored in a Separate Database Table. this Eliminates the Possibility of Cross Referencing One Identifying Information Using Another

For searchable identifiable attributes, such as names and unique identifiers, the proposed framework requires the storage of no more than one in a single database table. This ensures that attackers do not get access to one identifying information because of their previous knowledge of another (i.e., obtaining a social security number using the patient's name). The highest-level table has only one encrypted foreign key to the next lower-level table. Lower-level tables would have an encrypted foreign key for the next lower-level record and another encrypted foreign key for the previous higher-level table. The decryption of foreign keys within the software algorithm is necessary to enable querying the next table in either direction. Policymakers can choose whether to hierarchically position those tables in a chained format or to undergo grouping of attributes in various levels to improve performance.

3.2.2 Non-Searchable Identifiable Attributes Must Be Stored Encrypted in a Separate Table

The proposed framework suggests that all non-searchable identifiable attributes are stored in an encrypted format within a separate database table. No database table should contain columns of both, searchable and non-searchable data attributes at any time. Developers and security policymakers could define whether one database table contains all non-searchable identifiable attributes or choose to segregate each attribute or group of attributes in a different table depending on their relation to each other. Separating attributes in different tables renders the proposed framework more resistant to attacks, increases security, and further dilutes the potential harm of database attacks. One important aspect is that the more complex the model adopted, the less performance is anticipated.

3.2.3 Non-Identifiable Searchable and Non-Searchable Attributes Should Be Stored in the Reference Database Table

This framework suggests that non-identifiable attributes should be stored based on common database structures practice. Encryption is not a necessity for the attributes. However, the table contains the encrypted foreign key for the lowest level identifying table in the framework. This table is called the reference table in this work. This table's primary key can be referenced by a foreign key in various clinical encounters utilizing relational database features. The proposed framework ensures that the impact on performance is kept to the minimum when using aggregate functions for the analysis purposes of deidentified health and administrative information. Therefore, reverse identification is possible besides regular storage of non-encrypted attributes in the reference table. The proposed framework leaves the structuring and normalizing of database decisions for the system analysts and database administrators.

In case of migration to this model, analysts and database administrators need minimal changes to database tables below the reference table to address quasi-identifiers such as clinical encounter dates and caregiver information. Patient identification tables are replaced by the reference table and database integrity should not be affected assuming that the database has a reasonably normalized design. This is because the identification of patients and personnel only occurs at one table and health information and encounters refer to identification tables through a foreign key.

Developers and security policymakers may choose to enhance security further and reduce the impact of database attacks by encrypting non-identifying attributes. However, this could have a significant performance impact on reporting and application data aggregation power. For this paper, such extra encryption is out of scope and could be revisited in future work.

3.2.4 Health Encounters and Administrative Records Can Only Be Referenced Through Reference Tables Producing Limited Datasets

This approach requires that health encounters, administrative records, or any record protected under the HIPAA privacy rule or the security policy of the organization or the region should contain a foreign key -when needed- to the reference table containing non-identifiable information. At this point, any identifiers and quasi-identifiers, except encounters and administrative records dates, would be stored in a higher-level table above the reference table. Querying these attributes would require decrypting one or more encrypted foreign keys through the application backend. Furthermore, the resting state of the database instance is de-identified and any direct SQL injection attack or any other query that could be executed on the database server is not able to retrieve any electronic personal health information. However, it would be able to retrieve dated electronic health information, which is a limited dataset. This is addressed in the next rule.

3.2.5 Dates Must Be Masked Through a Random Increment or Decrement that Is Different for Each Patient

To achieve a true de-identified state, dates should be masked as they are considered quasi-identifiers and could be utilized by attackers with previous knowledge of encounter dates. The framework proposes a random increment or decrement that is considered to the framework as a non-identifying non-searchable attribute. As discussed in design principle 3, this interval is stored in a separate database table or with other non-searchable identifiable attributes. Such a static interval per patient would ensure visibility to proper clinical case timeline, physicians can still observe the progression of clinical cases on realistic timelines. A consideration when developing the interval determination algorithm should be the fact that seasonality and endemic information could be disrupted while they are of high clinical significance. To overcome this, policymakers can allow caregivers to re-produce limited datasets or re-identify information while adhering to the health information security and privacy that apply to their organizations, for example, the HIPAA privacy rule requires logging any access to limited or identified datasets.

3.2.6 Incremental Primary Keys Are not Allowed for any Table Above the Reference Table

With incremental primary keys, attackers can infer the relation between two tables through a sequence, an attacker might relate that entry number 1 in the patient names table refers to entry number 1 of the social security numbers table. To ensure maximal security, and to inhibit the ability of attackers to infer personal health information based on the sequence of insert and creation or timestamps. The proposed framework requires that incremental primary keys be not allowed for any of the database tables above the reference table. As an example, developers can use universally unique identifiers (UUID) for tables without a unique attribute.

3.2.7 Encryption Keys Should Be Different for Every Encrypted Foreign Key

Developers and policymakers achieve a higher level of protection when encryption keys are different for each foreign key, this ensures that if any foreign key is jeopardized through the software interfaces, the application tier, or improper key management, other foreign keys would still be protected and immune to the attack and the data leak would be to a minimum. Key management methods and procedures are out of scope for this work but could be examined in future work.

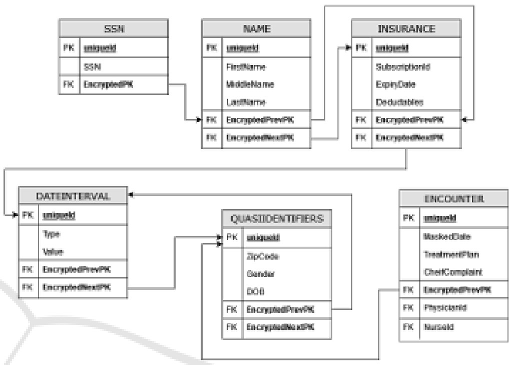


Figure 4: Proposed schema of EHR data attributes.

Adopting the schema proposed in Fig. 4 through implementing the 7 rules proposed in this section would result in loss of referential integrity between the various tables above the reference table. This is caused the encrypted foreign keys that are handled the application layer. This referential integrity loss was observed in all methodologies segregating identifiers and quasi-identifiers from health encounters. However, unlike other proposed work examined in this work, this framework sustains a one-to-one relationship between all tables above the reference table with no change to referential integrity with the clinical encounters. This simplifies implementing integrity constraints at the application layer to compensate for the referential integrity loss anticipated by adopting this framework.

3.3 Applying the Framework to an EHR Database

This section aims to apply this framework to a conceptual EHR database, during this phase a typical SQL database schema for an electronic health records system is used to adapt the framework, the software database is structured to have 70 different tables that cover primary, secondary, and tertiary health care services. For this study, we de-identify the database tables that store only primary health records, administration records, and patient identification tables to provide an example for a wider use.

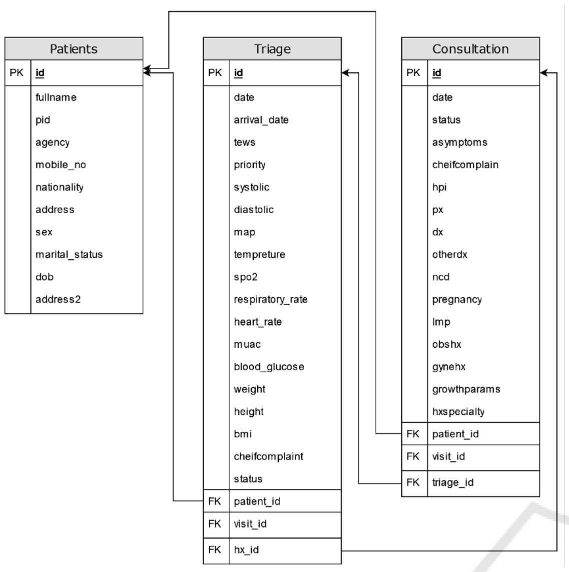


Figure 5: Original database structure.

Figure 5 shows the original structure of the database. Three database tables are de-identified using the framework proposed structure for this work.

- Patients Information Table: This table contains identifiers and quasi-identifiers of all patients processed through the software.
- Triage Information Table: This table contains information from various nursing stations in primary healthcare settings, the information stored in this table are the patient's vital signs, chief complaints, and a few administrative attributes along with service received dates.
- Clinical Consultations Table: This table contains the consultation information of all cases. It stores all consultation details as well as the diagnosis and the treatment plan of the patient, which are the most sensitive information to be protected.

To restructure the schema presented in Figure 5 abiding to the seven design principles outlined previously in this work, a categorization of data attributes need to take place based on the frequency and identifiably of the attributes. This categorization helps in identifying the correct level to store each attribute in the new schema. We concluded the categorization highlighted in Figure 6 of patient personal information attributes based on typical electronic health records systems functionality.

Given the encryption of foreign keys in the application database, it is anticipated that the database

Identifiability/Frequency	Least Frequent	Frequent	Most Frequent
Identifiers	mobile_no		fullname, pid
Quasi-Identifiers	nationality, address2	address	dob
Limited Data Attributes			
Non-identifying Data Attributes		marital_status	sex

Figure 6: Attributes categorization using the identifiability continuum.

loses referential integrity between the higher-level tables. Software developers can implement various constraints at the application layer to ensure referential integrity between those tables.

3.3.1 Step 1: Searchable Identifiable Attributes Must be Stored in a Separate Database Table

To adapt to the first rule, identifiable information that is searchable "Non-Encrypted" would have to be stored in separate tables to preserve confidentiality. This ensures that an attacker gaining access to the database would not be able to infer, or correlate identifiers based on previous knowledge of one or more of those identifiers. An example would be an attacker aware of a specific patient's name being able to retrieve their social security number due to their storage in one row. Both the patient's full name and patient unique identifier attributes highlighted in Figure 6 are considered searchable (frequent) identifiers. To abide by the framework rules, they are stored in separate database tables both with encrypted foreign keys relating to the next level table. Developers can choose to hierarchically structure those tables as separate levels of this framework or store the various attributes on the same level. If a similar level is chosen developers must use different encryption keys or vectors for both tables. This ensures that the encrypted foreign key value is not similar in both tables and cannot be used for reference.

Figure 7 illustrates the implementation of the framework for searchable identifiable attributes while storing each attribute in a separate level. This represents a more secure design in comparison to Figure 8. However, this design requires back-end functions to iterate through subsequent levels to arrive at the reference table used to relationally reference the clinical encounters resulting in performance degradation. This work uses this design in the database transformation and all results are shared to the most secure implementation of this framework. Developers and organizations can weigh the security benefits in comparison to the performance impact to determine whether

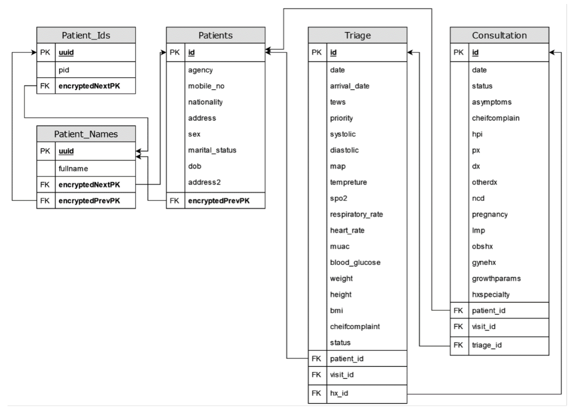


Figure 7: Searchable identifiable attributes must be stored in a separate database table for each attribute, separate levels design (more secure).

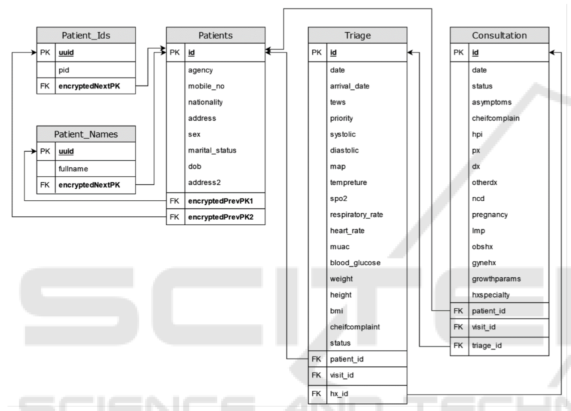


Figure 8: Searchable identifiable attributes must be stored in a separate database table for each attribute, same level design (less secure).

to add their searchable identifiable attributes in one or multiple levels.

To ensure that users with access to the database are unable to utilize relational features to infer ePHI or any other identifiable information. The encryption key or encryption vector should be different for Patient_Ids, Patient_Names, and Patients tables. To ensure proper adoption of the seventh rule of the framework, the following rules must be true:

- In Figure 7: Patient_Ids.encryptedNextPK $\neq$ Patients.encryptedPrevPK.
- In Figure 8: Patient_Ids.encryptedNextPK $\neq$ Patient_Names.encryptedNextPK.

3.3.2 Step 2: Non-Searchable Identifiable Attributes Must be Stored Encrypted in a Separate Table

To abide by this rule, all identifiers and quasi-identifiers that are non-searchable must be removed from the reference table and preferably stored in an encrypted format. As discussed previously, policymakers can choose whether to store both identifiers and quasi-identifiers at the same level or not as well as the possibility of grouping those attributes according to their relevance and the cross-matching possibility of re-identification. For example, if the insurance identification number is stored in the same table with the name or id of the insurance provider, the possibility of inference increases if attackers gain access to information in that specific table. Policymakers can choose to store those two attributes in separate levels of the framework to increase security keeping in mind the potential impact on performance. Both implementations are illustrated in Figures 9 and 10.

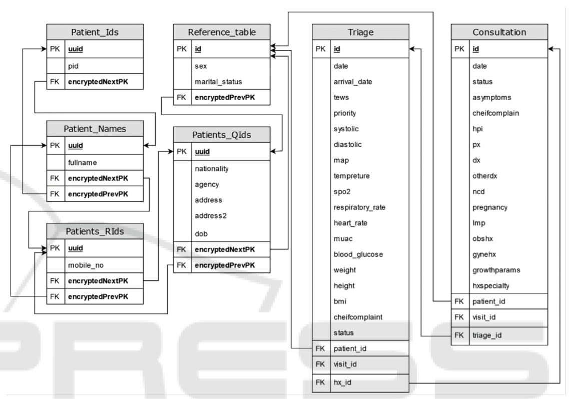


Figure 9: Non-searchable identifiable attributes must be stored encrypted in a separate table. separate levels design (more secure).

To prevent violation of the framework rules, the encryption key or encryption vector should be different for Patient_Ids, Patient_Names, Patients_RIds, Patients_QIds, and Reference_table tables. This results in the following rules to be true:

- Patient_Ids.encryptedNextPK $\neq$ Patients_RIds.encryptedPrevPK.
- • Patient_Names.encryptedNextPK $\neq$ Patients_QIds.encryptedPrevPK.
- • Patient_RIds.encryptedNextPK $\neq$ Reference_table.encryptedPrevPK.

Although Figure 10 illustrates a higher-performing design, it is less secure than the model illustrated in Figure 9.

3.3.3 Step 3: Non-Identifiable Searchable and Non-Searchable Attributes Should be Stored in the Reference Database Table

As discussed in the previous section, successful implementation of rules 1, 2, and 7 from the framework results in only non-identifiable information to

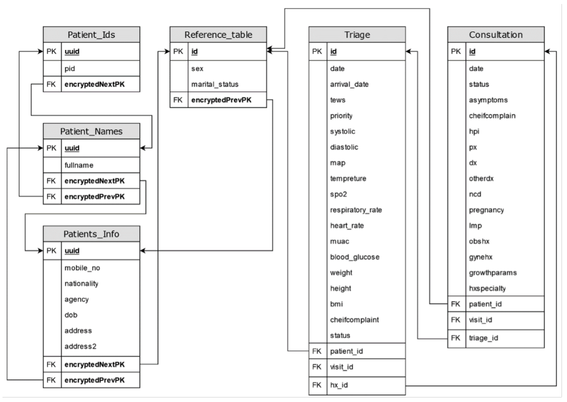


Figure 10: Non-searchable identifiable attributes must be stored encrypted in a separate table. Single table design (less secure).

be stored in the reference table. This allows EHR solutions to leverage relational database features to process and manipulate data stored within the reference table without any decryption required by the backend application or any change in the application's logic. Researchers continue to have the ability to leverage EHR data for public health, disease surveillance, and other research purposes. This is because the framework preserves non-identifiable information in the reference table. More complex research studies such as time series and case studies would require specific algorithms to be implemented in the back-end application.

3.3.4 Step 4: Dates Must be Masked Through a Random Increment or Decrement that is Different for Each Patient

To achieve a higher level of security for databases in their resting state, dates and timestamps are masked as they are considered quasi-identifiers. Attackers can infer patients' identifiable information if they have pre-existing knowledge of clinical encounters' time stamps. To achieve this, this model proposes a random increment or decrement automatically assigned to each patient at the registration stage. This factor is used to mask all records associated with the patients in all tables regardless of their location within the framework. The random static factor ensures that data integrity and quality for researchers remain intact for case progression and time series analysis. However, seasonality might be lost which could be tackled by using a less secure year increment/decrement factor. Given that dates are considered quasi-identifiers in health applications, the factor is stored at a similar level with other quasi-identifiers.

Figure 11 illustrates the final proposed database structure implementing all rules of the proposed framework. The main patient's table illustrated in Figure 3.2 was split into 5 smaller tables with encrypted foreign keys referring to the next and previous level tables. The framework preserved the original patients' identifiers in all encounters tables and resulted in no change in their structure enabling a simpler adoption of the framework due to the minimal changes needed in software logic to reflect change.

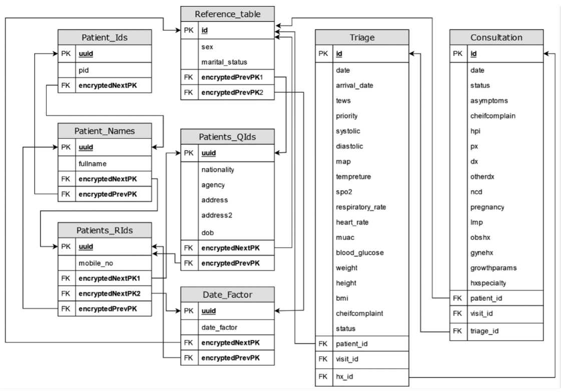


Figure 11: Final Proposed database structure, abiding to all framework rules.

The final proposed database structure stores searchable identifiable attributes in separate tables structured in a hierarchical manner (Rule 1). It also stores less frequently used identifiers at a different level from quasi-identifiers (Rule 2). All non-identifying attributes are stored in the reference table for easy retrieval (Rule 3). All encounters' tables refer to the reference table (Rule 4) preserving all the referential features of relational databases with no change reducing the impact on database utilization of data aggregation and research. The structure extends to store the date increment/decrement factor separately for each patient within the database (Rule 5) and abiding by (Rule 6) at all levels above the reference table. The framework utilizes universally unique identifiers (UUIDs) limiting the possibility of inference due to relevant records ordering in all tables. When implementing this structure, encryption keys or vectors are different for different levels ensuring that relational features of the database are not used to re-identify data (Rule 7).

The implementation of this approach in pre-existing EHR systems would require those changes to be executed at tables containing patient identifiers, with minimal to no changes at the clinical encounters tables. For applications utilizing best practices such as database normalization and modular application design, the implementation of this approach would be relatively simple and very similar to the approach presented in this paper. Efficient utilization of this approach would highly rely on adopting an application design that minimizes re-identification. Example approaches would be to temporarily store de-identified patient information in the session as providers are navigating the relevant patient history or utilizing object oriented architectures where re-identification would happen once for active patient's object.

4 CONCLUSION AND FUTURE WORK

De-identification of medical data has been a widely used solution to produce data extracts for research and analysis. The work was able to identify 7 framework principles that could de-identify any health information system database through Segregation of identifiable information in separate database tables based on their importance and frequency, omitting the use of relational database features between those tables through encryption of foreign keys, and addressing quasi-identifiers such as encounters dates through masking with a random increment/decrement that is stored in the same manner. The de-identification of a sample EHR schema database was successful migrating the original database structure to a structure conforming to the 7 principles of the framework.

In future work, our aim is to test the framework on a real-life EHR database and compare the performance against the original to determine the suggested framework efficiency.

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