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AI-Enhanced ETL Testing: Ensuring Data Accuracy and Integrity in Healthcare Analytics

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Abstract

Healthcare organizations are increasingly integrating data-focused systems and applications like business intelligence and analytics and data warehousing solutions to support data-driven decision-making. The accuracy and integrity of data within these solutions are essential to ensure that the insights and actions derived from them can be trusted. Data profiling is critical to ensuring data quality and is often performed as part of the ETL process at the beginning and end of ETL pipelines. However, end-to-end data accuracy validation and other aspects of quality and integrity are also important. As the volume and complexity of healthcare data continue to grow, so does the need for automation. This paper explores the benefits and challenges of using a combination of human-guided, machine-assisted, and AI-enhanced approaches to test the accuracy and integrity of data warehouse ETL pipelines and the implications and opportunities specific to ETL testing in healthcare analytics.

Keywords: Healthcare organizations, Data-focused systems, Business intelligence, Analytics, Data warehousing, Data-driven decision-making, Data accuracy, Data integrity, Data profiling, ETL process, ETL pipelines, End-to-end validation, Data quality, Automation, Healthcare data, Machine-assisted approaches, AI-enhanced approaches, ETL testing, Data warehouse, Healthcare analytics.

1. Introduction

The use of AI in the development of analytics capabilities for healthcare organizations is increasingly significant every year. Analytics applications combine and glean insights from detailed patient health and administrative data. The effective operationalization of analytics is heavily dependent on the delivery of clean, reliable data. High-quality data is essential to maintain patient safety and care quality. This demands processes to identify and remediate controlled and uncontrolled biases that exist within input streaming data. Business intelligence tools utilize process transformations to access, manipulate, and adjust source data inputs for integration into live analytic models and dashboards.

In healthcare, the accuracy and integrity of the testing process are crucial to achieving timely, accurate overall data integration that maintains the quality and safety of care delivery as well as supports the decision-making processes of managers and providers. Automated testing processes save testing time and allow staff to focus on test script design, ensuring data completeness, accuracy, and integrity. In contrast, paper-based testing methods utilizing manual testing processes can be both resource-intensive and time-consuming, while possessing the risk of human error. Transforming some routine manual aspects of testing to automated AI-enhanced testing and data anomaly detection not only decreases testing time and resource requirements but also helps to ensure a higher level of accuracy in data analytic processes. The objective of the current study is, therefore, to analyze and propose AI-based procedures that enable an integrated automated testing process while preserving rule- and metadata-driven logical testing. The application of AI technologies is expanding through cloud-based frameworks, platforms, and services designed to supplant on-premises solutions. These developments are set to increase the adoption of clinical intelligence solutions in healthcare because the process is a critical concern in building these solutions.

1.1. Background and Significance

Healthcare data are crucial in decision support and analytics for patient care, especially with the use of big data techniques that analyze diverse, large volumes, and varying formats of patient data from several sources. The process to prepare input data for such analytics is called Extract, Transform, and Load. Errors in ETL further propagate inaccuracies and errors in subsequent analytical models, with a potentially serious impact on patient outcomes and financial costs. Ensuring ETL data quality in this context is important and challenging. Currently, many ETL testing processes either focus on very structured data or require detailed knowledge of the ETL process involved. Manual ETL testing processes are error-prone, require a large amount of time, and are not scalable to the larger datasets and additional sources required in healthcare analytics. As ETL testing is required regularly to ensure data accuracy and integrity, it is important to address this developmental challenge. While there has been work on AI-supported ETL testing, such work tends to evaluate entire databases or differ greatly from our domain of healthcare analytics and the use case of complex database data.

We present a proof of concept, Health-ETL-Test, which helps the user identify potential data quality issues in cardiovascular risk analytics calculated across datasets from different sources and schemas by using a GPU-optimized random forest classification of low-level detailed differences in lookup values that are required for the ETL process in such healthcare query use cases. While other methods require health data knowledge to understand and apply, as well as extended time, we show how data can be automatically analyzed at a low level, thus supporting the users of the healthcare analytics results in the use case to ensure data accuracy and integrity. In this paper, we define our use case scenario, healthcare analytics configuration, and present our implementation and demonstrate use with provenance, classification algorithms performance results, and challenges encountered.

Fig 1 : ELT Testing

1.2. Purpose of the Paper

The main goal of this paper is to address some of the issues associated with the development of healthcare analytics, which are becoming increasingly significant in the contemporary era of cost-effective, value-based patient care. Analytics-derived insights can help healthcare organizations steer patients toward the most effective treatments using evidence-based personalized medicine, make the best use of healthcare resources using data-driven managerial strategies, and follow new regulatory requirements, using data to avoid costly penalties. ETL testing seems particularly suitable for Big Data because of the many nested and related dependencies that emerge when Big Data is processed.

However, ETL testing is still given low priority and is often excluded. An automated test case can detect a significant number and variety of errors in medical records: nonsensical diagnosis codes; gender-related diagnosis codes; implausible diagnoses, procedures, age, gender, and others. Most of these checks are necessary to accurately quantify the cost, utilization, and healthcare risk factors of the patient population and are required by organizations that buy the aggregate data. The diagnostic accuracy and cost-effective support of machine learning or other enhanced data. AI-enhanced ETL testing demonstrates that it can accomplish both goals of ETL testing faster, better, and cheaper than current state-of-the-art techniques used in academia and industry.

Equation 1 : Data Integrity Validation:

Data integrity ensures that data remains accurate, consistent, and reliable throughout its lifecycle. In the context of AI-Enhanced ETL testing, integrity can be assessed through the following equation:

$$D_{\text{integrity}} = \sum_{i=1}^{n} \left(\mathbb{I}_i(D_{\text{source}}) = \mathbb{I}_i(D_{\text{target}})\right)$$

Where:

Dintegrity is the overall integrity score of the data.

n is the number of records in the dataset.

Ii is the integrity function that checks whether the ith record in the source dataset matches its corresponding record in the target dataset.

Dsource and Dtarget represent the source and target datasets, respectively.

This equation sums the integrity checks for all records and validates that the source data maintains its integrity through the ETL process.

2. ETL Testing in Healthcare Analytics

The healthcare industry collects massive amounts of data used for diagnostics, long-term health monitoring, disease treatment and management, research analysis, and a variety of administrative tasks. The extraction, transformation, and loading (ETL) process is used to collect and transfer data to a data warehouse or analytics system for storage and analysis with business intelligence (BI) tools or use as repositories for business processes. The ETL process divides the issues related to data warehousing into areas such as data quality improvement and metadata management to ease technical development. However, the ETL process presents a substantial area of concern: ensuring sustained data access, integrity, and analytic performance. There are no standard methods to fully address these problems, especially when battling competitive pressures to produce new features, minimize time to market, and reduce development budgets for programming, infrastructure, and testing.

In traditional software development environments, extract, transform, and load (ETL) testing occurs at the staging server level. ETL testing is not a straightforward verification process like you will find in most development environments. The database also serves as a publishing mechanism for the data stored in the ETL process in the data warehouse or analytics repository. Without checking the quality of data, stakeholders will not fully trust self-service analytic products since many issues have historical data causes. The QA process normally uses query syntax to extract data from the database: data that has not been formally published into long-term storage at the central repository. Software companies specializing in ETL testing talk about volume testing as a new problem, but testing the volume of data doesn't imply the data is innocent or clean, only that the amount of data is manageable.

2.1. Overview of ETL Processes

An ETL (Extracting, Transforming, and Loading) process is designed to perform the functions associated with data extraction from a source system, with data cleansing, wherein the data undergoes data quality checks, with data transformation that involves converting the data from its original form to the form necessary to best serve a predetermined purpose, which is the populating of a data repository, and finally populating the repository for business intelligence processing. During the business intelligence processing that follows, healthcare data guidelines become critical in both the interpretation and meaning of the data. Healthcare data have life-critical implications for the evaluation of practice and research performance, impacting care delivery, patient safety, and service access, while ensuring healthcare resource optimization. Healthcare data quality, therefore, is of paramount importance for healthcare researchers, analysts, and management teams, and indeed for the public as well. The ETL process lays the foundation for healthcare quality data analysis.

During the ETL process, the user is concerned with data quality not only on how to detect data errors but also how to prevent the introduction of errors during processing. Clinical data anomalies can lead to significant errors and misrepresentations in data analysis. Users perform various data quality analysis activities to ensure the integrity of the data being used for whatever downstream analysis they plan. Merely checking that values fall within specified bounds does not amount to ensuring the integrity of the data. There has been much healthcare research concerning the detection of ETL data discrepancies, with many methods suggested to both detect and diagnose ETL data, but little research has been conducted into the prevention of these discrepancies. Proposed methods mainly center on data modeling improvements or the imposition of a control schema within the ETL process, which naturally detects possible errors. Prompted by these limitations, there is an increasing awareness from the data governance community over the concern of how secure software engineering principles can be seamlessly incorporated into existing ETL processes.

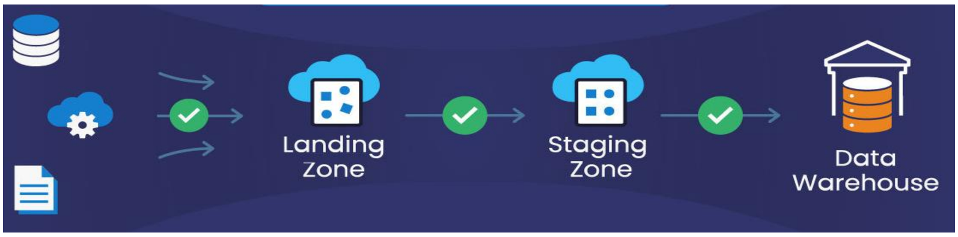

Fig 2 : The ETL Testing Process Detailed

2.2. Challenges in ETL Testing in Healthcare

The healthcare business intelligence landscape is fast-growing. With industry standards, regulations, and patient care requirements becoming increasingly stringent, it also becomes complex. The transformation of healthcare data into a more meaningful and usable format via the ETL process for use in BI and analytics has never been more important. Healthcare ETLs integrating claims and payment data with clinical information are particularly challenging. Claims and payment data, used primarily for the operational fundamental working of a healthcare payer, are particularly challenging, thanks to a complex data schema with variants. Its integration and connection with clinical data from disparate electronic medical and health records make the ETL preparation of this data a much larger data preparation challenge than normal.

Another challenge is the increasing focus on patient-centric care expected to be achieved via data standardization to enable the seamless transfer of data across different touchpoints in the healthcare ecosystem. Other challenges include compliance to ensure the patient's data privacy rights are protected, the accurate cost of care calculations required for value-based contracts, the precision build of data marts for business units for their respective and divergent goals, and the overflow of the data warehouse with legacy data, impacting performance which signals the starting point of longer ETL load times. There are also the usual ETL testing challenges of:

Validating volume – millions of claims are generated and paid by the healthcare payer every month and claims them to be compared with what the ETL is processing, which would be non-viable. Claims data are processed in snippets on the ETL, making it impossible to recreate the complete data. Accurate validation of ETL data is required since any error may result in underpayment or overpayment. Proliferating multi-channel patient touchpoints that result in healthcare payers processing thousands of transactions daily. AI can add value by detecting hidden information, especially those not visible to the human eye, making it a versatile and efficient tool to support the ETL preparation of complex healthcare data. The need to test the data with various types of software to ensure data remains consistent across different types of applications in the healthcare field makes AI a valuable tool for the detection of side effects and helps in optimally running the ETL. The elimination of false positives helps in gaining efficiency. With integration testing validating intricate ETL workflows, AI could even be considered the next-generation ETL tester.

3. Role of AI in ETL Testing

The ETL process for big data platforms requires a comprehensive approach to data validation and testing. AI and machine learning techniques are providing data engineers with innovative testing options and the ability to test large data sets. Current testing data for ETL processes necessitate the extraction of an entire file for the testing exercise. Furthermore, if there are new designs, it may require manual corrections with each file separately. AI testing is designed to review the logic test and framework of the various coding segments. The main methods and mechanisms of AI implementation involve classification, linear regression, clustering, time series, and fitting forecasting models, while the primary methods of implementing machine learning for AI testing and quality assurance involve decision trees, feedforward neural networks, and self-organizing maps. Role of AI in ETL Testing The ETL process for big data platforms requires a comprehensive approach to data validation and testing. AI and machine learning techniques are providing data engineers with innovative testing options and the ability to test large data sets. Current testing data for ETL processes necessitate the extraction of an entire file for the testing exercise. Furthermore, if there are new designs, it may require manual corrections with each file separately. AI testing is designed to review the logic test and framework of the various coding segments. The main methods and mechanisms of AI implementation involve classification, linear regression, clustering, time series, and fitting forecasting models, while the primary methods of implementing machine learning for AI testing and quality assurance involve decision trees, feedforward neural networks, and self-organizing maps.

Equation 2 : Data Accuracy Validation (Pre- and Post-Transformation):

AI-enhanced ETL testing can involve verifying that transformations between raw and target data preserve the data's accuracy. One way to approach this is by comparing the pre- and post-transformation values:

$$A_{\text{accuracy}} = \sum_{i=1}^{n} |T(D_{\text{source},i}) - D_{\text{target},i}| \leq \epsilon$$

Where:

Aaccuracy is the overall accuracy validation score.

$T(D$source,$i)$ represents the transformed value of the ith record from the source dataset.

Dtarget,i is the corresponding value in the target dataset after the ETL transformation.

ϵ is an acceptable margin of error (tolerance threshold).

This equation checks that the difference between transformed and target data values is within an acceptable range, indicating that the transformation process has preserved the accuracy of the data.

3.1. Benefits of AI in ETL Testing

AI has taken ETL to the next level in modern data projects. This text explains the benefits of AI in ETL testing across healthcare, including detailed business use cases, application areas, and several customer stories. A key way AI adds value to the full range of data management and analytics projects is by helping ensure data quality. Ensuring quality data should be a core data and analytics project goal, but data quality is difficult to achieve in practice. Only 3% of managers are highly confident in their data use. The same survey revealed that 33% of stakeholders are not confident in their organization's data. The research found that 78% of stakeholders experience challenges with their data sources, and it was reported that 70–80% of business analysts spend time trying to validate their data in the financial services industry. It reasons that a simple route to delivering business value is to unlock and deliver high-quality data.

AI can enhance ETL testing and meaningfully contribute to ETL testing goals. It is critical to break down these goals, many of which are operational process-oriented, yet align with strong security and privacy practices. First, it's important to validate data accuracy and integrity against source systems and SLA. Healthcare organizations maintain SLAs on data loads both internally and externally as part of a data exchange process, recognizing that key business operations depend on accurate and timely data delivery. Next, it's important to ensure that data hasn't been lost along the ETL process or left behind during testing. Issues of lost or dropped data are disruptive to data operations. Having completed gap testing, it's important to validate that all expected data arrived and was processed as expected.

When data is generated internally and sourced from multiple cloud and company databases, their validation processes need to be met before data is combined for purposes of study, such as validation rules, gaps, and completeness checks. This data often has a mix of structured and unstructured data sources with different data types and formats. Organizations require the ETL process to 1) account for a wide range of data source inputs and data types, 2) functionalize the validation tests, gap tests, and completeness tests to ensure accuracy and reliability, and 3) be able to trace back to the original data source(s), records, and fields to validate data corrections that may happen over the life of the dataset. Compliance rules for healthcare include HIPAA, CFR 42, and CFR 45. The data is often combined with business intelligence reporting and analytics tools, and businesses need this data available to measure their performance with a certain level of performance and accuracy.

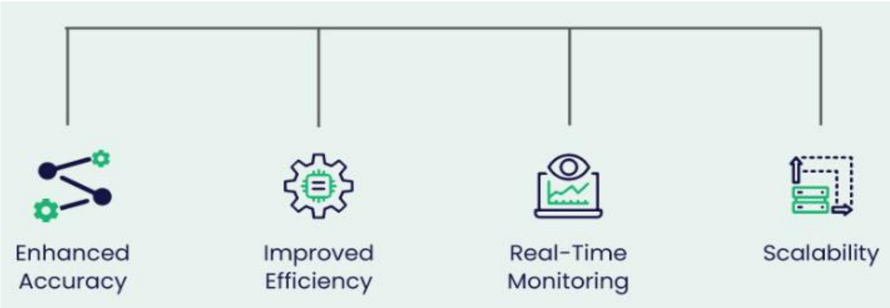

Fig 3 : Benefits of ETL Validator Feature

3.2. AI Techniques and Algorithms

In this section, we first describe the architecture and design of the inductive testing engine, which forms the basis for our AI-enhanced ETL testing framework. We then detail the AI techniques and algorithms we used in the design and implementation of inductive testing, including profile learning, schema refining, and transformation model discovery. Finally, we outline how inductive testing integrates these AI-enhanced components in the testing validations at the field, schema, and integrity rule levels.

Schema Refining: After generating an initial schema assuring the validity of the profile learned for a given column, we apply function dependency discovery and automatic schema refinement to establish proper column relations. For this purpose, we leverage a function dependency and functional ratio discovery framework based on neural networks. The algorithm is fed with value-query results and the learned value profiling as input and conducts inductive learning of functional dependencies by training a neural network model from those queries for the given column relation. Finally, our automatic schema refinement strategy populates known, structurally sound relations into the initial schema to further propagate relevant information to associated columns for both source and target schemas.

4. Case Studies and Examples

4.1. Case Study: Friends of Acid Health

4.1.1. Background and Data Description Amid the highest recorded opioid-related death rates in the U.S., the Friends of Acid Health project is an ongoing pilot project designed to test the feasibility and effectiveness of harm reduction and social network interventions in people experiencing homelessness and opioid use disorder in the Philadelphia region. Faculty members investigating the issue had been running a pilot FRAH-based study, but the data was stored in an outdated, proprietary system and had not been organized to answer important research questions. This incomplete and unstructured dataset generated substantial stakeholders' concerns, so researchers requested the participation of the team.

4.1.2. ETL Test: The Relationship and Non-Overlap Tests Faced with this incomplete and unstructured dataset, preliminary analysis had shown that about a quarter of the names in both lists were found in both the "people to reach out to" as well as the "people who had passed away." The client asked for confirmation if the work to date presented an actual or likely real duplication. More critically, they asked if any of the names were substantially likely to not be duplicated. In other words, stakeholders wanted to determine if it was possible that any given individual could have both been missed and still be present somewhere in the output, indicating an extraordinary likelihood of an iatrogenic death.

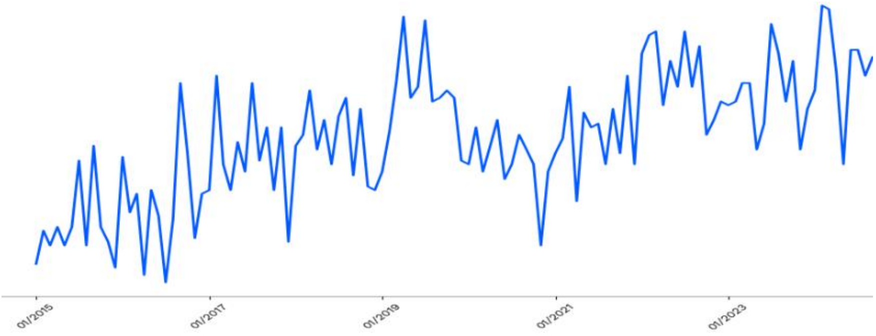

Fig 4 : Popularity of "ETL Automation"

4.1. Real-world Applications of AI-Enhanced ETL Testing in Healthcare

As demonstrated in the case studies, AI-enhanced ETL testing techniques will enable healthcare analytics projects to achieve a higher level of data accuracy and integrity through more comprehensive test coverage and increased use of automation. This will directly translate to cost savings in ETL testing projects, as predefined and custom-built test rules can be executed in an automated and efficient manner. In real-world ETL testing projects, the percentage of custom-built tests executed reached 85% to 95% of the total project test coverage, while available ETL testing and validation tools only contributed to around 5% to 15%. In addition, the custom nature of the approach allows for deep ETL testing and root cause analysis over a wide range of ETL components, from data staging to end-user reporting.

The proposed approach using AI and other advanced technologies in ETL testing offers capabilities that are not available in current ETL testing and validation tools. The application of AI in ETL testing leverages the power of machine learning to identify key data characteristics, reconcile the relationships between data sources and destinations by using neural network models, and then validate the completeness, correctness, and consistency of ETL data transformation. With the ability to prioritize testing efforts and the reusability of predefined test rules, it lays the foundation to conduct tests over datasets that are pre-identified to be of high impact, high complexity, or high risk. Moreover, by learning from data transformation models, gray areas in data transformation processes can be discovered and validated.

5. Future Directions and Conclusion

Improvement in the interpretability of the anomaly detection techniques is one of the key areas of future work. This could be done by extending visualization techniques to help the developer understand the cause of errors. Our approach can be extended to conformance checking of other analytics scenarios, and this requires a lot of domain expertise. We would like to involve experts in the conformance checks; for instance, when computing the KPIs, we would like to confirm the logic with the business rules. This would result in K individual criteria for the given KPI, which would be used to generate K threshold ranges for the KPI. We also need techniques to handle the cases where the ETL script transforms the data.

In conclusion, this paper proposed and implemented a DNN-based approach in the context of healthcare analytics for finding discrepancies between the current and the previous versions of the RHR distributed warehouse system. A hybrid approach consisting of a combination of keyword search and pattern matching, with a word embedding mechanism being the common link, was demonstrated. However, it is worth mentioning that the proposed approach is not restricted to use in the conventional ETL testing environment.

Equation 3 : Performance of ETL Process (Execution Time):

Finally, AI-enhanced ETL systems must operate efficiently. This can be quantified by measuring the execution time for the ETL pipeline, ensuring that the process is both accurate and timely:

$$T_{\mathrm{ETL}} = \sum_{i=1}^{n} \mathrm{Time}_i(\mathrm{ETL\ Step}_i)$$

Where:

TETL is the total execution time for the entire ETL pipeline.

Time$i$(ETL Step$i$) is the time taken for the ith step in the ETL pipeline (Extract, Transform, or Load).

n represents the total number of ETL steps.

This equation helps in measuring the overall performance and efficiency of the AI-enhanced ETL process, ensuring that it meets performance requirements in addition to maintaining data quality.

5.1. Emerging Trends in AI-Enhanced ETL Testing

The contributions of AI-enhanced ETL testing towards healthcare analytics can be realized through the practical application of various emerging trends and new features in AI. In this context, several recent trends with AI-enhanced ETL testing can yield significant improvements in data accuracy and integrity.

- Recovery-oriented: Instead of applying runtime unit tests or ad hoc nightly batch tests to each component of data processing, an emerging recovery-oriented AI-enhanced ETL testing approach ensures that each data load operation can be restored after abnormal terminations, deadlines, or data corruptions. Moreover, the recovery cost could be specified and minimized by optimizing the underlying resource allocation and ETL validation order.

- AI at scale: Although AI, particularly deep learning, has achieved impressive accuracy and consensus results over various domains, adopting such data-driven approaches to handle routine functional, scalability, and performance objections raised in healthcare data flow is not practical due to the need for maintaining the depth, width, and weight parameters of outer-edge data processing modules.

- AI fairness-aware: Healthcare data are often assumed to be sensitive personal or protected attributes, such as race, sex, age, weight, height, and professional title, and these personal attributes can be leveraged to train preloaded AI models to predict new data for judging white-box performances. Unfortunately, such performances can be adversely affected by unfair unintended biases, such as unfair errors and unfair errors between sensitive attributes and actual data labels.

- Federation of AI models: A problem with traditional AI models is that few robust AI models generalize the domain knowledge, feature extraction, and data completion that are commonly used to conduct model interpretations and fulfill the manifold healthcare reporting, response time, and audit trail constraints of all related parties in a streamlined or interactive manner.

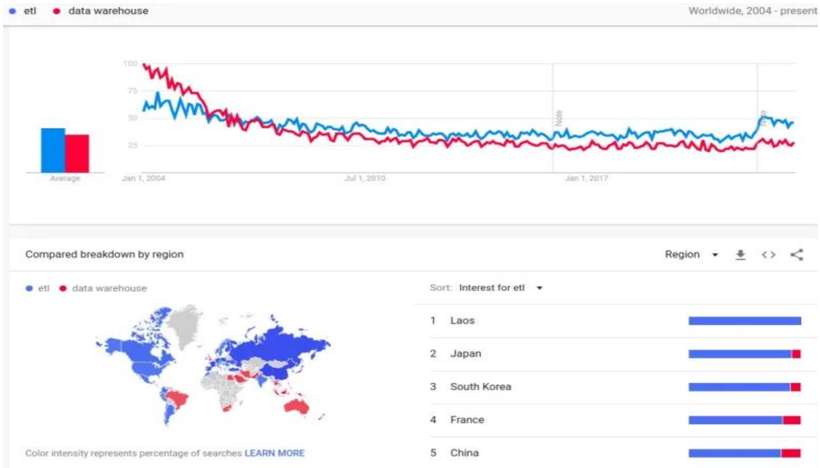

Fig 5 : ETL vs. data warehouse

5.2. Conclusion and Key Takeaways

In this chapter, we discussed how AI algorithms can be used to automate both functional and nonfunctional testing of the ETL process. We elaborated on the ETL testing framework, incorporated AI-enhanced capabilities in implementing testing points, and provided various algorithms for embedding these capabilities. In conclusion, significant progress has been made in the area of ETL testing, but there are ample opportunities to improve testing automation, and AI is a powerful technique to exploit. Healthcare analytics has the additional dimension of patient safety and health. Hence, AI-enhanced ETL testing has the potential to not only improve data accuracy and integrity of healthcare data but also to mitigate factors affecting patient safety.

Key Takeaways: 1. An increasing number of application scenarios wherein AI algorithms are used to automate both functional and non-functional testing of the ETL process have been reported. 2. Algorithms are presented for embedding these capabilities in a variety of testing points. For each testing point, the data are explored and extracted using automated data profiling, and then different candidate tests are run, and their outcomes are observed. AI helps both in the initial data profiling and in choosing and running the tests. In the first case, end users can use AI to identify undefined or even unexpected content. Once the set of candidate tests is identified, they can use AI to monitor the aggregate of the tests to see if there are any significant differences in the computed values from the ETL period to the baseline period.

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