

Abstract

Pharmacovigilance involves collecting, analyzing, and reporting data on adverse events, allowing for informed regulatory decisions. Manual systems face challenges in handling data volume, potentially leading to oversight and delays. Automation with advanced technologies can be a practical solution to mitigate these challenges and ensure efficient data management.

The potential application of Large Language Models (LLMs) in pharmacovigilance is explained, starting with an overview of the process covering all stages of the lifecycle. The pivotal process of scrutinizing documents for relevant adverse effects is emphasized, along with measures to enhance effectiveness. The strategy for generating informative summaries, specifically focusing on adverse effects and their antecedent occurrences, is delineated. The imperative requirement for factual accuracy validation through the implementation of a fact-checking mechanism is highlighted. The framework's efficacy is demonstrated with a focus on output fidelity and summary informativeness. Quantifiable evidence of the benefits of the method is provided, advocating for the adoption of this framework in pharmacovigilance. The conclusion addresses potential refinements.

Pharmacovigilance

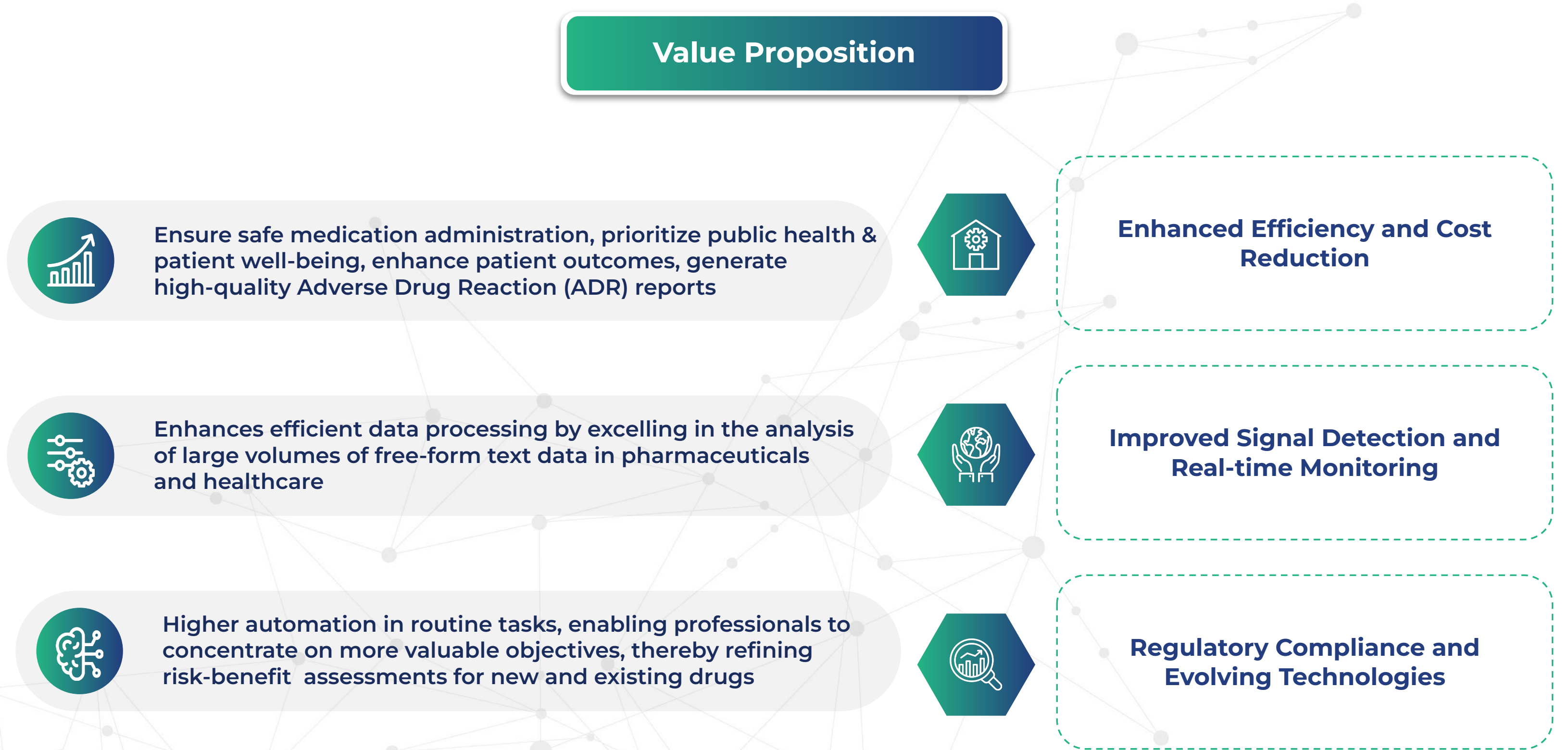
Pharmacovigilance (PV) is the science and activities related to the detection, assessment, understanding, and prevention of adverse effects or any other drug-related problems [1].

- Ensures patient safety by monitoring and evaluating drug safety throughout its life cycle.
- Detects and minimizes the risks associated with pharmaceutical products.
- Contributes to the overall improvement of public health.

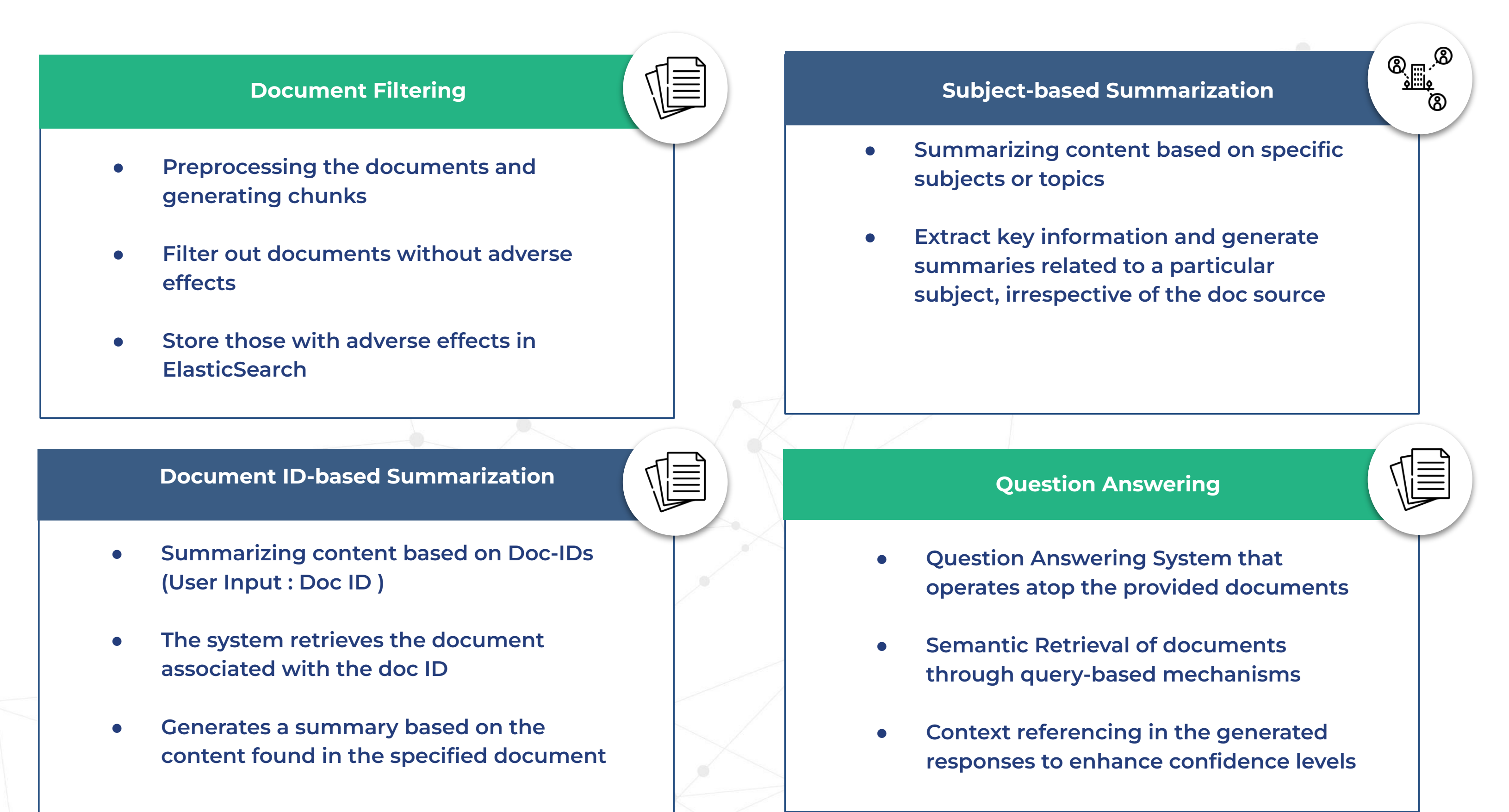


Motivation

The adoption of AI is transforming traditional manual processes, resulting in reduced time and resource consumption. One significant trend is the increasing use of Natural Language Processing (NLP) and machine learning for automated data extraction and analysis [2]. In terms of signal detection and real-time monitoring, AI's proficiency in analyzing large datasets motivates its application for quicker identification of safety concerns, with a growing trend of integrating AI-driven monitoring systems for real-time surveillance.



Capabilities of Our Solution



Architecture

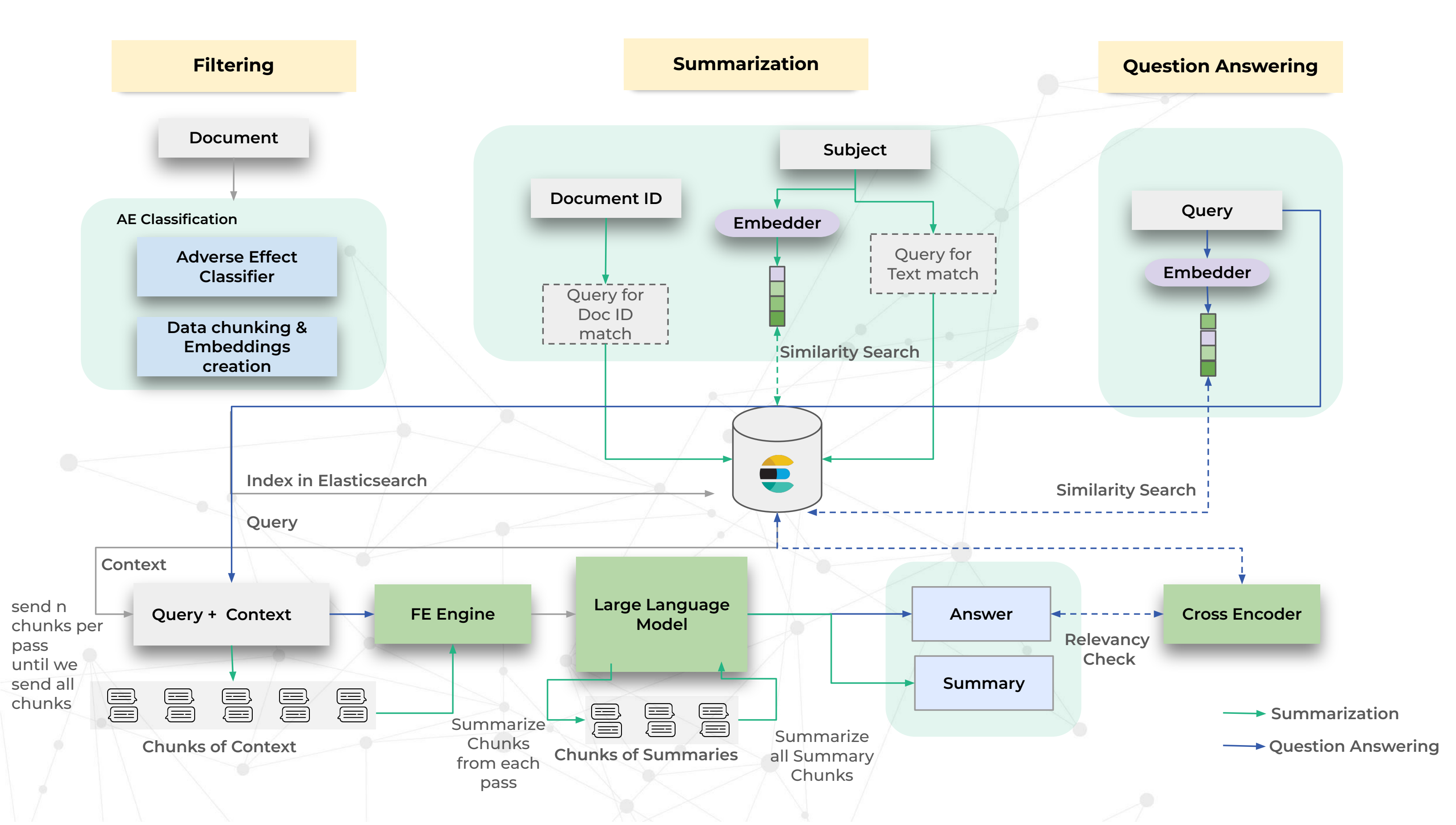


Figure 1. Comprehensive Architecture of the Solution

Document Filtering

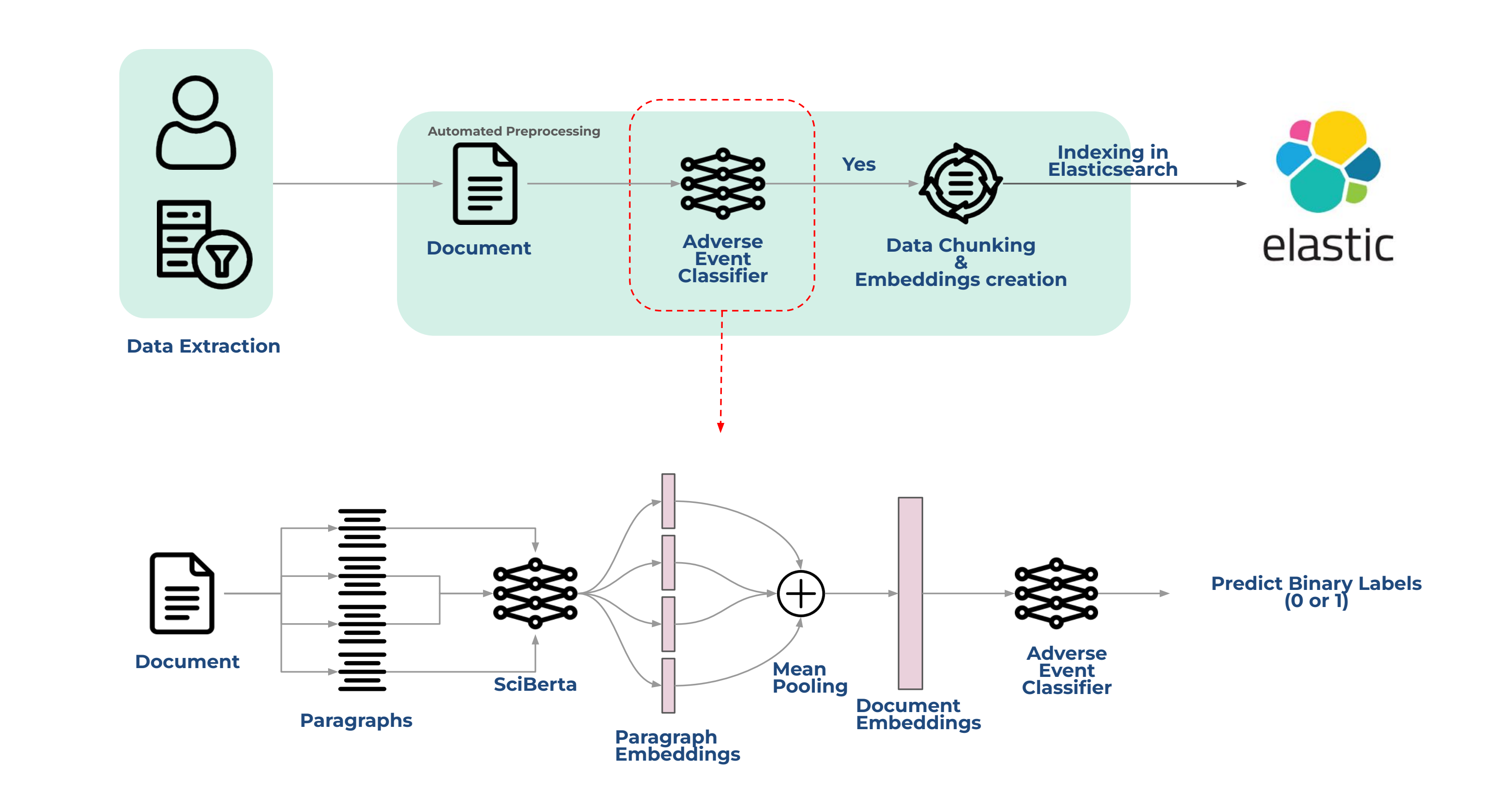


Figure 2. Documents undergo filtration via a Neural Network Classifier to remove non-adverse event documents, while those with adverse effects are stored

Question Answering and Summarization

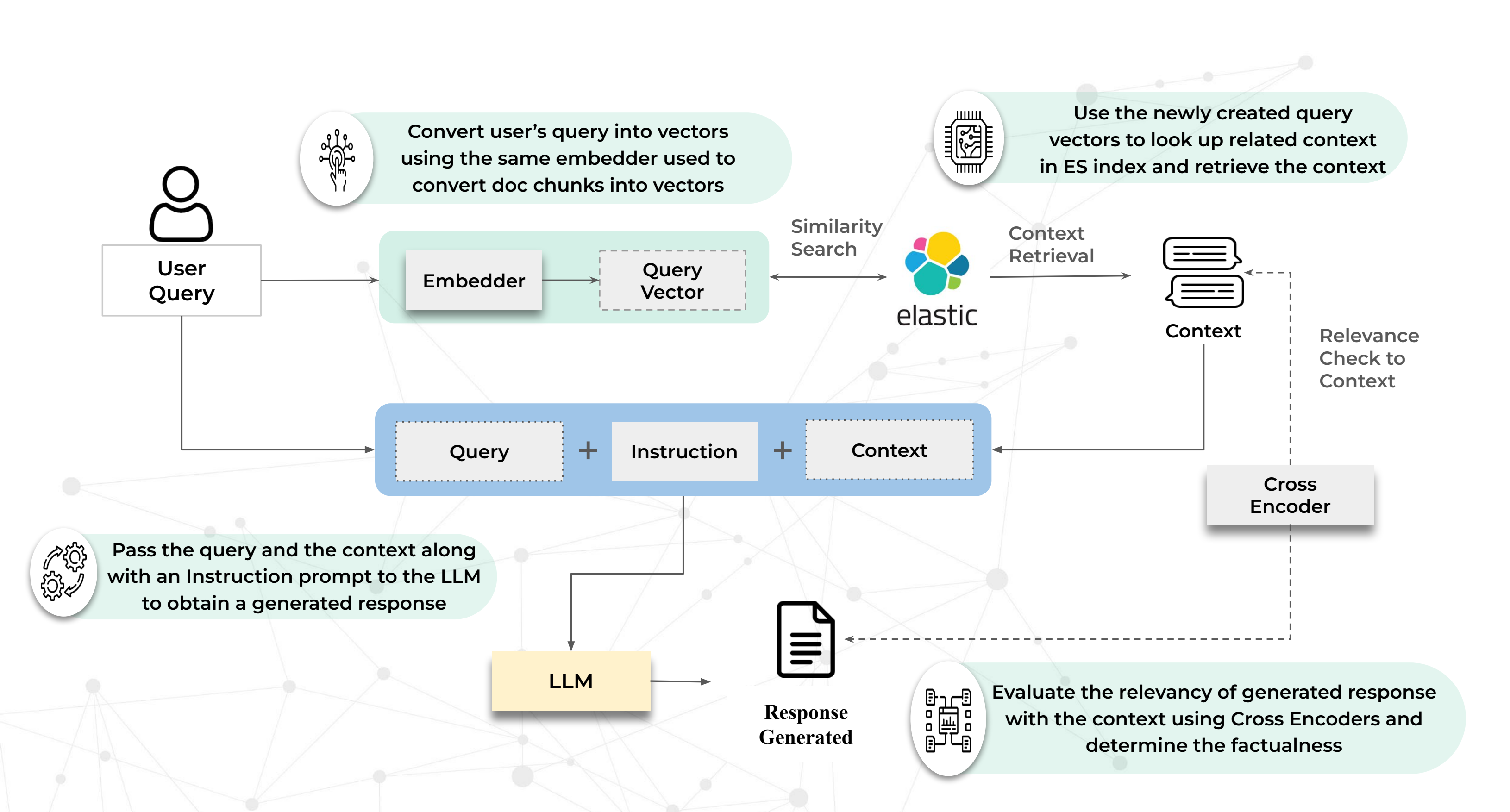


Figure 3. Architectural design of a Question Answering framework integrated with adverse event documents, leveraging Large Language Models

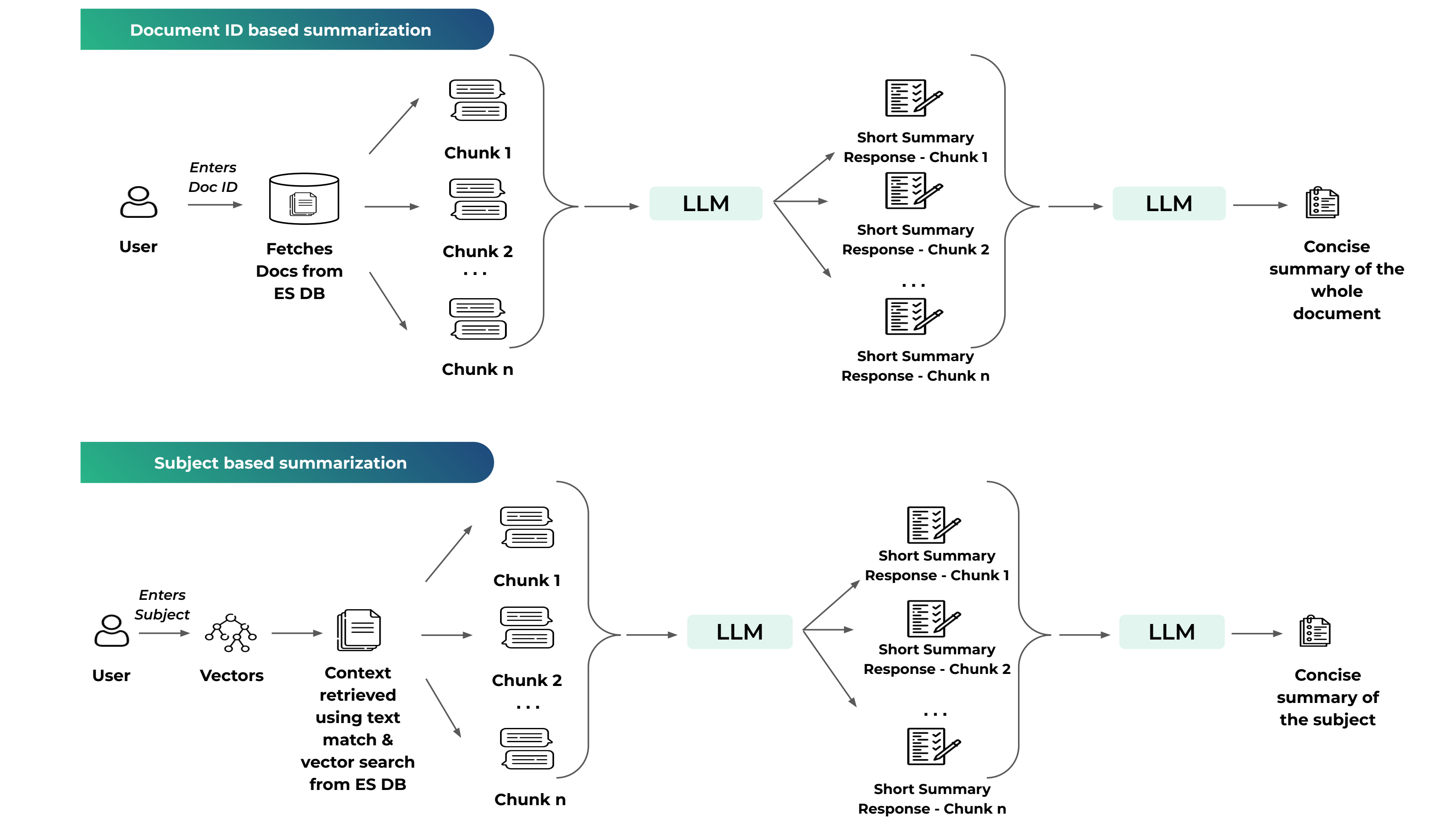
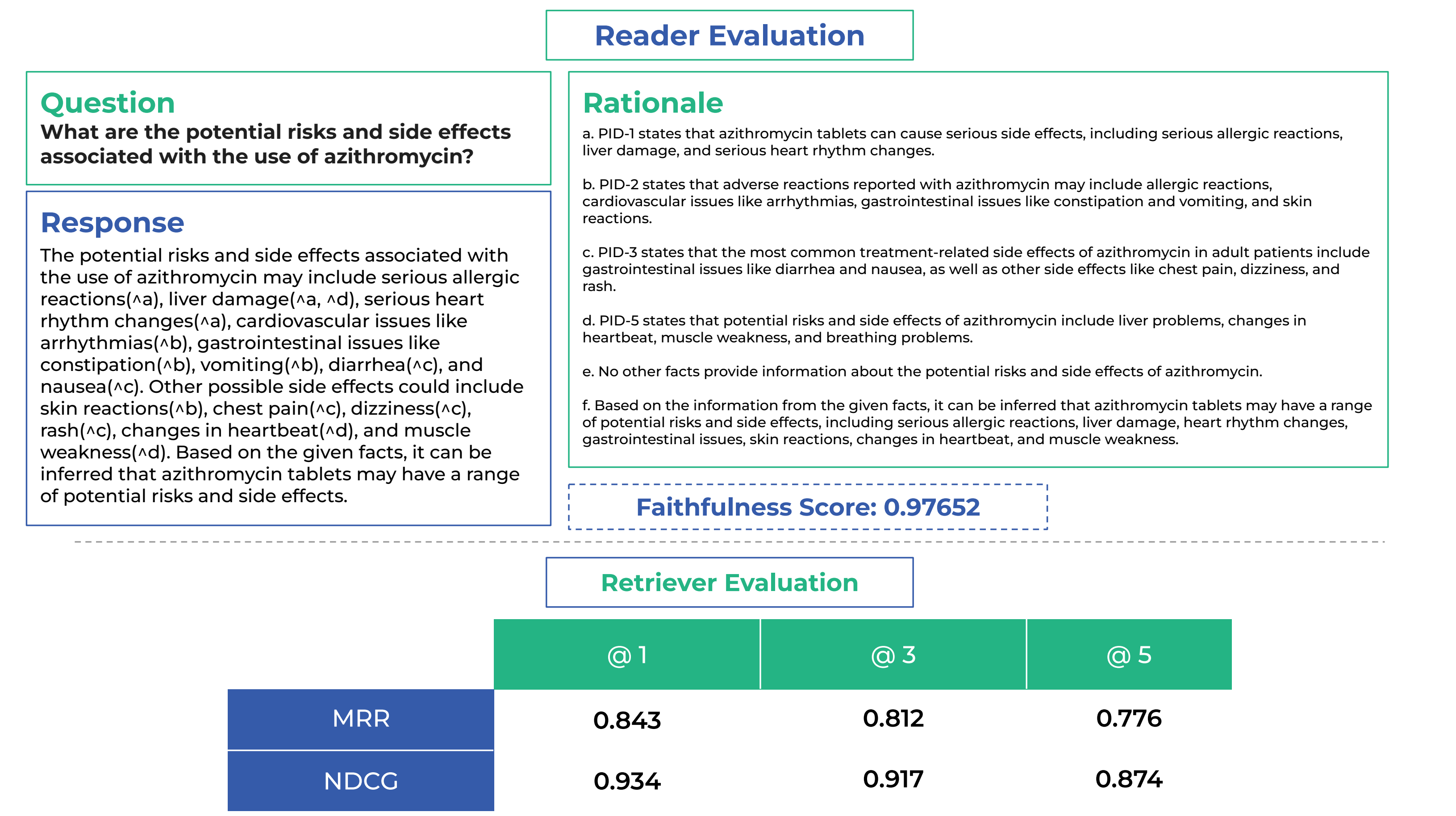


Figure 4. The architecture comprises Subject-based Summarization and Document-based Summarization modules, enabling users to generate summaries either for individual documents or for specific subjects (drugs), tailored to their requirements

Validation and Results



References

- P. Beninger. Pharmacovigilance: an overview. *Clinical therapeutics*, 40(12):1991–2004, 2018.
- A. J. Thirunavukarasu, D. S. J. Ting, K. Elangovan, L. Gutierrez, T. F. Tan, and D. S. W. Ting. Large language models in medicine. *Nature medicine*, 29(8):1930–1940, 2023.