Biobank registry implementation: An evaluation of NoSQL databases for Philippine Cancer-Phenome Biobanking System

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Abstract

Background and objective:. The field of healthcare is rapidly accumulating data of complex types and formats. The current methods of storing data relies heavily on traditional relational database management system (RDBMS) which have notable limitations in managing clinical and biomedical data. Thus, a constant demand for alternative approach is in place. Among the available solutions, NoSQL databases had been cited as a viable option due to its numerous advantages in handling healthcare data challenges.

Methods:. This study evaluated different types of NoSQL databases using an database evaluation framework tailored for healthcare context.

Results:. The application-specific evaluation criteria showed that document-based type is the best choice for extensibility, flexibility, and query readability whereas key-value pair is the most efficient in performance and scalability. Moreover, columnar-wide has the edge in storage capacity.

Conclusion:. Among the shortlisted databases, MongoDB - a document type NoSQL was found to be the recommended choice for the current implementation and immediate need of the biobank information system.

Keywords: Clinical data, relational database, NoSQL, biobanking, database evaluation framework, health information system

1. Introduction

The increasing size and complexity of data being generated in healthcare industry is reaching to the point of being unmanageable [1, 2]. This was brought about by the technological advances in medical and biomedical fields which have highlighted the importance of collecting and storing data to benefit clinical research and medical services.

Currently, storage of clinical data largely relies on relational database management systems [3, 4] and has been the most common approach of data storage since the 90's [5]. From the time of its origins in the 1970's, the relational model had been adapted widely in many database management systems [6, 7] and had remained unchanged for decades [2]. This modeling approach had become the de facto standard for most industries, but remains ineffective in the field of healthcare due to the characteristics of clinical and biomedical data.

Healthcare data are dynamic, hierarchal, sporadic, and heterogeneous in nature. It is stored in various types including free text, coded data elements, images, signals, logs, or notes that is formatted in either structured, semi-structured, or unstructured presentation [2, 4, 8, 9, 10]. The heterogeneity of formats, high volume exchange, and dynamic structure makes it difficult to model and manage health data using the traditional relational database [4, 11, 12, 13].

In addition, one of the major drawback of relational database is the need for pre-designed schema. Predefining the data structure is impractical since pre-determing the combination and variety of data fields to be collected in a medical record is unrealistic [4].

Succintly, RDBMS is not flexible, scalable, and extensible to overcome the problem of constantly changing requirements, various formats, increasing volume, and the continuous need for updates in healthcare data [3, 4, 11, 12, 13].

Against these backdrops, there is a constant demand

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and practical need for alternatives outside the conventional relational data modeling approach. Consequently, there are increasing researches and industry projects on databases that are driven by the practical experience of the conflicting static nature of relational database and dynamic characteristics of healthcare data [2].

Out of the wide spectrum of viable alternatives, this study identified NoSQL database as supported by literature to be suitable in addressing the challenges of healthcare data. NoSQL approach had attracted the attention of non-clinical industries and researchers due to its flexibility, scalability, velocity, and availability which addresses the limitations of relational databases [2, 8, 14, 15]. While there are significant advantages of using NoSQL database, there is limited research which has evaluated the use of NoSQL databases in the healthcare domain.

Additionally, it is not always straightforward to declare which database type is better than the other. Concerns are raised in selecting which among the list of 225 NoSQL databases [16] can best address the healthcare data challenge. To date, there is a paucity of literature that provides guiding principle, standard protocol, or framework on how to evaluate of database for healthcare industry.

In light of the foregoing, this study attempted to evaluate three NoSQL database types (i.e. document based, columnar wide, key-value pair) using an evaluation approach that focuses on healthcare domain.

The sections below are organized as follows. Section 2 offers an overview on research project context and the evaluation approach taken. Section 3 describes the methodology performed for the testing and prototyping of each NoSQL database type. The final results of the application-specific evaluation criteria are discussed in section 4. Subsequently, a conclusion is given in section 5.

2. Background

2.1. Project Context

Establishing that relational database have notable limitations in managing the nature of healthcare data [3, 4, 11, 12, 13] is one thing. Proposing an alternative solution that undergoes a systematic way of evaluation is another. The latter is the undertaking that this paper aimed to implement.

In relation to Philippine scenario, one of the initiative of Philippine-California Advanced Research Institutes (PCARI) Project is to implement of Philippine Cancer Phenome-Biobanking System. The development of this pilot project will serve as a model health information system (HIS) with optimism of going national scale. The data challenges mentioned are applicable to the context of the biobank information system. Critical to the success of the system is the appropriate evaluation and selection of data modelling approach and database technology.

Technology selection or evaluation framework are constructs predominantly used in the field of business sectors with focus only upon management and financial decisions [17], but dearth of source exists when discussing technology or database evaluation for healthcare sector. Moreover, most selection practices and evaluation models in digital health technologies are informed by traditional means: word of mouth, internet search, consultant's advice, expert's opinion [18], emerging systems, and technology trend. There are limited models, empirical evidences, and guidelines that facilitate methodological evaluation of database for HIS.

Thus, this paper adapted a database evaluation framework that will evaluate NoSQL databases against context-based parameters.

2.2. Evaluation Approach

The principles of this study's evaluation framework was inspired from themes of Digital Selection Framework [18] and the context-driven component evaluation process of Technology Selection Framework for Health Interventions [17]. The aim is to provide reproducible and reusable process in evaluating database that can address healthcare data requirements. The steps are illustrated in Figure 1 and this study's application are outlined below.

1. *Specification Scoping.* Narrowing down the type of HIS is vital given that the storage, extraction, and transaction of data vary relative to the nature of the health information system and the context of its application. The HIS for this project is a biological specimen inventory and clinical registry type system. This type of application is not transaction intensive but rather storage and reporting exhaustive. With this consideration, the study anticipated the need for a database that can manage voluminous and aggregatable data.
2. *Clinical Contextualization.* Defining the requirements within the context of a clinical domain assures that the functionalities are clinically relevant and not technology focus solutions. Multiple sessions of focus group discussions (FGD) and key informant interviews with the technical and allied health professionals were done as method of elicitation for this step.
3. *Criteria Formulation.* The study's empirical findigs is as equally important as the metrics itself. The essence of this framework is pinned around the criteria. This research consolidated and prioritized the functional and non-functional requirements collated from the qualitative approach to form the basis of the evaluation criteria. The metrics measured in this study are application specific. Nevertheless, the methods applied are generalizable to other database evaluation.
4. *Technology Selection.* On the grounds that the nature of clinical data is highly evolving and dynamic, one of the immediate selection filters is the capability to adapt to schema changes. In consequence,

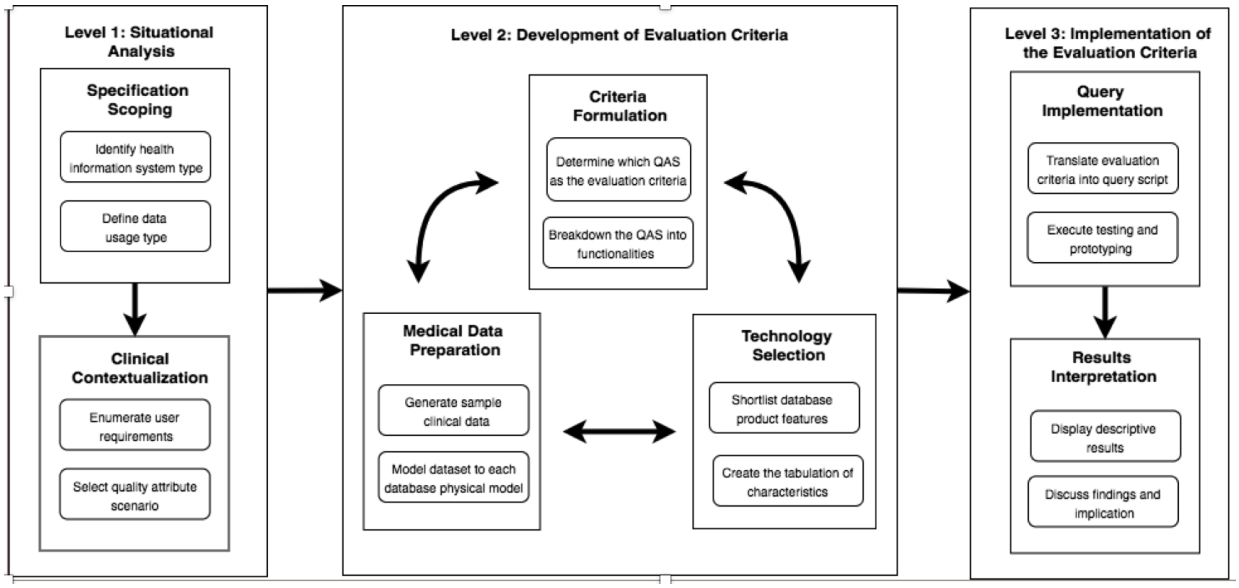


Figure 1: Database Evaluation for Healthcare

schema-less modelling approach was the logical option; hence, focus on NoSQL was the scope of the implementation. This study evaluated only the highly represented and most popular database for each type of the NoSQL category [19]. The selected NoSQL databases are MongoDB for the document category, Cassandra for the columnar, and Redis for the key-value. This paper presented the three different NoSQL types: document based, columnar wide, and key-value pair.

5. *Medical Data Preparation.* The research utilized 1 million unique patient records. This clinical data were in Health Level 7 - Fast Health Interoperable Resource, release Standard Trial Use 3 (HL7 - FHIR, STU3) format. In using this FHIR standard, schema mapping and modelling of the clinical dataset into the physical data storage of each NoSQL database type was necessary. This step is mandatory as each database technology has corresponding physical data model and underlying technical requirements that need to be configured prior to the actual loading of the dataset.
6. *Query Implementation.* The query scripts were fundamentally derived from the evaluation criteria. Each criteria, if applicable, were converted into multple database query statements or scripts. Each script was executed multiple times against different workloads on several dataset sizes in different testing configurations to allow rigorous comparison amongst each selected database.
7. *Results Interpretation.* Summary of results were displayed tabular or graphical presentation showing the comparison of each NoSQL types against the identified evaluation criteria.

3. Method

3.1. Evaluation Criteria

The data gathered from stakeholders' discussions and interviews were translated into quality attribute scenarios (QAS), functionality lists, use cases, business requirements, and software specifications. Following the guidelines of QAS workshop set by Barbacci (2003) [20] and further prioritization of functionality lists resulted into the final evaluation criteria: performance, scalability, storage, readability, flexibility, and extensibility

3.2. Clinical Datasets in HL7-FHIR

Medical data formatted in standard information modeling ensures interoperability, compatibility [4], and conceptual normalization. Further, data prepared in a structured form enhances machine processability and searchability [21].

For this study, the dataset used were structured in HL7-FHIR STU3 standard. Using FHIR specification enforces the use of modular components called "resources". The principle of modularity enables the resource to be logically exchanged and consumed by external systems either as a standalone or bundled resources.

The FHIR clinical datasets were synthetically produced using an open-source generator called Synthea. This award winning [22] synthetic patient record generator was started by the MITRE Corporation as part the Standard Health Record Collaborative program [23]. The goal of the tool is to create synthetic data that is both high-quality and realistically capable of yielding patient health records using demographic and statistical disease prevalence model. Synthea is used as the primary clinical dataset generation toolkit [24] and is capable of producing both FHIR and Clinical Document Architecture (CDA) formats [23]

Out of the 12 available resources in Synthea, only 3 resources namely: patient, condition, and diagnostic report were filtered, mapped, and stored separately in the physical data model of each selected database. The other resources that were bundled with the raw data were parsed and excluded.

These resources are sufficient to test the evaluation criteria that directly involves basic functions such as insert, upsert, scan, read, update, and delete. The database operations of clinical registry and specimen repository mainly revolve around storage and retrieval of patient's clinical personal identifiable information, diagnosis, conditions, diagnostic reports, and procedures. Hence, these resources are the bare minimum to meet the requirements of biobank HIS. The selected resources data composition are shown in Table 1 below.

Table 1: Clinical Dataset Composition

Resource Type	Number of unique records	Average size per record
Patient	1,000,000	3,980 bytes
Condition	5,430,000	5,000 bytes
Diagnostic Report	5,630,000	675 bytes

3.3. NoSQL data modelling

Considering that each NoSQL type has different approach on how data is stored, a series of modelling, mapping, and text manipulation processes were taken to satisfy the physical data model prerequisites of each database. For instance, since Redis follows a key-value convention, the dataset must be transformed to represent a key-value notation. The section below describes how the datasets were mapped according to each database technical requirement.

1. *MongoDB* stores data into collections of JSON documents. A collection is the technical equivalent of a RDBMS table, it exists within a single database and may contain single or multiple documents. A document, on the other hand is the row equivalent in relational database parlance. It is the most basic unit of data in MongoDB. It can contain flattened JSON objects with simple name-value pair, or a deeply nested nature containing multiple embedded or referenced documents. The document-oriented approach allows for the aggregation and nesting of related data via arrays and subdocuments within a single document, easily accommodating the denormalization necessary to eliminate the joins characteristic of relational database queries (Klein, et.al, 2015). The MongoDB schema in this study consists of a single database named "fhir" and multiple collections called "patient", "procedure", "diagnosticreport", and "condition". The 1 million patient records were parsed according to the FHIR resource it contained, and were stored into its corresponding collections. Figure 6.1 below shows the mapping of the raw FHIR Patient resource into the MongoDB document-oriented approach. To establish referential relationship of the FHIR.patient with FHIR.condition, the raw data of FHIR Condition resources were added with the "patientId" field in the root element alongside with other attributes (e.g. Condition, id, clinicalStatus). Figure 6.2 shows how the data transformation was done to accommodate the MongoDB referential requirements. The same data manipulation from raw FHIR JSON to MongoDB JSON document object was done to procedure and diagnostic report resources.

2. *Cassandra* stores data into tables similar to relational database. The table which commonly referred to as column families (CF) are consist of bundled or grouped columns. But unlike relational, these CF can contain primitive and complex name-value data types. Complex types like the map collection type (with the other two types - as the set type and the list type) makes Cassandra "dynamic" as it can handle unrestricted and unbounded number of columns. Each element of a map collection type is stored internally as one Cassandra column. In the relational perspective, the map collection type is comparable to a different table only and that it can be stored within a single column. Instead of having foreign key references to the separate table, Cassandra's approach is to directly contain the supposedly separate table into just one of its columns. Modeling the one-to-many relationship between patient and condition, diagnostic report, and procedure in Cassandra is different from MongoDB. Since Cassandra does not store nested JSON, additional work for data transformation is necessary. For example, if one patient lives in many addresses, the address column is transformed as a map collection data type. The use of a collection type accommodates the fact that a patient can have more than one address (e.g. primary address, mailing address. There are many approaches to the modeling details of Cassandra, design considerations on the partitioning, clustering, denormalizing, and distributing methods of data models are heavily motivated by different purposes and objectives. However, in this study the modelling goal is to maintain the granularity and independence of each FHIR resources at the same time to establish referential relationship with each other. The study intends to achieve this by storing each FHIR resources into separate tables but also allot an extra column as reference (i.e. "patientId") to each other, particularly the patient table.

3. *Redis*, everything in Redis is stored in a denormalized way. This approach provides a minimalist key-value store with neither the nested document structure of

MongoDB nor the columns-within-columns structure of Cassandra. Data stores are organized in buckets within a namespace. Each namespace contains unique rows of key-value pairs where each value is attached to a unique key and can be any data type. The one-to-many relationship between patient and condition, and diagnostic report proved to be a challenged in Redis. The basic key-value pair structure is not sufficient to support the type of queries required by the prototyping. Extracting the search match of data in value column that is stored as JSON is not possible. To resolve this deficiency, the study opted to make use of Redis' built-in commands (i.e. HMSET). These commands provide a wrapper suitable for fast and efficient manipulation of key-value. Like any FHIR resources, the values are stored in keys that can be accessed with a specialized subset of commands. With this command, similar behavior of the columnar data store like Cassandra was replicated for Redis

3.4. Testing and Prototyping

To ensure consistency of measurement and isolation of extraneous variables that may impact the evaluation results, this study made use of a mature, properly documented, well cited, and the de facto database testing client. Yahoo! Cloud Serving Benchmarking (YCSB) was chosen as the open source testing client for comparative evaluation of the data stores. It is the leading choice and industry-standard for performance benchmarking of cloud based databases (Patil, et.al, 2011). YCSB is an internal research and development project of Yahoo! that was open-sourced in 2010 in order to reach a wider community (Cooper, 2010). It has two main components: First, it contains various interfaces, integration drivers, connectors, libraries, and processes for a number of databases. At the time of writing, YCSB has over forty-six (46) database interfaces currently available for testing. And, YCSB also allows addition of other databases that are not currently included in the list. Lastly, YCSB has generic workloads and reporting framework which are extensible libraries that manages the execution of the different types of database task and the output of the reporting format.

The measurement of performance evaluation was conducted in a cloud based computing environment.

For the environment deployment, the study used Linode Cloud Servers as the third-party cloud provider. All working versions (see Table 2) like the database test client (YCSB), patient mass generator, NoSQL databases, and operating system for the server instance were kept identical to provide consistency.

The testing environment were also dockerized in a virtual container to allow convenient reinstallation and simulation. Furthermore, each cloud instance servers were set-up under the following specifications

NoSQL databases is in a rapidly innovative landscape with currently having 225 [16] and continuously increasing;

Table 2: Parameters for Testing Environment

Specification	Capacity	Unit
Radom Access Memory (RAM)	90	GB
Central Processing Unit (CPU)	4	Cores
Solid State Drive (SSD) Stores	90	GB
Transfer	7	TB
Network In	40	Gbps
Network Out	7000	Mbps

it is important to note that the following versions were installed in the instance Table 3 .

Table 3: Technology Specifications

Dependencies	Name	Version
Operating System	Linux Ubuntu	16.04
Patient generator	Synthea	2.0.0
Database testing client	YCSB	0.14.0
NoSQL Columnar wide	Cassandra	3.11.3
NoSQL Document based	MongoDB	3.6.3
NoSQL Key-value type	Redis	4.0.11

Single node may not be practical and efficient for industry level and production grade. However, it is worth noting that using single instance can provide a basic level of information that can be used as means of base comparison against multiple node configuration. Moreover, single node provides the insights on the capabilities of each identified database without the extraneous variables like network latency, infrastructure design, and internet connectivity. Furthermore, the aim of this study is to compare the variables based on the specified evaluation criteria. Fault tolerant, replication, and recovery were not implied, stipulated, or included during the elicitation of end user requirement.

4. Results and Discussion

. In this section, the results of the three NoSQL database, are discussed based on our experience in the database development and their applications for the storage of structured clinical data, from the perspectives of performance, scalability, storage, query readability, flexibilit, and extensibility

4.1. Performance

The performance of the benchmark focuses on the latency of requests when the database is under dataset sizes. Table above shows the comparison of performances for the all databases when factored in against the different workloads and dataset sizes. Redis is the fastest when dealing with the minimal set of data (i.e. 1,000 records). As the number of records increased, it is observed to be outperformed by MongoDB and Cassandra on the non-READ

Table 4: Performance and Scalability Workloads

Workload	Distribution	Name	Description
Workload A	Read: 50% Insert: 50%	Read heavy	Retrieval of an existing record and creating a data in a field/s
Workload B	Read: 95% Update: 5%	Read mostly	Retrieval of an existing record and overwriting a data in a field/s
Workload C	Read: 100%	Read only	Searching a particular field/s in all existing records
Workload D	Read: 95% Insert: 5%	Read latest	Inserting data in an empty field in a record and retrieving the field/s
Workload E	Scan: 100%	Short Ranges	Searching for limited number of contiguous records
Workload F	Read-Insert-Update: 100%	Read-Insert-Update	Creating a new record, updating the created record and retrieving the field/s
Workload I	Insert: 100%	Insert only	Inserting bundled records all at once

related operations (i.e. Workload E, F, and I). Moreover, it is constantly the most efficient on all READ related operations (i.e. Workload A to D) for all different dataset sizes. MongoDB fared best on both INSERT related operations (i.e. Read-Insert-Update and Bulk Load) while Cassandra topped the Short Range workload. To infer if these latency differences were meaningful, it was computed and found that significant differences exist for all workload when subjected to different dataset sample sizes.

4.2. Scalability

Scalability is interpreted as the capacity of to handle increasing load by having simultaneous and parallel task. The measurement focus of scalability in this study pertains to the maximum number of database operations in a single second (i.e. throughput) under increasing threaded processes or parallel loads. Real-life application of threaded transactions can be seen during scenarios of multiple users using the system simultaneously. The results in table above was deployed using the configuration of 128 threads using the 1,000 records, which is an optmistic projection on biobanking system usage. Results showed that Redis still outperformed others in all database operations (i.e. Workload A to I). Also as shown in the table, Workload I or Bulk Insert operations was left blank from this criteria, because using simultaneous multiple bulk inserts encountered issues of duplicate 'unique' identifiers for MongoDB and Cassandra; hence, it was excluded from the results for all database.

With the configuration of 128 threads on 1,000 patient records in a centralized or single node computing environment, it was found (as shown in Table 14.2) that there are significant differences in the scalability among the selected databases for all types of workload. In addition, Table 14.1 revealed that Redis is significantly the most scalable for most of the workloads (except Workload F). On the contrary, the post analysis showed that Cassandra was the least scalable. This result supported the performance of Redis for 1,000 patient records shown in Figure 14.1; concisely, this experiment showed that Redis have the most efficient performance and scalability when subjected to smaller dataset (e.g. 1,000 patient records).

4.3. Storage

The table 5 shows the comparison of storage sizes when compared against the raw file, dataset sizes, and different databases. The four groupings of dataset were scaled by a factor of ten (10x); remarkably however, the storage size differences of in-between groupings had an average 90 percent more than the previous. For instance, the difference between first group (i.e. 1,000 records) to the next group (i.e. 10,000 records) is roughly 90 percent and the difference for the succeeding group (i.e. 10,000 and 100,000 records) is also about 90 percent.

This indicates that the data storage storage scaling behavior of all three databases is strongly consistent. However, when the databases were compared to the average size of FHIR Patient resource in its raw JSON format, it was observed that the size changes by substantial degree. Among the three, Cassandra had the best storage rate of 61 percent decrease in size while the Redis had the most disk storage consumption with increase of 38 percent from the original file. However, these remarkable storage rate differences are by no means statistically significant when when subjected to inferential computation.

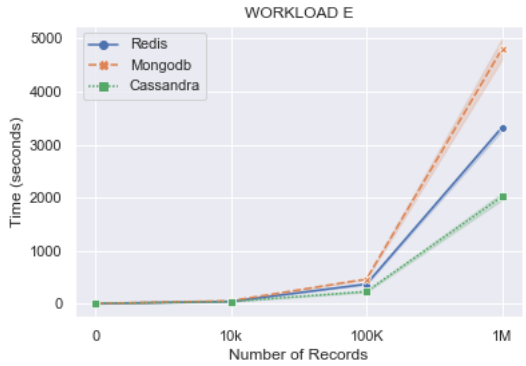
4.4. Query Readability

Four (4) scenarios were selected to represent different database operations: insert, update, search-aggregate, and multiple transactions. These query syntaxes are valid query language statements but in an abridged form. Meaning, not all database table variables and fields were shown

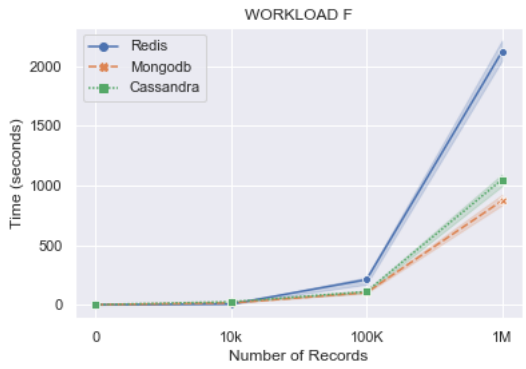
Table 5: Storage Sizes (GB) for FHIR Patient Resource

NoSQL Type	NoSQL Database	Number of Records 1,000	10,000	100,000	1,000,000	Average size per resource	Storage Ratio
JSON files					3.98 x 10-2	40.00 KB	
Columnar	Cassandra	1.56 x 10-3	1.56 x 10-2	1.56 x 10-1	1.54	1.54 MB	+61.30%
Document	MongoDB	3.46 x 10-3	3.45 x 10-2	3.45 x 10-1	3.45	3.45 MB	+25.12%
Key-value	Redis	1.06 x 10-2	1.04 x 10-1	1.04	10.5	10.5 MB	-38.37%

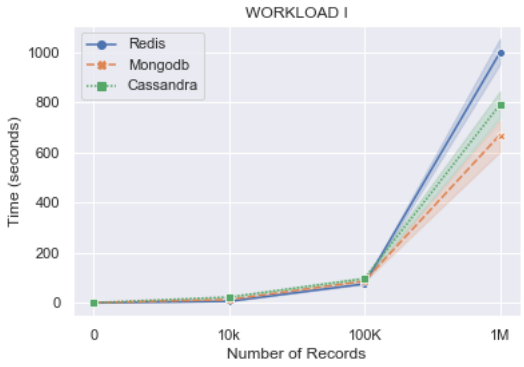
Figure 2: Latencies of Workloads A to F and I – Latency of Read Database Operations for Different Number of Records



(a) Short Ranges



(b) Read-Insert-Update



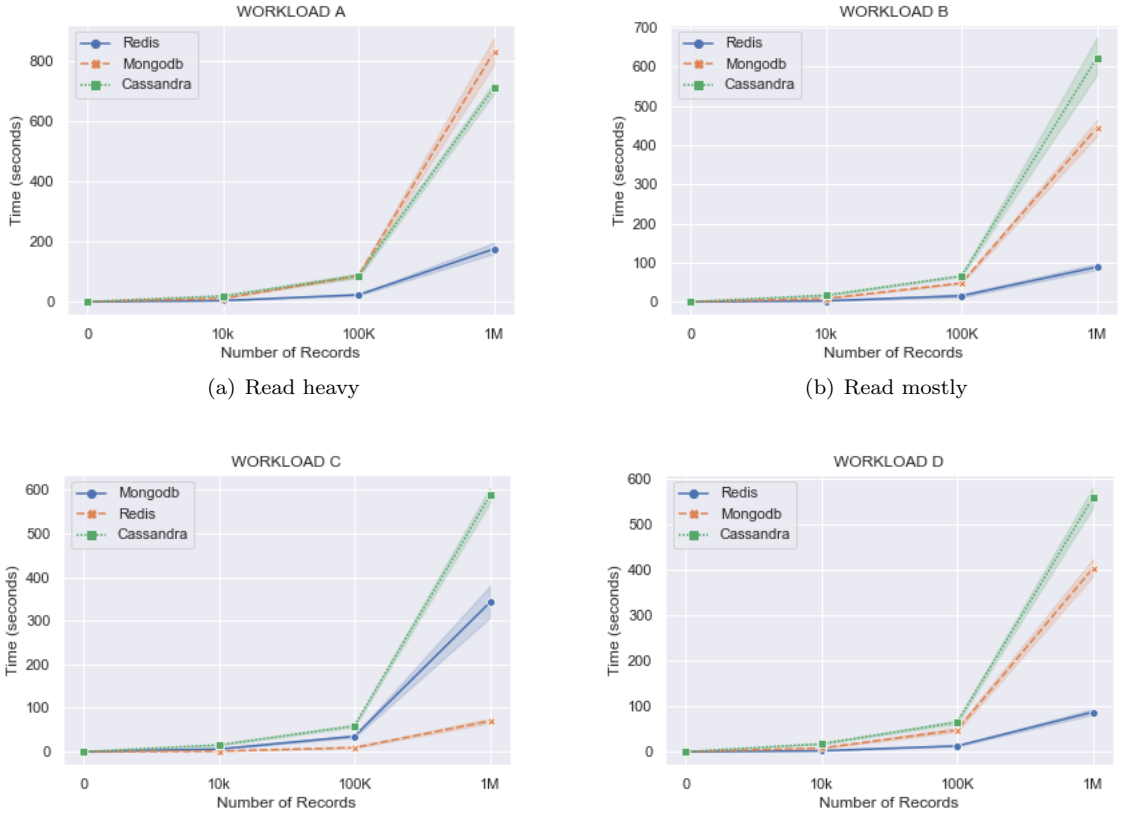
(c) Bulk Insert

in order to avoid technical intimidation among the study participants. The main goal of the query readability evaluation was to assessed the intuitiveness and ease of understanding of each database query structure and semantics. Though the results rely on the participants' biases or lack thereof, it cannot be dismissed on grounds of subjectivity because measuring intuitiveness can also be targeted among participants with certain level or complete unfamiliarity to the particular subject of interest or topic. The participants' responses were then subjected to inferential statistics and shown below.

4.5. Flexibility

Flexibility can be interpreted from many perspectives, among the common are technology architecture, deployment process, and schema capabilities. In this study, discussion of flexibility is taken from the latter perspective. By definition, it is defined as the capability to store dynamically changing data without having a predefined schema [12, 3]. However, flexibility is not totally equivalent to having no schema, but rather on the capacity to accommodate changes without substantial overhead requirements. Cassandra involves the need to write an additional parser in order to import and fit the raw nested JSON data into the columnar-wide type format that it currently supports. For versions above 0.7, it was required to have columns and its data types be defined upfront [25]. From the initial approach of "schemaless", it had transitioned into a "schema-optional". Which meant, that it is heading back to where relational databases started: having predefined columns and data types. Thus, the original roadmap of being a schemaless approach was abandoned. This requirement is not necessary for native document-based databases like MongoDB among others. The raw data are simply imported using the original format of the dataset files; hence, full flexibility in data structure is experienced. In between is Redis, which requires minimal data transformation but is still considered schemaless. The data manipulation is need for the unique identifier of each item in a data in order for it to be segregated and stored separately as the key column, the rest of the data is kept and bundled in the value column. To review, Cassandra is the the least flexible as it requires upfront pre-design of schema while MongoDB is most flexible as it can store any raw data in a flat or deeply nested JSON format.

Figure 3: Latencies of Workloads A to F and I – Latency of Read Database Operations for Different Number of Records



(a) Read heavy

(b) Read mostly

(c) Read only

(d) Read latest

4.6. Extensibility

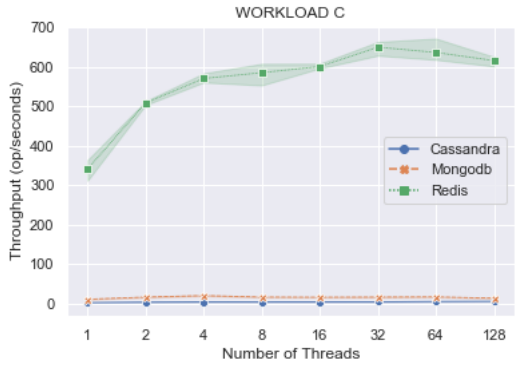
Extensibility is capability to accommodate additional revisions on attributes, columns, and data types without the overhauling need to reconstruct or create new database [26]. Though, a lot of workarounds are available to model for extensibility and cover the inefficient schema design, at a certain point if the core infrastructure is inadequate, there is only so much patching that can be done before reaching the limits of the platform [**?**]. Thus, a native, built-in, and inherent infrastructure is preferred to a "patch work" type of solution and temporary workaround.

When comparing extensibility within NoSQL groups, no notable difference is observed since all the data structure can be extended either vertically (i.e. columnar-wide type) or horizontally (i.e. for both document-based and key-value types). Addition of new fields, columns and nested values are allowed without the need of much overhaul to existing schema for each approaches. However, it is noted that there is constraint of extensibility particularly to the Cassandra, as it requires additional "alter table" script in order for the new changes to be committed.

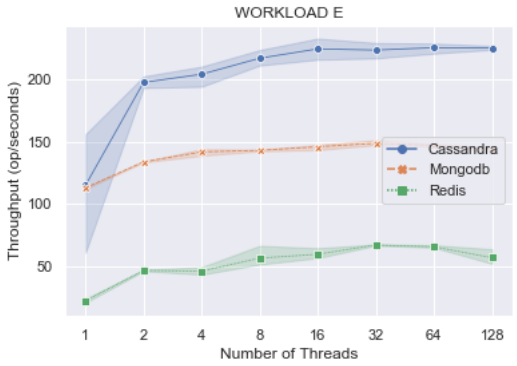
5. Conclusion

NoSQL database technology offers flexibility, extensibility, efficiency, and scalability where the traditional relational database fell short. This research adapted an evaluation framework for NoSQL databases and developed corresponding set of activities for its actual prototyping and testing. The study also described the execution of technical implementation set by the guidelines of the framework. With the foreknowledge that the type and the requirements of the application dramatically determine the appropriateness of database technology to use, the methodology highlighted the qualitative approach of eliciting the user requirements and the process of transforming into quantifiable evaluation criteria. Further, this paper aimed to make the methodology reproducible and the framework generalizable whilst adaptable to specific situations. Using the framework of evaluating data storage for healthcare domain, the study indicated that the NoSQL approach is a viable alternative to other traditional database design as it provides better query performance and scalability while still retaining certain degree of extensibility and flexibility. Among the shortlisted databases, MongoDB - a document type NoSQL was found to be the recommended choice for the current implementation and immediate need of the biobanking HIS.

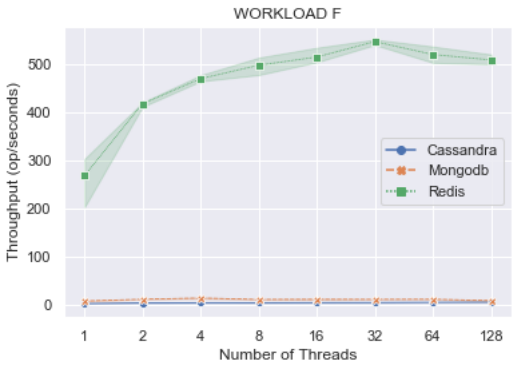
Figure 4: Latencies of Workloads A to F and I – Latency of Read Database Operations for Different Number of Records



(a) Read only



(b) Short Ranges



(c) Read-Insert-Update

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Approved the implementation: Dr. Maria Antonia E. Habana, Dr. Rodney B. Dofitas, Designed the workflow: Philip C. Sales (PCS). Performed the experiment: PCS, Programmed the scripts: PCS, Mycar Angelo B. Chu (MBC). Analyzed the results: PCS. Reviewed the paper: MCV, Dr. Alvin B. Marcelo (ABM), Prof. Ariel S. Betan (ASB), Prof. Bryann Chua, Dr. Jun Inciong. Wrote the paper: PCS, ABM, ASB, MCV.

Statement of Reproducibility

To guarantee reproducibility of the results, all source codes, command scripts, configuration files, and Jupyter notes were deposited in a Github repository. All generated clinical datasets, benchmarking output files are also pregenerated and kept in same folder. In order to make the entire testing environment available for replication, server deployment configurations were packaged as container and is also publicly available in DockerHub link. Instructions written in the REAME.md was provided as quick-start guide for the actual implementation.

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