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EDITED BY
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REVIEWED BY
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Singidunum University, Serbia
Edgard Muñoz-Coreas,
University of North Texas, United States

*CORRESPONDENCE
Agostino Marengo
agostino.marengo@unifg.it

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Quantum algorithms and complexity in healthcare applications: a systematic review with machine learning-optimized analysis

Agostino Marengo* and Vito Santamato

Department of Agriculture, Food, Natural Resources and Engineering Sciences, University of Foggia, Foggia, Italy

This paper presents a systematic review of quantum computing approaches to healthcare-related computational problems, with an emphasis on quantum-theoretical foundations and algorithmic complexity. We adopt an optimized machine learning methodology—combining Particle Swarm Optimization (PSO) with Latent Dirichlet Allocation (LDA)—to analyze the literature and identify key research themes at the intersection of quantum computing and healthcare. A total of 63 peer-reviewed studies were analyzed, with 41 categorized under the first domain and 22 under the second. This approach revealed two primary research directions: (1) quantum computing for artificial intelligence in healthcare, and (2) quantum computing for healthcare data security. We highlight the theoretical advances underlying these domains, from novel quantum machine learning algorithms for biomedical data to quantum cryptographic protocols for securing medical information. A gradient boosting classifier further validates our taxonomy by reliably distinguishing between the two categories of research, demonstrating the robustness of the identified themes, with an accuracy of 84.2%, a precision of 88.9%, a recall of 84.2%, an F1-score of 84.5%, and an area under the curve of 0.875. Interpretability analysis using Local Interpretable Model-Agnostic Explanations (LIME) exposes distinguishing features of each category (e.g., references to biomedical applications versus blockchain-based security frameworks), offering transparency into the literature-driven categorization, with the latter showing the most significant contributions to topic assignment (ranging from −0.133 to +0.128). Our findings underscore that quantum algorithms offer significant potential to enhance data security, optimize complex diagnostic computations, and provide computational speedups for health informatics. We also identify outstanding challenges—such as the need for scalable quantum algorithms and error-tolerant hardware integration—that must be addressed to translate these theoretical advancements into real-world clinical impact. This study emphasizes the importance of hybrid quantum-classical models and cross-disciplinary research to bridge the gap between cutting-edge quantum computing theory and its practical applications in healthcare.

KEYWORDS

quantum algorithms, computational complexity, quantum machine learning, Particle Swarm Optimization, healthcare data security

1 Introduction

Quantum computing represents a revolution in the field of informatics, leveraging the principles of quantum mechanics to process information in ways that surpass the capabilities of traditional computers. Unlike classical bits, which can only take the value of 0 or 1, qubits can exist in a superposition of states, enabling parallel calculations and significantly higher computational power (Chow, 2024). Moreover, this technology introduces the concept of quantum entanglement, a property that allows qubits to be correlated such that a change in the state of one immediately influences the other, regardless of distance. This phenomenon further enhances computational potential, enabling solutions to complex problems such as optimization and the simulation of multifactorial systems (Bernal et al., 2024; Pomarico, 2023).

In the healthcare sector, quantum computing offers significant benefits, pushing the boundaries of personalized medicine. For example, quantum algorithms for molecular simulations can accelerate the development of new drugs and predict molecular interactions with unprecedented accuracy. This approach paves the way for targeted treatments for diseases that have been difficult to address, such as certain types of cancer and neurodegenerative disorders (Blunt et al., 2022). Another emerging area is the improvement of computational epidemiology, where the analysis of large datasets through quantum computing allows for more precise modeling of disease spread (Joshi, 2024). These advanced models can support public health authorities in planning more effective interventions during pandemics and other health crises (Wang et al., 2023). Quantum computing also improves the efficient management of hospital resources and treatment planning, optimizing healthcare processes through sophisticated algorithms (Ur Rasool et al., 2023). A particularly promising area is the integration of quantum artificial intelligence (QAI) in healthcare, which combines artificial intelligence with quantum computing to enhance drug development, diagnosis, and treatment by processing vast amounts of data and executing complex calculations (Sunki et al., 2025). The combination of machine learning with quantum capabilities has already demonstrated its potential in the classification and analysis of complex medical images, enhancing diagnostic accuracy, particularly in fields such as radiology, where early and accurate diagnoses can save lives (Yan et al., 2024). QAI has also shown significant promise in the processing of genomic data, improving prediction techniques for precision medicine (Li et al., 2021). Another innovation is the quantum Internet of Things (QIoT), which is transforming smart healthcare by integrating quantum computing with IoT devices. This technology improves data security, accelerates diagnoses, and personalizes treatments (Sutradhar et al., 2024). For instance, QIoT sensors can monitor patients with chronic conditions, sending alerts to physicians in case of anomalies, ensuring timely care (Albahri et al., 2021).

The decision to focus specifically on quantum computing, rather than on other computational paradigms such as conventional AI or classical high-performance computing, lies in its unique potential to address unresolved computational challenges in healthcare. Quantum technologies offer not only exponential speed-up for specific problems, but also novel mechanisms such as superposition, entanglement, and quantum tunneling that enable new approaches to optimization, secure data transmission, and the modeling of complex biological systems. These capabilities are particularly relevant in medical domains where classical systems still face critical bottlenecks in scalability, interpretability, and processing power.

Despite these promising applications, quantum computing is still in its early stages and faces significant challenges, including error correction, the management of quantum decoherence, and the development of scalable hardware. However, recent advancements such as the development of quantum computers with dozens of stable qubits and the implementation of machine learning algorithms for error correction represent fundamental steps toward the large-scale adoption of this technology (Cenedese et al., 2023). With ongoing research advancements, quantum computing is poised to become a transformative element in healthcare, offering innovative tools to address complex problems and improve patients' quality of life (Thantharate and Thantharate, 2024). Although the demonstrated potential is immense, the existing literature reveals significant gaps. Specifically, the applications of quantum computing in healthcare are often limited to isolated case studies, lacking a comprehensive framework that explores its large-scale potential. Furthermore, few studies directly integrate quantum computing approaches with advanced machine learning techniques to tackle complex problems, such as the modeling of high-dimensional clinical data or personalized therapies.

In particular, existing methodologies that combine topic modeling with metaheuristic optimization tend to rely on supervised architectures or complex multi-parameter configurations, which limit their generalizability and interpretability. No prior work has proposed a fully unsupervised, single-variable optimization strategy for topic discovery in a systematic review focused on quantum computing in healthcare. This reveals a methodological gap in designing lightweight, transparent, and reproducible tools for thematic synthesis in emerging research domains. This study aims to bridge these gaps through a combined approach of systematic literature review and machine learning techniques. This approach will enable the synthesis of the state-of-the-art, identification of key development areas, and proposal of new operational frameworks for integrating quantum computing into existing healthcare systems. The main contributions of this study are as follows. First, it provides a comprehensive and structured systematic review of quantum computing applications in healthcare, articulated around two core research questions: enhancing data security (Q_1) and advancing AI-driven healthcare applications (Q_2). Second, it introduces an unsupervised and reproducible methodological framework that combines Particle Swarm Optimization and latent Dirichlet allocation for thematic extraction and topic classification. Third, it validates the thematic structure through a gradient boosting model and interpretable AI tools, ensuring methodological transparency and reliability. Finally, the study delivers an experimental classification architecture, and a curated dataset intended to support future interdisciplinary research at the intersection of quantum computing and healthcare.

The study will be structured into several sections. Section 2 will provide an overview of the state-of-the-art and gaps in the literature, identifying the basis for the systematic review. Section 3 will describe the methodology employed, detailing the process of collecting, selecting, and analyzing sources. Section 4 will present the results and related discussion, highlighting the study's implications. Section 5 will present experimental extension of the study, introducing a predictive model to analyze the two main topics identified in quantum computing for healthcare. Finally, Section 6 will conclude the work by summarizing the main contributions, discussing limitations, and suggesting future research directions in the field of quantum computing applied to healthcare.

2 Background

Quantum computing (QC) is emerging as one of the most revolutionary innovations in modern computing, with extraordinary potential impact on the healthcare sector. Thanks to its unique ability to process complex data and solve problems on a scale unimaginable for traditional computers, QC is opening new horizons in biomedical research and clinical applications (Shakor and Khaleel, 2024; Gou et al., 2024). Among the most significant areas of application, drug discovery stands out as one of the most promising fields. Quantum algorithms enable extremely precise simulations of molecular interactions, accelerating drug development processes and improving candidate selection. This technology not only allows for the rapid identification of therapeutic candidates but also facilitates the personalization of treatments based on the genetic and molecular characteristics of patients (Shakor and Khaleel, 2024; Łukaniszyn et al., 2024; Szymaszek et al., 2024). The result is a highly targeted approach capable of reducing side effects and enhancing treatment efficacy, which is crucial for complex diseases such as cancer (Kumar et al., 2023; Padhi and Charrua-Santos, 2021). Simultaneously, QC is revolutionizing genomic sequencing. Genetic data analysis requires unprecedented computational power, especially for identifying rare mutations or genetic variants that might elude conventional technologies. With its ability to rapidly process large volumes of data, QC is making a significant contribution to precision medicine by providing essential tools to understand the genetic basis of many diseases and develop targeted therapies (Łukaniszyn et al., 2024; Thomford et al., 2018; Manickam et al., 2022). Another domain where QC is showing transformative potential is medical imaging. Advanced algorithms developed for this technology allow for the analysis of diagnostic images with a level of detail and accuracy never achieved before. This capability is critical for the early detection of diseases, significantly reducing the risk of diagnostic errors (Gou et al., 2024; Padhi and Charrua-Santos, 2021; Jamshidi et al., 2023). Moreover, the integration of QC into imaging systems enhances the overall efficiency of diagnostic processes, enabling more timely and targeted treatments (Nosrati and Nosrati, 2023). In addition to direct clinical applications, QC is also being employed in optimizing healthcare processes. Computational models based on quantum algorithms can significantly improve the management of hospital resources, optimizing treatment planning and supply chains (Manickam et al., 2022; Nosrati and Nosrati, 2023). This approach not only reduces operational costs but also increases the efficiency of healthcare services, a crucial aspect in an era where the sustainability of healthcare systems is a global priority. Although QC is still an emerging technology, its progress suggests a future where it will become a fundamental component of modern healthcare. The combination of QC with other advanced technologies, such as artificial intelligence and the Internet of Things, promises to radically transform the healthcare landscape. Its applications extend beyond drug discovery and advanced diagnostics to the creation of digital twins for personalized patient monitoring and the optimization of tailored care (Kumar et al., 2023; Jamshidi et al., 2023; Nosrati and Nosrati, 2023). While quantum computing offers revolutionary prospects for the healthcare sector, promising to transform both clinical and operational practices, continued investment in the research and development of these technologies is essential to overcome current challenges and fully realize their potential.

2.1 Challenges and gaps in the literature

Despite being considered a revolutionary technology, quantum computing (QC) faces complex and multidimensional challenges that hinder its development and large-scale implementation in the healthcare sector, as highlighted in the scientific literature.

One of the main barriers is the technological maturity of QC. The stability of qubits, essential for the operation of a quantum computer, is limited by decoherence, a phenomenon that disrupts calculations and reduces their reliability. Current advancements in hardware engineering and error correction, while promising, are not yet sufficient to ensure scalable and reliable solutions (Chow, 2024; Balasubramaniam and Surendiran, 2024). This limitation restricts the application of QC in clinical settings, where system reliability is a top priority. Another challenge involves integration with existing healthcare infrastructures. Many healthcare institutions rely on legacy systems that were not designed to support quantum technologies. Moreover, the adoption of QC requires compatibility measures to prevent compromising the security and functionality of existing systems. Innovative solutions, such as unified architectures integrating blockchain and QC, could represent a pathway worth exploring, but they remain in experimental stages (Balasubramaniam and Surendiran, 2024; Odeh et al., 2024). The security of healthcare data is another critical concern. Although QC has the potential to enhance encryption and protect sensitive data from cyberattacks, it can also pose a threat to classical cryptographic systems currently in use. Research in post-quantum cryptography is essential to prevent vulnerabilities that could endanger highly sensitive medical information (Odeh et al., 2024; Zhang et al., 2024). Another gap highlighted in the literature is the lack of specialized expertise. QC demands interdisciplinary training that combines advanced knowledge of quantum physics, computer science, and medicine. However, the educational programs currently available are insufficient to meet the growing demand for specialists in this field. This shortage of expertise not only limits adoption but also hampers innovation in QC applications for healthcare (Hernandez, 2024). Finally, the literature emphasizes the need to address economic and infrastructural challenges. Implementing quantum systems requires significant investments in hardware, research, and training. Without sustainable financial support, QC risks being confined to pilot projects or highly specialized applications rather than transforming the healthcare sector on a global scale (Wang, 2024; Tian and Shi, 2024).

These challenges underscore the necessity of a multidisciplinary approach to unlock QC's full potential in healthcare. Such an approach should include investments in technological research, targeted educational programs, and supportive policies to promote the security, sustainability, and integration of QC into existing healthcare infrastructures.

2.2 Future directions and research keywords

To transform quantum computing (QC) from an emerging innovation into a driving force in the healthcare sector, it is essential to undertake targeted research and development initiatives, addressing current challenges with ambitious yet practical strategies. The opportunities offered by QC can be realized through collaborative efforts among experts and institutions, but they require key interventions in several fundamental areas. The creation of specialized algorithms is an absolute priority. Medical data, characterized by high heterogeneity and complexity, demand tailored algorithms capable of addressing clinical needs such as early diagnosis, personalized drug discovery, and advanced genomic data processing. These algorithms must not only be powerful but also scalable and seamlessly integrable into existing workflows, ensuring practical and tangible impacts. Another critical pillar is the promotion of interdisciplinary collaborations. The convergence of quantum physicists, computer engineers, and healthcare professionals is essential for developing solutions that are not only technologically advanced but also aligned with the real needs of the healthcare sector. Shared initiatives, such as pilot projects and collaborative research platforms, could accelerate the path toward widespread QC adoption. At the same time, standardization and the definition of clear regulations are indispensable for building a reliable technological ecosystem. Global guidelines should address critical issues such as healthcare data security, ensuring compliance with existing regulations and promoting interoperability between traditional and quantum systems. Stakeholder trust will be a fundamental lever to drive investments and foster innovation. Finally, education and awareness play a crucial role. To address the shortage of specialized expertise, it is necessary to develop interdisciplinary educational programs that combine quantum physics, computer science, and biomedical applications. In parallel, awareness campaigns aimed at the healthcare sector can enhance understanding of QC's practical benefits and encourage the adoption of these technologies.

To guide a systematic literature review that explores progress and gaps in these areas, three primary keywords are proposed. These terms represent the essential cores for identifying and analyzing existing literature, ensuring a structured and focused approach:

I *Quantum Healthcare*: Covers the general applications of QC in the healthcare sector, including diagnostics, treatment, and optimization of clinical processes.
II *Quantum Algorithms*: Focuses on the development and implementation of specific algorithms for medical applications, such as drug discovery and genomic data analysis.
III *Quantum Security*: Represents aspects related to healthcare data security, with a focus on post-quantum cryptography and the protection of sensitive information.

These keywords will guide the systematic review process, allowing the delineation of an accurate state-of-the-art and the identification of priority research areas. In this way, it will be possible to provide a comprehensive overview of opportunities and challenges, contributing to the definition of a roadmap for the future of quantum computing in healthcare.

2.3 Research questions

To guide a systematic investigation into the application of quantum computing (QC) in healthcare, it is essential to focus on two key aspects that reflect the field's priorities and emerging challenges:

- *Q_1: How can quantum technologies enhance data security and ensure the integrity of healthcare information?*

  The first research question addresses the role of quantum computing in security and privacy protection within healthcare systems. As medical infrastructures increasingly rely on digital records and interconnected devices, ensuring the confidentiality, integrity, and resilience of sensitive information is a critical challenge. Quantum cryptography, quantum-enhanced secure machine learning, and privacy-preserving AI techniques offer innovative solutions to counter cyber threats, mitigate unauthorized access, and enhance trust in data exchanges. Investigating these mechanisms will provide insights into the development of scalable and robust security frameworks, essential for the safe integration of quantum computing into healthcare environments.

- *Q_2: How can quantum computing improve medical diagnostics and AI-driven healthcare applications?*

  The second research question focuses on the computational advancements enabled by quantum computing, particularly in artificial intelligence-driven healthcare applications. The complexity and volume of healthcare data—including medical imaging, genomic sequences, and patient records—demand sophisticated processing capabilities beyond classical computing. Quantum-assisted AI, quantum machine learning, and optimization algorithms have the potential to accelerate diagnostic accuracy, optimize treatment planning, and enhance predictive analytics. Understanding how these quantum-powered solutions can be integrated into existing healthcare workflows will be crucial for their practical deployment and adoption.

These research questions encapsulate the two fundamental pillars necessary for the successful adoption of quantum computing in healthcare. On one hand, it is crucial to establish secure and reliable data management frameworks by leveraging quantum-enhanced security techniques, ensuring the protection and integrity of sensitive medical information. On the other hand, quantum technologies offer unprecedented computational power that can drive advancements in AI-driven diagnostics and predictive modeling, enabling more accurate, efficient, and personalized healthcare solutions. Addressing these challenges will not only help overcome existing barriers but also pave the way for a well-structured, secure, and effective integration of quantum computing into modern healthcare systems.

3 Methodology

To address the research questions, a combination of systematic literature review and machine learning techniques was employed, focusing on exploring the core aspects of quantum computing in healthcare. The methodological approach adhered to established guidelines and was structured into distinct phases: defining a precise research strategy aligned with the research questions, applying rigorous inclusion and exclusion criteria to ensure relevance and quality, selecting studies that directly address the identified challenges, and conducting an in-depth analysis of the data. Each step was meticulously detailed to ensure transparency, reproducibility, and alignment with the objectives of investigating algorithm development, interdisciplinary collaboration, and standardization in QC applications for healthcare (Santamato et al., 2024).

3.1 Computational infrastructure and work environment

The computational environment used for this research was designed to ensure efficient and scalable data processing, leveraging advanced tools for machine learning and computational optimization. The implementation was carried out on an Apple M1 Pro system with 16 GB of RAM and a 1 TB SSD, running macOS Sequoia 15.0.1, providing high computational capacity for processing large datasets and executing complex models.

The entire workflow was developed in Python 3.11, integrating a set of optimized libraries for data management and machine learning. The computational pipeline utilized Scikit-learn for machine learning models, Pandas and NumPy for data manipulation, Matplotlib for visualization, NLTK for text preprocessing, and Pyswarms for swarm intelligence-based optimization. The adoption of Particle Swarm Optimization (PSO) allowed for the integration of evolutionary optimization mechanisms within the computational environment, enhancing the efficiency of decision-making and adaptive processes. The infrastructure was configured to support automated and optimized operations, ensuring effective management of computational resources and memory usage. The choice of a multi-core configuration enabled faster and more responsive processing, reducing execution times for both analysis and optimization tasks. Additionally, the system was designed to be modular and adaptable, facilitating the integration of new methodologies and allowing for scalability to larger datasets without compromising efficiency.

3.2 Search strategy

A thorough search of electronic databases was conducted to identify peer-reviewed articles published between 2021 and 2025, a period characterized by significant advancements in Quantum Computing and its growing influence across multiple fields. The databases utilized for this review included ACM Digital Library, Emerald, Google Scholar, IEEE Xplore, PubMed, ScienceDirect, Scopus, and SpringerLink, ensuring a diverse and comprehensive selection of relevant academic sources. The search approach employed Boolean operators such as AND and OR to refine and structure the selection process. The use of AND facilitated the identification of studies that addressed multiple interconnected aspects, ensuring a focused retrieval of literature, while OR broadened the scope by incorporating related but distinct topics within Quantum Computing. This method allowed for both specificity and inclusiveness, ensuring a balance between precision and comprehensive coverage. To maximize the identification of relevant studies, the search was conducted across titles, abstracts, and keywords, ensuring that only the most pertinent articles were considered. The review was deliberately limited to peer-reviewed journal articles and review papers, excluding conference proceedings and preprints to prioritize rigorously vetted and high-impact research. Furthermore, only English-language publications were included, covering both open-access and subscription-based content to ensure accessibility to a wide range of academic contributions.

This systematic and well-defined search strategy reduced the likelihood of omitting critical studies while adhering to best practices for literature reviews in computational sciences and emerging technologies. The structured use of Boolean operators and filtering techniques ensured that only highly relevant publications were selected, establishing a strong foundation for the subsequent examination of Quantum Computing research.

3.3 Inclusion and exclusion criteria

To ensure the selection of high-quality and relevant studies, a well-defined set of inclusion and exclusion criteria was applied. The eligibility of articles was determined based on the following factors:

I Language and Relevance: The selected studies were required to be written in English, the dominant language in scientific and technical publications, and had to focus explicitly on Quantum Computing, Healthcare, Algorithms, and Security. Both open-access and subscription-based resources were included to enhance accessibility and ensure comprehensive coverage of the literature.

II Empirical Foundation: Only research articles presenting empirical findings or substantial theoretical contributions in the field of Quantum Computing were considered. Studies that provided practical insights, case studies, or applications relevant to the research themes were prioritized.

III Publication Type and Timeframe: Eligible studies included peer-reviewed journal articles published between 2021 and 2025, ensuring that only recent and methodologically sound contributions were included. Conference papers and preprints were excluded to maintain a focus on validated and high-impact scholarly work.

Any studies that did not satisfy these conditions were excluded from the review. Specifically, papers written in languages other than English or those that did not directly examine the interplay between Quantum Computing and the key research domains were not considered. By implementing these rigorous selection criteria, only methodologically robust and thematically relevant studies were retained, forming a solid foundation for further analysis in the review process.

3.4 Query application

The article selection process commenced with the application of a general query to retrieve publications relevant to Quantum Computing, Healthcare, Algorithms, and Security. The initial search was structured to capture studies that included these keywords in the title, abstract, or keywords, ensuring an inclusive dataset. The query was applied across eight major academic databases—ACM Digital Library, Emerald, Google Scholar, IEEE Xplore, PubMed, ScienceDirect, Scopus, and SpringerLink—and resulted in an initial dataset of 1,474 articles. Although comprehensive, this broad retrieval process also included studies of varying relevance and methodological rigor, some of which did not fully align with the study's research objectives.

The first-stage query used for this broad search was:

a) Initial Query: *TITLE-ABS-KEY (quantum AND healthcare) AND TITLE-ABS-KEY (quantum AND algorithms) AND TITLE-ABS-KEY (quantum AND security)*

This formulation ensured that only studies explicitly mentioning Quantum Computing in relation to Healthcare, Algorithms, and Security were included in the initial dataset.

To refine the dataset and isolate high-quality, methodologically sound articles, a structured query with explicit inclusion and exclusion criteria was subsequently applied. This enhanced search approach allowed for an automated filtering process, narrowing the dataset to the most relevant and peer-reviewed studies. The refined query included the following parameters:

b) Advanced Query with Inclusion/Exclusion Criteria: *TITLE-ABS-KEY (quantum AND healthcare) AND TITLE-ABS-KEY (quantum AND algorithms) AND TITLE-ABS-KEY (quantum AND security) AND PUBYEAR > 2020 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (OA, "all"))*

This structured query enabled an automated selection of articles based on the following criteria:

I Publication Year: Only studies published between 2021 and 2025 were included (PUBYEAR > 2020 AND PUBYEAR < 2026), ensuring that the review reflected recent and up-to-date research.
II Document Type: The search was restricted to original research articles and systematic reviews (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")), excluding conference papers and preprints.
III Source Type: Only studies published in scientific journals (LIMIT-TO (SRCTYPE, "j")) were considered to ensure peer-reviewed rigor.
IV Language: The dataset was limited to English-language publications (LIMIT-TO (LANGUAGE, "English")), aligning with standard scientific practices.
V Accessibility: Both open-access and subscription-based articles were included (LIMIT-TO (OA, "all")), providing a comprehensive representation of the literature.

Applying this refined query significantly reduced the initial dataset from 1,474 articles to 133, representing a curated selection of highly relevant, peer-reviewed contributions. This systematic filtering process was critical in constructing a focused, methodologically rigorous foundation, ensuring that the selected studies aligned with the research objectives and provided a robust basis for further analysis.

3.5 Data extraction and analysis

The process of data extraction and analysis followed a systematic and structured methodology, integrating machine learning techniques to optimize study selection and classification. Figure 1 presents a PRISMA Flow Diagram Enhanced with Machine Learning, outlining the key steps involved in filtering, categorizing, and refining the selected literature.

The identification phase began with an extensive search across eight major academic databases—ACM Digital Library, Emerald, Google Scholar, IEEE Xplore, PubMed, ScienceDirect, Scopus, and SpringerLink—which retrieved an initial dataset of 1,474 papers. The query was designed using Boolean operators (AND, OR) to ensure a comprehensive selection of relevant papers. Specifically, OR was used to include studies related to Quantum Healthcare, Quantum Algorithms, and Quantum Security, while AND was applied to refine the search by integrating additional filtering criteria, such as publication years and document types.

During the screening phase, 133 papers were retained after applying inclusion and exclusion criteria, ensuring that only peer-reviewed, English-language journal articles published between 2021 and 2025 were considered. After removing 7 duplicate papers, 126 remained. After a rigorous full-text review, 55 studies were excluded as they did not align with the research questions, leaving 71 eligible studies. At this stage, a threshold-based anomaly detection method was applied to identify and exclude outliers ($n = 8$) from the final dataset. The outlier detection process was based on the maximum topic probability assigned to each paper by the Latent Dirichlet Allocation (LDA) model. Specifically, the dominance threshold was set at 0.6, meaning that any paper with a maximum topic probability below this threshold was classified as an outlier. These papers exhibited a uniform topic probability distribution, indicating that they did not strongly belong to any of the extracted topics and were therefore excluded to maintain the thematic coherence of the analysis. To enhance the categorization of the final dataset, machine learning techniques were applied. Latent Dirichlet Allocation (LDA), an unsupervised learning model, was used for topic modeling, enabling the automatic discovery of thematic clusters within the dataset. The number of topics was not pre-defined; instead, Particle Swarm Optimization (PSO) was employed as an optimization technique to determine the most coherent and meaningful topic distribution. PSO dynamically adjusted the number of topics by minimizing the variance in topic probabilities across documents, ensuring optimal clustering of research themes.

The final dataset comprised 63 papers, categorized into two primary research topics, each with a balanced number of studies (Topic 1 = 41, Topic 2 = 22). This systematic, data-driven approach reinforced the rigor of the study selection process, ensuring a robust and thematically coherent systematic review.

3.6 Data selection criteria

The final dataset of 63 articles was meticulously curated to ensure a robust foundation for thematic analysis, maintaining alignment with the systematic approach applied in this study. The selection criteria emphasized relevance, methodological rigor, diversity of perspectives, and data type, ensuring a comprehensive and structured literature

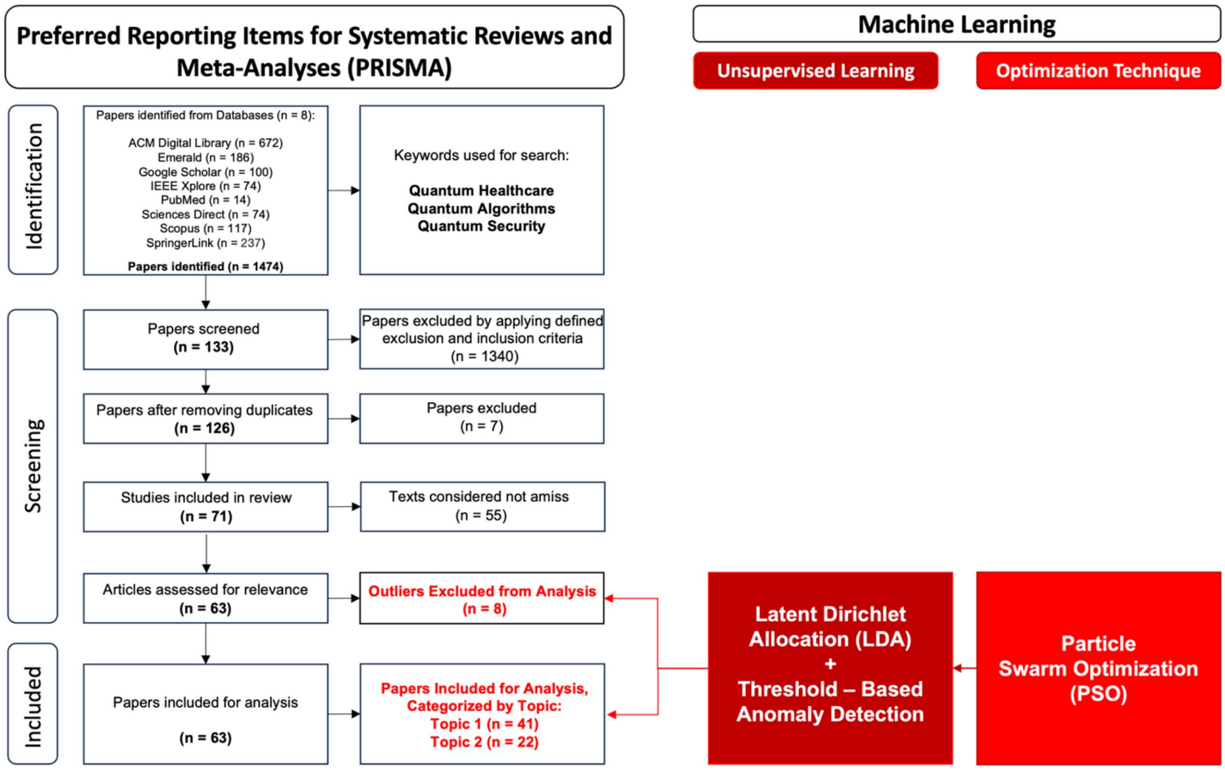

FIGURE 1
PRISMA flow diagram enhanced with machine learning for study selection and classification.

review on Quantum Computing, with a specific focus on Healthcare, Algorithms, and Security.

I Relevance: Each article was assessed based on its direct contribution to understanding the role of Quantum Computing in Healthcare, Algorithms, and Security. Particular attention was given to empirical studies investigating key aspects such as quantum algorithms for healthcare applications, security challenges in quantum systems, and advancements in quantum-based computational models. Articles that were only marginally related to the core topics, even if technically relevant, were excluded to maintain a coherent thematic focus.

II Quality and Rigor: High academic standards were prioritized to ensure the scientific integrity of the selected studies. Only peer-reviewed journal articles were included, excluding conference proceedings and preprints. Special attention was given to the methodology, depth of analysis, and empirical validation of each study, ensuring that the dataset comprised reliable and rigorously validated contributions.

III Diversity of Perspectives: The dataset was structured to capture the multidisciplinary nature of Quantum Computing research, with a focus on Healthcare, Algorithms, and Security. Studies from various fields, including computational sciences, cryptography, medical informatics, and emerging quantum technologies, were included to provide a comprehensive perspective on how Quantum Computing is being explored in different technological and applied contexts.

IV Type of Data: The dataset emphasized empirical research, incorporating qualitative, quantitative, and mixed-method studies. The selection included experimental research on quantum security, case studies on quantum applications in healthcare, algorithmic evaluations, and systematic reviews. This diversity in data sources enhanced the depth and breadth of the analysis, allowing for a nuanced exploration of trends and challenges in Quantum Computing, specifically within Healthcare, Algorithms, and Security.

By applying these systematic selection criteria, the final dataset of 63 articles ensured both thematic relevance and methodological robustness, offering a strong foundation for analyzing the role of Quantum Computing in Healthcare, Algorithm Development, and Security Innovations.

3.7 Screening and selection

A systematic method was employed to identify, filter, and process the dataset, ensuring a rigorous selection of relevant studies on Quantum Computing with a focus on Healthcare, Algorithms, and Security. The screening process incorporated automated and manual techniques, alongside machine learning-driven optimization, to refine the dataset. Initially, duplicate entries were removed by leveraging Python-based preprocessing techniques. The dataset was processed using Pandas for data manipulation and NLTK for natural language processing, ensuring that each study was assessed based on its title and author information to detect exact duplicates. This was followed by a manual verification to eliminate any remaining redundancies overlooked by the automated step. Following deduplication, a structured review of the articles was conducted by applying predefined inclusion and exclusion criteria. Any disagreements among researchers regarding the inclusion of specific studies were resolved through discussion until a unanimous consensus was reached. This phase allowed the data set to be refined to 63 articles included in the review from 71 articles considered eligible, from which an additional 8 studies were excluded as outliers identified for nonalignment. The selected articles were structured into a spreadsheet format to facilitate systematic processing. To ensure consistency, a comprehensive stopword list was created by merging standard stopwords from NLTK with a customized list of terms deemed irrelevant to the study's thematic focus. The text cleaning process involved removing numerical values and punctuation, converting text to lowercase, and eliminating stopwords. The cleaned document d_{clean} was defined as follows equation 1:

$$d_{clean} = \{ w \in d_{raw} : w \notin S \} \tag{1}$$

where d_{raw} represents the original document, w is a word in the document, and S is the combined stopword set. To transform the cleaned textual data into a numerical representation, CountVectorizer was applied to generate a document-term matrix (DTM). Terms with a document frequency (df) above 95% or below 2 were removed to minimize noise, ensuring that only relevant terms contributed to topic identification. The weighting function was defined as equation 2:

$$D_{i,j} = freq(w_j \in d_i) \, where \; 0.02 \le df(w_j) \le 0.95 \tag{2}$$

where $D_{i,j}$ represents the frequency of term w_j in document d_i.

The Latent Dirichlet Allocation (LDA) model was then employed to uncover latent topics within the dataset. LDA operates under the assumption that each document is a mixture of topics, while each topic consists of a distribution of words. The topic distribution for a given document d is drawn from a Dirichlet distribution, as defined by equation 3:

$$\theta_d \sim Dirichlet(\alpha) \tag{3}$$

where θ_d represents the vector of topic probabilities for d, and α controls the sparsity of the distribution. For each word w in d, a topic z is assigned using equation 4:

$$z \sim Multinomial(\theta_d) \tag{4}$$

The word is then generated from the topic-specific word distribution β_z equation 5:

$$w_n \sim Multinomial(\beta_z) \tag{5}$$

To ensure the number of topics was optimized, Particle Swarm Optimization (PSO) was implemented. Instead of predefining K topics, PSO dynamically optimized the topic distribution, reducing variance across topic probabilities and ensuring thematic coherence. The optimization process minimized the dispersion of topic probability scores, effectively tuning LDA to produce a robust, data-driven categorization.

PSO was employed to determine the optimal number of topics (K) for the LDA model. The fitness function used in the optimization process aimed to maximize the coherence of topics while minimizing redundancy. The optimization process followed these key steps: each particle in the swarm represented a potential value of K (i.e., the number of topics). The objective function evaluated the coherence score of the LDA model for each proposed K. The velocity v_i and position x_i of each particle were updated iteratively using the standard PSO equations 6, 7:

$$v_i^{(t+1)} = w v_i^{(t)} + c_1 r_1 \left(p_{best,i} - x_i^{(t)} \right) + c_2 r_2 \left(g_{best} - x_i^{(t)} \right) \tag{6}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{7}$$

where w is the inertia weight, balancing exploration and exploitation, c_1, c_2 are acceleration coefficients influencing personal and global best solutions, r_1, r_2 are random numbers sampled from a uniform distribution U (0,1), $p_{best,i}$ is the best position found by particle i, and g_{best} is the global best position across the swarm. The optimization continued until convergence was reached, identifying the optimal K that maximized topic coherence.

Once the optimal number of topics was determined via PSO, each document was assigned a dominant topic based on the highest probability $P(kd)$ calculated as follows equation 8:

$$Assigned \; Topic(d) = \arg\max_k P(k \mid d) \tag{8}$$

This assignment ensured that each paper was classified under the most relevant research theme, while still recognizing that LDA allows for overlapping thematic distributions across documents. To enhance interpretability, a function was implemented to extract and display key terms associated with each topic, providing a clear semantic representation of each category.

To maintain a high-quality dataset, a threshold-based anomaly detection technique was applied to detect and exclude outliers. Articles exhibiting a uniform probability distribution across multiple topics were classified as outliers, as they lacked a clear thematic association. Outliers were identified based on a dominance threshold $\delta = 0.6$, where equation 9:

$$f(x) = \begin{cases} True, \, if \; \max_k P(k \mid d) < \delta_k \\ False, otherwise \end{cases} \tag{9}$$

Papers with max topic probabilities below 0.6 were excluded, as their unclear topic alignment indicated that they did not strongly contribute to the study's key research domains. A total of 3 outliers were identified and removed.

The results, including assigned topics and excluded outliers, were exported to a spreadsheet file to ensure transparency and reproducibility. This structured approach facilitated an efficient and systematic analysis, offering a clear thematic classification of the literature. By integrating LDA for topic modeling, PSO for optimization, and threshold-based anomaly detection for outlier exclusion, the screening and selection process was methodologically rigorous, ensuring thematic consistency in the systematic literature review on Quantum Computing with a focus on Healthcare, Algorithms, and Security.

3.8 Predictive algorithm

In the experimental analysis discussed in Section 5, a Gradient Boosting predictive algorithm was implemented to classify research papers into the thematic categories identified during the systematic review. The classification task was designed to assess the potential of quantum computing in the healthcare sector, ensuring an accurate and interpretable model. The target variable was defined as a binary variable, consisting of the two topics identified through the combination of Systematic Literature Review, Latent Dirichlet Allocation (LDA), and Particle Swarm Optimization (PSO). The features were represented by three binary variables, selected as transversal factors present across the analyzed studies. The classification was performed using a Gradient Boosting model, which iteratively builds an ensemble of decision trees to minimize classification error. The final prediction was obtained as a weighted sum of individual weak learners, following the general equation 10:

$$\mathrm{F}(\mathrm{x}) = \sum_{m=1}^{M} \gamma_m h_m(x) \tag{10}$$

Where F(x) is the final predictive model, $h_m(x)$ represents the output of the m-th weak learner (a decision tree), and γ_m is the corresponding weight learned during training. The model was optimized using a loss function based on log loss, suitable for binary classification equation 11:

$$L(y, F(x)) = -\sum_{i=1}^{N} \left[y_i \log(p_i) + (1 - y_i)\log(1 - p_i) \right] \tag{11}$$

where y_i is the true label (0 or 1) of the i-th document, and p_i is the probability estimate of belonging to one of the two thematic categories. The integration of a Gradient Boosting-based predictive model ensured a robust and effective approach for categorizing studies related to quantum computing in healthcare. The strategic selection of features improved model accuracy and interpretability, reinforcing the methodological rigor of the analysis and providing a clear understanding of the impact of key factors in the emerging landscape of quantum computing applications in healthcare and technology.

3.9 Data measurement

The topics identified through LDA and PSO will undergo further classification based on cross-cutting characteristics common to all 63 selected studies. This additional step will allow for refinement and contextualization of the thematic clusters, ensuring that they represent broader interdisciplinary connections and emerging trends in the study of Quantum Computing, with a particular focus on Healthcare, Algorithms, and Security. To ensure an accurate assignment of topics, a performance evaluation of the predictive model was conducted using advanced statistical metrics, based on the confusion matrix. The key metrics considered are as follows:

I AUC-ROC (Area Under the Curve-Receiver Operating Characteristics)—This metric evaluates the model's ability to distinguish between thematic categories. The AUC-ROC score ranges from 0.5 (random classification) to 1 (perfect classification). The macro-average score is calculated as equation 12:

$$AUC_{macro} = \frac{1}{n} \sum_{i=1}^{n} AUC_i \tag{12}$$

where n represents the number of topics, and AUC_i is the AUC computed for each topic i, given by equation 13:

$$AUC_i = \int_0^1 TPR_i \left[FPR_i^{-1}(u) \right] du \tag{13}$$

II Accuracy—Represents the proportion of correct classifications relative to the total number of instances analyzed equation 14:

$$Accuracy = \frac{\sum_{i=1}^{n} True\ Positives_i + \sum_{i=1}^{n} True\ Negatives_i}{\sum_{i=1}^{n} Total\ Population_i} \tag{14}$$

III Precision—Measures the proportion of correct positive predictions relative to all instances predicted as positive for a given topic equation 15:

$$Precision_i = \frac{TruePositives_i}{True\ Positives_i + \sum_{j=1, j \neq i}^{n} False\ Positives_{ji}} \tag{15}$$

where $False\ Positives_{ji}$ represents the number of times topic j was incorrectly classified as topic i.

IV Recall (Sensitivity)—Evaluates the model's ability to correctly identify all relevant cases for a given topic while minimizing false negatives equation 16:

$$Recall_i = \frac{TruePositives_i}{True\ Positives_i + \sum_{j=1, j \neq i}^{n} False\ Negatives_{ij}} \tag{16}$$

where $False\ Negatives_{ij}$ represents the number of times a topic i instance was misclassified as another topic.

V F1 Score—Represents the harmonic mean of Precision and Recall, providing a balanced evaluation when both metrics are equally important equation 17:

$$F1\,Score_i = 2\,x\,\frac{Precision_i\;x\;Recall_i}{Precision_i + Recall_i} \tag{17}$$

VI Matthews Correlation Coefficient (MCC)—Measures the overall quality of predictions, considering both true positives and true negatives. MCC ranges from-1 (completely incorrect classification) to 1 (perfect classification) equation 18:

$$MCC = \frac{CxS - \sum_k P_k x\, T_k}{\sqrt{\left(S^2 - \sum_k P_k^2\right) x \left(S^2 - \sum_k T_k^2\right)}} \tag{18}$$

Where C is the sum of correct predictions (true positives + true negatives), S is the total number of predictions, P_k represents the total predictions for topic k, T_k represents the actual instances for topic k.

These metrics validated the model's reliability, ensuring that the identified topics accurately reflect the key themes of research in Quantum Computing. The further classification based on cross-cutting characteristics will enhance the depth of the analysis, providing a more detailed representation of interdisciplinary connections and emerging trends in the fields of Healthcare, Algorithms, and Security.

4 Results and discussion

The integration of Particle Swarm Optimization (PSO) with Latent Dirichlet Allocation (LDA) provided a robust framework for identifying and optimizing thematic structures within the selected literature on Quantum Computing in Healthcare, Algorithms, and Security. This section presents the results obtained through the optimization process and discusses the implications of the identified topics in relation to the research questions. After analyzing and identifying the cross-cutting characteristics of the selected studies, a predictive machine learning model will be developed to help us better understand how the topics align coherently with the research questions.

4.1 Comparison with optimization strategies in topic modeling

The integration of probabilistic topic modeling with evolutionary optimization algorithms has produced a range of methodological solutions, often marked by structural complexity or a strong reliance on supervised architectures. In certain approaches, PSO has been applied to determine the optimal number of topics, but the optimization process is guided by supervised objectives, such as the accuracy or F1-score of external classifiers trained on the generated topic features. While these methods may be effective in annotated and controlled settings, their applicability is significantly reduced in exploratory contexts where supervision is absent and thematic generalization is a core objective (Krishnan et al., 2021). Other models have replaced LDA entirely, using PSO to generate semantic clusters directly through dense vector representations. In these configurations, topics emerge as geometric centroids within an embedding space, eliminating the probabilistic structure that traditionally captures the distributional relationships between documents and topics. As a result, the interpretability and generative nature of the model are compromised (Miles et al., 2022). Some solutions have proposed joint optimization of several internal parameters of LDA, including α and β, using PSO. Although such methods offer fine-grained control over the generative process, they also introduce substantial computational overhead and rely on delicate balancing across hyperparameters that may be highly sensitive to data characteristics. In the absence of prior knowledge or structural constraints, these approaches risk instability and limited generalizability (Onan, 2018).

In this study, it was deliberately decided to avoid optimization of internal hyperparameters such as α and β, and instead focused exclusively on the variable K, the number of topics to be generated. This choice was motivated by two key considerations. First, it avoids overreliance on arbitrary prior assumptions that often lead to overfitting or model instability. Second, it preserves the simplicity, clarity, and interpretability of the original LDA model by keeping its generative structure intact. The optimization process is thus centered on the most thematically impactful parameter, ensuring that the model adapts to the data without distorting its underlying structure. Optimizing K via PSO in a fully unsupervised setting yields a topic configuration that is semantically coherent, adaptable, and free from the interactional noise typical of multi-parameter tuning. This design makes the framework lightweight, replicable, and transparent qualities that are essential in the context of systematic literature reviews. To the best of our knowledge, this is the first application of a PSO-based strategy for automatic topic selection in a systematic review focused on quantum computing in healthcare, highlighting both its methodological novelty and its domain-specific relevance.

4.2 Methodological justification of the chosen approach

The Latent Dirichlet Allocation model was selected as the core mechanism for thematic extraction, as it remains one of the most established, interpretable, and reliable solutions for identifying latent topics in unstructured text corpora. Unlike more recent methods based on dense vector representations, such as BERTopic, Embedded Topic Models, or Non-negative Matrix Factorization, LDA provides a probabilistic distribution of topics across documents and of words across topics, offering an effective balance between semantic coherence and interpretability. This makes it particularly suitable for exploratory and systematic analyses of scientific literature (Charitopoulos et al., 2025; Hanny and Resch, 2024). While neural-based models may yield finer semantic granularity, they often rely on pretrained vector spaces and require more complex architectures, thereby increasing computational cost and reducing model transparency.

For the optimization phase, Particle Swarm Optimization was employed to automatically determine the optimal number of topics, as it adapts efficiently to discrete, low-dimensional search spaces. PSO offers a solid balance between exploration and exploitation of the objective function, with fast convergence rates and flexible configuration, making it a stable, lightweight, and reproducible solution in unsupervised settings (Raji et al., 2022). Traditional alternatives such as grid search have shown to be less efficient due to their exhaustive nature and lack of adaptivity (Elgeldawi et al., 2021). Bayesian optimization, although theoretically advanced, relies on surrogate functions and prior distribution assumptions over the search space, which are often misaligned with exploratory scenarios where the objective is simple and well-defined, such as the maximization of topic coherence (Sultana et al., 2022; Zulfiqar et al., 2022). Other metaheuristic algorithms, including genetic algorithms, were also considered, but tend to exhibit greater tuning instability and computational overhead when applied to single-variable optimization problems (Divasón et al., 2023). These methods often depend on crossover, mutation strategies, and constraint balancing, making them less suitable in the absence of strong structural priors. In contrast, PSO enables effective search without the need for surrogate models or probabilistic assumptions, making it particularly suitable for determining the number of topics in a fully unsupervised environment. Its simplicity and adaptability to discrete configurations support its methodological alignment with the nature of the problem addressed (Raji et al., 2022; Divasón et al., 2023).

Recent applications of Particle Swarm Optimization in healthcare-related domains further support its effectiveness in similar contexts. In cybersecurity frameworks, PSO has been employed to optimize hybrid models for intrusion detection and bio-inspired feature selection with notable gains in accuracy and computational efficiency (Qi et al., 2024; Bakro et al., 2024). In edge and cloud computing for healthcare monitoring systems, PSO-enhanced models have shown improvements in threat detection, quality of service, and remote diagnostic accuracy, supporting scalable and secure health data management (Pavithra et al., 2023; Lalit et al., 2024). Other studies have demonstrated the success of PSO variants in deep learning architectures, time series forecasting, and disease prediction tasks in cloud-based environments, confirming its suitability for optimizing non-convex objective functions in low-dimensional settings, particularly within complex health infrastructures (Xu and Ren, 2022; Ramachandran et al., 2023; Bo and Lei, 2025). These findings corroborate the choice of PSO in this study, emphasizing its stability, adaptability, and methodological compatibility with unsupervised topic modeling in systematic literature reviews.

In recent years, several nature-inspired algorithms have emerged, such as Crayfish Optimization, Reptile Search Algorithm, and Red Fox Optimizer, aiming to overcome limitations of classical approaches. However, comparative studies show that while these newer methods can be competitive in specific applications, they do not demonstrate systematic superiority over PSO. Their higher sensitivity to control parameters and the lack of extensive validation in topic modeling contexts make them less robust for general-purpose use (Abd Elaziz et al., 2023; Fakhouri et al., 2024; Mohammed and Rashid, 2023). PSO remains advantageous particularly when the optimization task involves a single discrete variable, and the objective function is straightforward and computationally accessible.

This selection is also consistent with the foundational principle expressed by the No Free Lunch Theorem, which states that no optimization algorithm can universally outperform all others across every problem class. The effectiveness of any metaheuristic must be assessed in relation to the specific problem structure, context, and analytical goals (Wolpert and Macready, 1997). The choice of PSO in this study reflects a methodological rationale grounded in simplicity, efficiency, and a balanced compromise between adaptability and interpretability, rather than in the assumption of absolute superiority.

4.3 PSO-driven optimization of topic modeling

The Particle Swarm Optimization (PSO) approach was employed to dynamically determine the optimal number of topics for the Latent Dirichlet Allocation (LDA) model, ensuring that the thematic distribution was based on semantic coherence and relevance. Particle Swarm Optimization (PSO) is an optimization algorithm inspired by the social behavior of bird flocks and fish schools. In this method, a population of candidate solutions, referred to as "particles," navigates the search space by leveraging both individual and collective experiences to locate the optimal solution. This approach has been extensively studied and applied across various fields of engineering and computer science (Gad, 2022). For instance, by integrating ensemble pruning with topic modeling optimized through Particle Swarm Optimization (PSO), it is possible to enhance predictive performance by fine-tuning the parameters of the Latent Dirichlet Allocation (LDA) model, including determining the optimal number of topics (Wang et al., 2019).

Integrating PSO into the topic modeling process eliminated the arbitrary selection of the number of topics, providing a quantitative and methodologically rigorous solution. The objective function governing the optimization process was designed to maximize topic coherence, formulated as the minimization of the negative coherence score equation 19:

$$\min_{K} C(K) \tag{19}$$

where K represents the number of topics to be optimized, while $C(K)$ is the average topic coherence score, calculated based on the semantic similarity between the terms belonging to the same cluster. This formulation allowed for the identification of the optimal number of topics, ensuring maximum intra-topic homogeneity and minimal semantic overlap across different groups, facilitating an informative and meaningful segmentation of the analyzed corpus.

The computational implementation of PSO was conducted using the *pyswarms* library, executing iterative optimization with the following command:

```
import pyswarms as ps
# Definition of the PSO optimizer with specific parameters
optimizer = ps.single.GlobalBestPSO(n_particles=10, dimensions=1, options={'c1': 1.5, 'c2': 1.5, 'w': 0.9}, bounds=(np.array([2]), np.array([6])))
# Execution of the optimization to determine the optimal number of topics
best_cost, best_pos = optimizer.optimize(evaluate_lda, iters=20)
```

# Optimal number of topics identified
best_num_topics = int(best_pos[0])

This iterative process tested different configurations of topic numbers, evaluated their coherence scores using LDA, and selected the configuration that achieved the highest coherence.

To ensure an optimal balance between exploration and exploitation in the search for the ideal number of topics, the following hyperparameters were adopted:

- Inertia weight (w) = 0.9; Balances the trade-off between solution space exploration and local convergence.
- Cognitive coefficient (c1) = 1.5; Determines the weight of an individual particle's experience in the optimization process.
- Social coefficient (c2) = 1.5; Defines the degree of influence exerted by the global best solution found by the swarm.
- Number of particles = 10; Ensures sufficient exploration of the parameter space without compromising computational efficiency.
- Number of iterations = 20; Allows for the progressive refinement of the solution until convergence is achieved.
- Topic number range: 2–10; Restricts the search to prevent over-segmentation or excessive generalization of topics.

This configuration enabled PSO to converge toward an optimal solution, ensuring a coherent and meaningful thematic partitioning. The optimization process identified the optimal number of topics as 2, with a final cost function value of 9.087, indicating a high level of thematic coherence within the optimized topic distribution. The best particle position converged to 2.32, which was rounded to 2. To assess the robustness of the optimization process, 30 independent PSO runs were executed. The fitness scores across these runs yielded the following statistical indicators: best = 9.087, worst = 39.121, mean = 20.591, median = 21.575, standard deviation = 11.780, and variance = 138.779. These results confirm the convergence stability and consistency of PSO in identifying a reliable and semantically coherent topic structure. These findings suggest that a two-topic segmentation provides the best balance between granularity and coherence, preventing excessive fragmentation while ensuring clear and meaningful classification.

To further assess the robustness and consistency of the optimization process, the Particle Swarm Optimization (PSO) algorithm was executed across 30 independent runs. Figure 2 displays the distribution of the fitness function values obtained in each run. The median fitness value was approximately 21.8, while the minimum and maximum values observed were 8.8 and 39.1, respectively. The interquartile range lies between ~9.3 and 29.0, indicating that most runs yielded consistent results without significant outliers. The box is shown in light blue, while the central orange line indicates the median of the distribution.

Figure 3 illustrates the average convergence behavior of the PSO algorithm over 20 iterations. Starting from a mean fitness of about 28.1, the optimization rapidly improves within the first 5–7 iterations, gradually stabilizing around 20.6. The blue curve with circular markers shows the average fitness value across all particles and runs at each iteration. This pattern reflects efficient convergence dynamics and confirms that the PSO configuration used (c1 = 1.5, c2 = 1.5, w = 0.9, 10 particles, 20 iterations) enables reliable identification of the optimal number of topics with minimal performance variability across runs.

These results confirm that the PSO-based optimization is not only effective but also repeatable and stable, ensuring methodological reliability and replicability in unsupervised topic modeling. Table 1 provides a structured representation of the topics identified through the application of Latent Dirichlet Allocation (LDA) optimized with Particle Swarm Optimization (PSO), highlighting their association with the key research questions (RQ1 and RQ2). Each thematic category is described through the most representative keywords, a summary of its content, the related research domain, and an

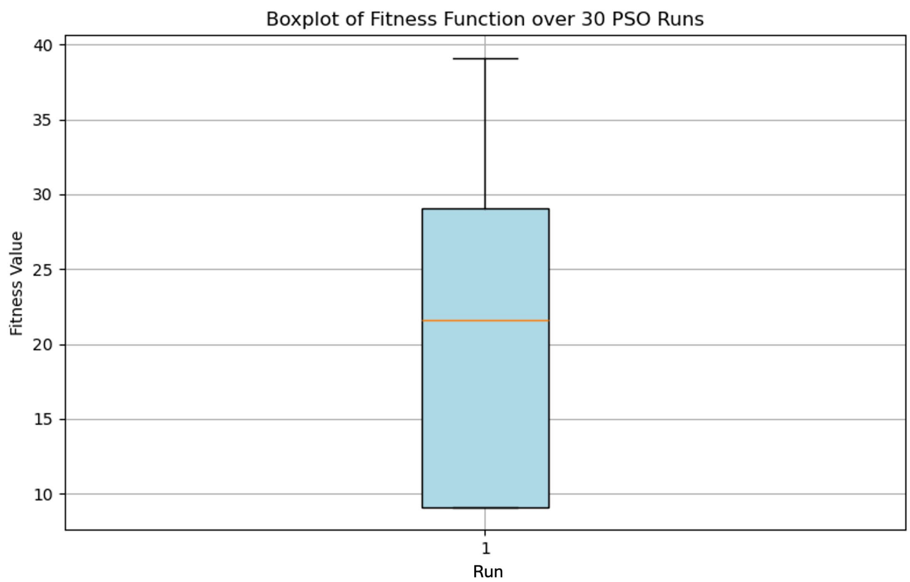

FIGURE 2
Boxplot of fitness function values across 30 independent PSO runs.

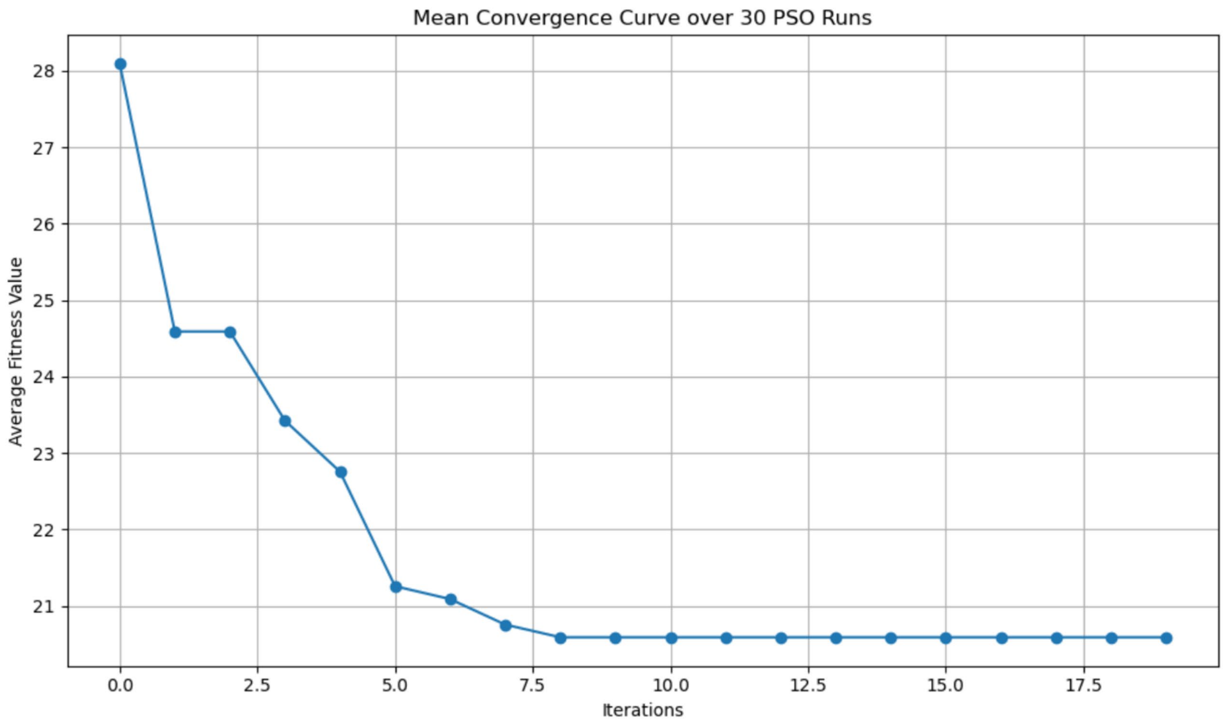

FIGURE 3
Mean convergence curve of PSO across 30 runs over 20 iterations.

TABLE 1 Association of topics with research questions.

Topic	Keywords	Description	Research questions	Short name
1	Quantum, Data, Security, Learning, Healthcare, Computing, Research, Systems, Technologies, Key.	Quantum computing applications in data security, learning algorithms, and healthcare infrastructure, addressing cybersecurity and technological challenges in quantum healthcare systems.	Q_1	Quantum Computing & Security in Healthcare
2	Quantum, Computing, Data, AI, Healthcare, QC, Potential, Research, Study, Machine.	The integration of AI and quantum computing in medical applications, exploring advancements in quantum-assisted AI for diagnostics, predictive modeling, and healthcare optimizations.	Q_2	AI & Quantum Computing for Healthcare

identifying label that facilitates reference to the different conceptual clusters.

Table 1 establishes the connection between the extracted research topics and their corresponding research questions, forming a structured framework to explore the thematic scope of the study.

The first topic revolves around quantum computing applications in healthcare security, learning systems, and infrastructure. The keywords highlight a focus on data security, system integration, and AI-driven learning models. As quantum computing becomes more prevalent, ensuring robust cybersecurity, data privacy, and secure machine learning frameworks in healthcare is essential. The associated research question (Q_1) investigates how quantum technologies can enhance the security, privacy, and interoperability of healthcare data. This includes solutions such as quantum encryption, privacy-preserving AI, and the integration of secure quantum computing in medical infrastructures.

The second topic focuses on the potential of AI-driven quantum computing in healthcare applications, particularly in medical diagnostics, predictive modeling, and computational medicine. The inclusion of terms like AI, quantum computing, and machine learning suggests that this topic explores the intersection of quantum computation and artificial intelligence for healthcare advancements. The corresponding research question (Q_2) examines how AI-enhanced quantum computing can optimize diagnostics, predictive healthcare models, and treatment strategies. By leveraging quantum-enhanced machine learning and simulations, this approach aims to revolutionize decision-making processes in medicine, improve personalized treatments, and increase computational efficiency in analyzing large-scale healthcare datasets.

The relationship between Q_1 and Q_2 underscores the complementary nature of these two research areas. On one hand, quantum security plays a crucial role in ensuring the privacy, protection, and secure exchange of sensitive medical data, addressing the growing need for cybersecurity in an increasingly digital healthcare environment. On the other hand, quantum computing and AI build upon this secure foundation, enabling advanced data processing, predictive analytics, and more accurate clinical

TABLE 2 Document frequencies by topic.

Topic	Counts	% of Total	Cumulative %
Quantum Computing & Security in Healthcare	41	65.08	65.08
AI & Quantum Computing for Healthcare	22	34.92	100.00

decision-making. By working in tandem, these two domains pave the way for a healthcare ecosystem that is not only secure but also more efficient, intelligent, and capable of leveraging quantum-driven innovations to enhance patient care and medical research. The analysis of Table 2 highlights a research landscape with a strong emphasis on security and computational advancements. While Quantum Computing & Security in Healthcare accounts for 65.08% of the total documents, reflecting a significant focus on data protection, privacy, and secure system integration, AI & Quantum Computing for Healthcare represents 34.92%, emphasizing the transformative role of AI and quantum computation in medical applications.

This distribution underscores the interdependence of these two areas: while quantum computing has the potential to revolutionize medical diagnostics, AI-driven decision-making, and predictive analytics, its successful implementation relies on robust quantum security frameworks to protect sensitive medical data and ensure interoperability with existing healthcare infrastructures. The findings reinforce the need for a dual approach in quantum healthcare research—one that advances computational capabilities while simultaneously ensuring the privacy, security, and resilience of healthcare data systems. The PSO-driven topic optimization ensured that the thematic classification reflected the natural distribution of knowledge within the domain of Quantum Computing in Healthcare. The results highlight that:

I Two dominant thematic areas clearly emerge: (1) Quantum Computing & Security in Healthcare, (2) AI & Quantum Computing for Healthcare.
II The approach based on PSO and LDA produced a robust segmentation, maintaining thematic diversity while avoiding topic dispersion.
III The identification of topics benefited from the dynamic selection of the number of clusters, as opposed to static approaches that could introduce bias in segmentation.

The ability of PSO to adapt dynamically to the latent structure of the dataset, identifying the optimal number of topics, represents a significant methodological contribution to literature analysis in the field of Quantum Computing and Healthcare.

4.4 Quantum Computing & Security in Healthcare

The adoption of Quantum Computing and advanced security technologies is radically transforming the healthcare sector, addressing critical challenges related to data protection, computational efficiency, and cybersecurity. Innovations in this field focus on advanced cryptographic techniques, quantum algorithms, and artificial intelligence applied to security, contributing to the protection of increasingly complex digital infrastructures.

The analyzed studies are distributed across five key areas, representing the main research and development directions in Quantum Computing & Security in Healthcare. One major focus is the development of quantum algorithms, designed to enhance security and computational efficiency in healthcare and cryptographic systems. At the same time, researchers are exploring the integration of sensor networks and secure data aggregation methods, which play a crucial role in protecting healthcare information. Another significant research area revolves around lattice-based cryptography and quantum security, leveraging advanced techniques to safeguard sensitive data from increasingly sophisticated cyber threats. Artificial intelligence is also a key player in strengthening healthcare data security, improving information protection and management through cutting-edge solutions. Lastly, the synergy between quantum and classical computing is paving the way for hybrid models that combine the strengths of both paradigms, offering superior performance and enhanced security in healthcare information systems.

These research areas outline the future directions of quantum computing and security technologies in healthcare, aiming to ensure robust data protection and strengthen the resilience of digital infrastructures.

4.4.1 Quantum computing and algorithms

Quantum computing is rapidly revolutionizing computational strategies in healthcare by introducing new methods for data security, medical analysis optimization, and advanced cryptographic protocols. As the demand for secure and efficient processing of clinical data increases, researchers are leveraging quantum algorithms to address complex challenges in biomedical informatics, cryptography, and drug discovery.

A central area of innovation is quantum cryptography, which plays a critical role in protecting sensitive medical data. Wireless Body Sensor Networks (WBSNs), essential for remote patient monitoring, remain highly vulnerable to cyberattacks. To mitigate these risks, hybrid cryptographic techniques that combine symmetric and asymmetric encryption have demonstrated notable improvements in data protection. One study (Chowdhary et al., 2020) highlighted the effectiveness of combining Elliptic Curve Cryptography (ECC), Hill Cipher (HC), and Advanced Encryption Standard (AES), resulting in a balanced approach that enhances both computational efficiency and security. Metrics such as entropy, Peak Signal-to-Noise Ratio (PSNR), Number of Pixels Change Rate (NPCR), and Unified Average Changing Intensity (UACI) confirm the suitability of these techniques for secure telemedicine and remote monitoring. Beyond cryptography, quantum sensing is advancing the frontiers of medical diagnostics. By implementing Kitaev's Phase Estimation Algorithm (PEA), quantum sensors can surpass the Standard Quantum Limit (SQL), enabling highly accurate detection of static magnetic fields. These advances promise to enhance non-invasive diagnostic imaging through more sensitive and scalable quantum devices (Danilin et al., 2024). In parallel, quantum machine learning (QML) is emerging as a powerful tool for analyzing complex, multidimensional healthcare data. Hybrid classical and quantum approaches, implemented on quantum simulators, have demonstrated superior accuracy compared to traditional clustering methods. These results are paving the way for personalized medicine and advanced predictive analytics (Deshmukh et al., 2023). The growth of these technologies is also giving rise to quantum software engineering (QSE) as a distinct field. Transitioning from classical to quantum systems requires new development paradigms. Solutions such as Quantum Intermediate Representations (QIRs) and Quantum Program Dependence Graphs (QPDGs) address critical challenges in error mitigation and hybrid system design (Murillo et al., 2025). The convergence of quantum computing and artificial intelligence is leading to important breakthroughs in diagnostics and drug development. Quantum-enhanced neural networks, support vector machines, and variational quantum classifiers enable faster and more accurate disease classification, risk prediction, and drug interaction modeling, demonstrating the disruptive potential of quantum systems in computational medicine (Zeguendry et al., 2023). Another pillar of quantum development lies in nanotechnology, particularly in the use of semiconducting, superconducting, and topological nanowires as scalable platforms for qubits. These innovations are improving coherence, error correction, and gate fidelity, all of which are essential for enabling large-scale quantum computing in healthcare (Mimona et al., 2024). The pharmaceutical sector is already benefiting from quantum capabilities. Quantum algorithms significantly reduce the computational costs of simulating complex molecular structures. These simulations accelerate drug discovery by enhancing predictions of protein–drug interactions and supporting precision medicine strategies (Blunt et al., 2022). In addition, quantum simulations of many-body systems offer new avenues for biomedical modeling. Through variational quantum algorithms and error mitigation techniques, researchers can simulate biological processes and disease mechanisms with greater precision (Fauseweh, 2024). Quantum computing is also advancing materials science and catalysis modeling, particularly in the design of new drug compounds and biochemical processes. By applying quantum chemistry algorithms, researchers are simulating catalytic reactions with exceptional accuracy. This approach helps optimize synthesis pathways and lower experimental costs (Hariharan et al., 2025).

4.4.2 AI and healthcare data security

Artificial intelligence is becoming a foundational pillar in healthcare data security and management. It enables more efficient, reliable, and intelligent protection mechanisms in an era where the volume of medical data is growing exponentially. Ensuring the integrity, confidentiality, and accessibility of sensitive information is critical. AI-powered technologies, when combined with augmented reality (AR), virtual reality (VR), blockchain, and the Internet of Things (IoT), are transforming how patient data is collected, stored, and protected. One of the most promising applications of AI in this domain is the integration of wearable devices within digital health platforms. These technologies support continuous monitoring, rehabilitation, and the management of chronic conditions, improving the quality and responsiveness of remote care. In this context, the metaverse offers immersive environments that use biometric sensors and haptic feedback to enable secure, real-time health tracking. Despite this progress, technical limitations and regulatory gaps still exist, calling for further research to ensure the safe and effective deployment of wearable healthcare technologies (Vahdati et al., 2024). The metaverse is also emerging as a transformative space in healthcare more broadly. Virtual environments powered by AI can enhance surgical precision, therapeutic delivery, and the security of sensitive data. The convergence of AR, VR, and blockchain enables the secure exchange of medical records and the seamless integration of Electronic Health Records (EHRs). Within these ecosystems, AI plays a central role in improving interoperability and ensuring data authenticity, restricting access to authorized healthcare professionals only. However, important concerns around privacy, ethics, and technological maturity remain (Wang et al., 2024). As cybersecurity threats evolve, clinicians find themselves at the forefront of a rapidly changing risk landscape. AI is increasingly being employed to detect and mitigate these threats, offering real-time monitoring and automated response mechanisms. Technologies such as Intrusion Detection Systems (IDS), multi-factor authentication (MFA), and homomorphic encryption provide robust tools for safeguarding patient information without compromising usability. Blockchain-based solutions further enhance data integrity by creating immutable patient records that are resistant to tampering and aligned with regulatory compliance requirements. Recent applied developments show that the integration of blockchain and quantum technologies is already being implemented in real-world settings. In the healthcare domain, for instance, the adoption of distributed cloud platforms that combine blockchain for data integrity management and quantum threat protection protocols has been documented in Internet of Medical Things (IoMT) scenarios, where clinical data access is governed by secure and verifiable mechanisms (Krishnappa et al., 2024). In parallel, approaches integrating blockchain, quantum computing, and zero-trust architectures have been proposed to strengthen the security of complex healthcare systems, demonstrating how these technologies can work synergistically to protect clinical information in distributed and high-risk environments (Kalinaki et al., 2023).

While these combined systems show promise, it is important to clarify how Quantum Key Distribution (QKD) compares to traditional cryptographic methods currently used in healthcare environments. Conventional encryption algorithms, such as RSA and AES, rely on the computational difficulty of certain mathematical problems, which may become solvable with the advent of quantum computing. In contrast, QKD offers security based on the fundamental principles of quantum mechanics, ensuring that any attempt to intercept the key transmission is immediately detectable. This makes QKD inherently more secure against future quantum attacks. In a healthcare context, where the confidentiality of electronic health records, genomic data, and diagnostic information is paramount, the adoption of QKD can provide a provable safeguard against both current and emerging threats. Although it currently requires dedicated infrastructure and presents higher implementation costs, QKD is increasingly being considered a strategic investment for critical communication channels, particularly in hospital networks and high-value clinical data exchanges.

Legal and ethical issues surrounding AI and cybersecurity continue to represent major obstacles. Addressing these challenges requires coordinated collaboration between healthcare professionals, policymakers, and legal experts (Elendu et al., 2024). AI is also driving transformation within Industry 4.0 healthcare systems, where automation and digitalization are critical to both efficiency and security. The integration of AI, blockchain, IoT, and digital twins is enabling the creation of more resilient, secure, and patient-centered healthcare infrastructures. Machine learning models are improving non-invasive disease diagnosis, while smart health monitoring systems are enhancing the tracking of vital signs in real time. Despite these gains, data interoperability and privacy remain significant hurdles, requiring clear regulatory frameworks and robust security protocols (Cardamone et al., 2024). AR and VR are also playing an expanding role in data security. These immersive technologies are improving not only medical training and education but also real-time collaboration and secure patient data visualization. AI-enhanced AR and VR platforms offer personalized and protected environments for remote consultations, virtual surgical training, and therapeutic procedures. As adoption grows, ensuring ethical and secure implementation will remain essential (Al-Ansi et al., 2023). Finally, automation in Model-Driven Engineering (MDE) is empowering AI to take on a larger role in developing security-focused software for healthcare. Combining symbolic and non-symbolic AI with specialized task-based agents, MDE frameworks are producing adaptive software solutions aligned with the complex demands of healthcare institutions. The integration of security validation techniques and model alignment tools ensures that applications remain both scalable and secure (Burgueño et al., 2025).

4.4.3 Quantum-classical hybrid computing

The integration of quantum and classical computing is creating new opportunities for breakthroughs in computational performance, cybersecurity, artificial intelligence, healthcare, and automation. By combining the reliability of classical systems with the computational power of quantum mechanics, hybrid models are emerging as a practical solution to overcome the current limitations of both paradigms. These models enable the exploitation of quantum advantages without abandoning the compatibility and infrastructure of classical computing. One of the most promising applications of quantum classical hybrid computing lies in cybersecurity, particularly in defending against Distributed Denial of Service (DDoS) attacks. Machine learning models are essential for cyber threat detection, but they often require substantial computational resources to process large datasets. A novel approach using Quantum Support Vector Machines (QSVMs) has demonstrated enhanced speed, accuracy, and precision when detecting DDoS attacks in smart microgrid systems. By employing the Harrow-Hassidim-Lloyd (HHL) quantum algorithm, the model significantly reduces computational complexity, thereby improving the efficiency and resilience of cyber defenses (Said, 2023). Hybrid computing is also reshaping machine learning itself. Traditional classification algorithms often struggle with complex, non-linear datasets and are prone to overfitting or bottlenecks. Quantum classification models, by utilizing quantum kernels in high-dimensional Hilbert spaces, exhibit stronger learning capabilities. Comparative studies between classical and quantum SVMs show that quantum models outperform as dataset complexity increases, reinforcing the value of hybrid machine learning frameworks (Tychola et al., 2023). In industrial sectors, particularly oil and gas, Industry 4.0 technologies are driving the adoption of hybrid computing systems. Edge computing, digital twins, and quantum computing are being explored to optimize operations and support intelligent decision-making. AI-driven forecasting tools are already improving efficiency, and quantum enhancements are expected to accelerate simulations, enable real-time analysis, and automate key processes. This convergence is positioning hybrid computing as a key enabler of sustainable and scalable industrial solutions (Elijah et al., 2021). In healthcare and mental health analytics, the fusion of quantum computing and deep learning is accelerating progress. Traditional deep learning models are computationally expensive due to prolonged training times. Quantum Convolutional Neural Networks (QCNNs), through the integration of quantum variational circuits and transfer learning, reduce training complexity from $O(n^2)$ to $O(\log(n))$. This reduction enhances the performance of emotion recognition, psychological assessments, and medical imaging applications (Hossain et al., 2024). Privacy-preserving machine learning is another domain benefiting from hybrid architectures. Federated learning, when combined with quantum computing, addresses sensitive data-sharing concerns across healthcare institutions. A hybrid framework utilizing Quanvolutional Neural Networks (QNNs) enables decentralized training on non-independent and identically distributed (Non-IID) datasets. This approach allows institutions to train robust medical AI models without exchanging patient data, reducing communication overhead and preserving confidentiality (Bhatia et al., 2023). Evidence of empirical quantum advantage (EQA) is also emerging in healthcare data analysis. By applying quantum kernels to Electronic Health Records (EHRs), researchers have demonstrated superior classification performance in specific subsets of medical prediction problems. A proposed metric, the phase-space terrain ruggedness index (PTRI), helps predict when quantum models will outperform classical methods, contributing to the strategic identification of practical quantum advantages in biomedical contexts (Krunic et al., 2022). Despite these benefits, integrating quantum computing with classical IT infrastructures remains challenging. To address this, a middleware software architecture known as qSOA® has been developed. It enables seamless integration between quantum and classical systems using a standardized REST API, simplifying deployment and reducing technical barriers. This framework supports the accessibility and scalability of hybrid computing environments, allowing industries to integrate quantum technologies without overhauling existing systems (Hevia et al., 2024). Hybrid quantum classical computing is also showing potential in robotics, particularly in swarm-based search and rescue operations. Classical decision-making models in robotics demand high computational resources for tasks like motion planning. A quantum-based path-planning algorithm, built on Grover's search and quantum logic gates, enables faster convergence and improved path optimization. Simulations indicate that this method outperforms classical ant-foraging algorithms, providing more stable and efficient solutions in dynamic, unpredictable environments (Chella et al., 2023).

4.4.4 Sensor networks and data aggregation

The integration of sensor networks with intelligent data aggregation is playing a pivotal role in advancing modern healthcare systems, smart infrastructure, and secure digital ecosystems. With the exponential growth of data generated by Internet of Things (IoT) devices, intelligent sensors, and quantum-enabled networks, the demand for scalable, secure, and efficient data processing has become increasingly urgent. A significant development in this space is the growing use of intelligent sensors in workplace and industrial environments. These sensors utilize advanced algorithms, signal processing techniques, and data fusion models to extract and interpret real-time patterns. Intelligent machines powered by these sensors are enhancing human decision-making, enabling predictive maintenance, and optimizing operational performance. However, these advances also raise concerns about workforce displacement and the future of human-machine collaboration. As a result, many organizations are investing in upskilling programs and adaptive strategies to support a smooth transition toward the integration of intelligent technologies (Annamalai and Vasunandan, 2024). Beyond industrial settings, sensor networks are facilitating digital social innovation by contributing to global Sustainable Development Goals (SDGs). Digital Social Innovations (DSIs), powered by IoT, artificial intelligence, blockchain, and autonomous robotics, are helping address challenges related to public health, urban infrastructure, agriculture, and poverty alleviation. These systems enable the rapid collection and analysis of large volumes of social and environmental data, enhancing evidence-based policy-making. At the same time, ethical issues concerning data privacy, automation-driven job displacement, and social equity must be addressed to ensure inclusive and beneficial digital transformation (Dionisio et al., 2024). In the healthcare domain, one of the most impactful implementations is seen in Hospital-at-Home (HaH) systems. These models rely heavily on secure data transmission and device interoperability in home-based environments. A recent solution incorporates trust establishment and key management protocols built on post-quantum cryptographic primitives and Merkle tree structures. This approach allows medical IoT devices to authenticate and exchange data securely, even in offline scenarios. The architecture strengthens long-term data integrity and resilience, addressing key vulnerabilities in decentralized healthcare systems (Åkesson et al., 2025). In parallel, the growing demand for cost-effective and sustainable data storage has renewed interest in magnetic tape systems. Recent improvements in tape head technology, error correction algorithms, and adaptive encoding have made magnetic tape a viable long-term storage option. These systems offer high capacity and energy efficiency, making them ideal for institutions that require reliable archiving of large datasets, such as hospitals, research centers, and cloud providers (Lantz et al., 2025). The emergence of quantum-enhanced sensor networks marks the next frontier in this field. The combination of quantum computing, federated learning, and sixth generation (6G) wireless technology is revolutionizing the way IoT systems handle security and data aggregation. Conventional security frameworks often fall short in heterogeneous IoT environments, where devices operate in distributed and constrained networks. By integrating Quantum Key Distribution (QKD) and quantum-optimized aggregation algorithms, these systems establish secure communication channels, enable decentralized processing, and detect threats in real time. Moreover, 6G networks with edge-native intelligence allow data to be processed locally, reducing reliance on centralized servers and improving both bandwidth efficiency and data privacy (Javeed et al., 2024).

4.4.5 Lattice-based security and quantum security

The emergence of quantum computing is fundamentally reshaping the cybersecurity landscape, rendering many traditional cryptographic systems vulnerable and necessitating the development of quantum-resistant alternatives. In response, lattice-based cryptography and quantum security technologies are gaining traction as essential tools for protecting sensitive data in healthcare infrastructures, IoT networks, and blockchain-based systems. These innovations are focused on maintaining confidentiality, integrity, and system resilience in the face of evolving cyber threats. One of the sectors most at risk is medical imaging, which plays a vital role in diagnosis and treatment. As healthcare systems become increasingly interconnected, the vulnerability of medical image data to cyberattacks grows. To counteract this risk, a combination of blockchain, artificial intelligence, and quantum cryptographic methods is being deployed to enhance data security (Yan et al., 2023). In the IoT domain, secure authentication and data protection are critical. A post-quantum identity-based digital signature (PQ-IDS) scheme based on lattice cryptography has been introduced to defend against quantum threats. This model ensures the immutability, traceability, and confidentiality of communications between IoT devices (Zhang et al., 2024). Within the Internet of Medical Things (IoMT), secure access and authentication are equally essential. A recent protocol, PDAC-CoV, leverages lattice-based encryption to ensure secure communication while also improving computational efficiency in constrained medical environments. This solution helps prevent data breaches and supports secure transmission in real-time medical scenarios (Gupta et al., 2023). Blockchain infrastructures are also being evaluated for their susceptibility to quantum attacks. Platforms such as Ethereum, Bitcoin, and Ripple have been shown to exhibit vulnerabilities under quantum threat scenarios. To mitigate these risks, researchers are exploring quantum-resistant blockchain technologies that enhance energy efficiency and boost transaction throughput while maintaining robust cryptographic guarantees (Singh et al., 2024). Wireless Body Area Networks (WBANs), widely used in remote patient monitoring, face growing security risks. The Quantum Spider Cramer Shoup Public Key Cryptosystem (QS-CSPKC) protocol provides enhanced security for data transmission in WBANs, while also reducing energy consumption, making it a viable solution for secure and sustainable remote healthcare systems (Menaga and Vanithamani, 2023). In software security, long-term durability is vital. A novel security evaluation framework based on fuzzy logic and prioritization techniques has been developed to identify and strengthen vulnerabilities in cryptographic systems. This framework supports proactive risk assessment and continuous improvement in resilience against quantum threats (Alyami et al., 2021). Secure communication in unmanned aerial vehicles (UAVs), including medical drones, is another critical area. Quantum Cryptography-as-a-Service (QCaaS) uses Quantum Key Distribution (QKD) with the BB84 protocol to ensure encrypted, tamper-proof data transmissions. This system enhances the security of drone operations in both healthcare and defense applications (Ralegankar et al., 2022). Secure key exchange remains a pressing challenge in digital health systems. A three-party authenticated key exchange protocol combining Ring Learning With Errors (RLWE) and Elliptic Curve Cryptography (ECC) ensures secure, anonymous user authentication while defending against interception attacks and other intrusion vectors (Chaudhary et al., 2023). For blockchain-based IoT systems, a lattice-based multi-signature scheme (LBCMS) has been designed to improve security and computational performance. This approach enhances resistance to quantum attacks while facilitating secure data validation in decentralized environments (Bagchi et al., 2025). In healthcare devices, multimodal input integration has advanced significantly through engineering-driven innovations. Gesture recognition systems used in physical rehabilitation now benefit from improved reliability and responsiveness, increasing the accuracy of user inputs in assistive applications (Carayon et al., 2024). The field of sports performance monitoring and physical therapy is also benefiting from secure sensor technologies. The SMARCyPad system introduces a cost-effective cycling performance monitoring method using conductive fabric sensors, offering secure data transmission alongside physical rehabilitation benefits (Wu et al., 2023). Blockchain-based federated learning systems (BFL) are leveraging hybrid security frameworks to protect decentralized AI models. A system integrating post-quantum cryptography standards such as Dilithium, Falcon, and XMSS improves digital signature performance and ensures robust protection of patient data during distributed machine learning (Gurung et al., 2024). Finally, protecting low-power IoT devices requires specialized authentication solutions. A Root of Trust mechanism (RoTMR), based on Physically Unclonable Functions (PUFs) and hash-based signatures, provides secure remote authentication, protects firmware integrity, and defends against physical tampering and hardware attacks (Román et al., 2023).

4.5 AI & Quantum Computing for Healthcare

The integration of Artificial Intelligence (AI) and Quantum Computing is transforming the healthcare sector by enhancing diagnostic efficiency, optimizing treatment strategies, and improving predictive analytics. Advanced digital technologies and software development facilitate intelligent clinical data management, standardization of care, and automation of healthcare processes. Quantum computing enables high-precision molecular simulations, accelerating drug discovery and advancing personalized medicine.

These innovations are structured into three key areas. Digital technologies and software development enable intelligent healthcare platforms, advanced communication networks, and secure data management tools. Quantum computing in biomedical applications is revolutionizing diagnostics, data security, and predictive modeling for complex diseases. Finally, AI and neuromorphic computing enhance biological simulations, optimize artificial neural networks, and personalize medical education. The advancement of these technologies marks a turning point in healthcare, making systems more precise, sustainable, and adaptable to future clinical needs.

4.5.1 Digital technologies and software development

The evolution of digital technologies and quantum computing is transforming the healthcare sector, improving efficiency, scalability, and adaptability. mHealth platforms must balance automation and community collaboration, adapting to local healthcare structures (Eze et al., 2022). The integration of decision support engines based on international guidelines optimizes treatments and standardizes care. 5G/6G networks promise high efficiency and low latency, but increasing energy consumption requires more responsible network solutions. Intelligent resource management and reducing unnecessary data proliferation are essential to balance efficiency and sustainability (Cano and March, 2025). In parallel, quantum computing opens new possibilities for processing large volumes of clinical data, optimizing molecular simulations, predictive diagnoses, and personalized therapies. The integration of quantum algorithms with artificial intelligence enables tackling computationally complex problems, enhancing the speed and accuracy of healthcare analytics (Autili et al., 2025). Healthcare software development must integrate reliability, fairness, and transparency from the design phase. An emerging framework emphasizes four key areas: optimizing the development lifecycle, user-centric requirements engineering, scalable architectures, and robust verification methodologies (Akbar et al., 2024). This approach reduces algorithmic bias risks and increases trust in digital systems. The intersection of mobile technologies, communication networks, quantum computing, and software engineering is crucial for the digital transformation of healthcare. Addressing sustainability challenges, data governance, and ethical development is essential to ensure reliable and long-lasting solutions.

4.5.2 Quantum computing and biomedical applications

Quantum computing is revolutionizing the biomedical sector, offering unprecedented potential in data security, diagnostics, treatment optimization, and predictive modeling. The integration of quantum technologies with artificial intelligence, bioinformatics, and cryptography opens new frontiers for healthcare, making medical systems more secure, precise, and efficient. These advancements are transforming several key areas of healthcare, from disease detection and personalized medicine to data security and computational biology. The following sections outline the most significant contributions of quantum computing in biomedical applications:

I Quantum Computing for Diagnostics and Precision Medicine—Quantum Machine Learning (QML) is significantly improving early disease detection through advanced pattern recognition techniques. Applications in radiology, pathology, and genomics have demonstrated that quantum algorithms, such as Quantum Support Vector Machines (QSVMs) and Quantum Random Forest, surpass classical methods in accuracy and processing speed (Jeyaraman et al., 2024). Moreover, quantum computing applied to bioinformatics is enhancing biomarker identification and genomic analysis, optimizing personalized therapies and treatments tailored to patients' genetic profiles (Nałęcz-Charkiewicz et al., 2024). Quantum simulations are revolutionizing drug discovery by accelerating the study of molecular interactions and protein structures. Technologies such as the Quantum Variational Eigensolver (VQE) enable the modeling of chemical structures with unparalleled precision compared to classical computers, expediting pharmaceutical research and improving the understanding of molecular mechanisms (Pal et al., 2024). Additionally, a systematic review highlights the role of Quantum Machine Learning (QML) in healthcare, demonstrating its potential in enhancing biomedical data analysis, clinical decision-making, and personalized treatment strategies (Ullah and Garcia-Zapirain, 2024).

II Quantum Applications in Predictive Modeling—The integration of quantum machine learning and predictive healthcare is significantly impacting chronic disease prevention and management. Recent studies highlight the advantages of Quantum-Enhanced Machine Learning (QuEML) in heart disease prediction, showing superior results compared to classical models in terms of diagnostic accuracy and processing speed (Babu et al., 2024). Similarly, QSVMs have improved mortality prediction in early-onset colorectal cancer patients, demonstrating high precision even in unbalanced medical datasets (Yu et al., 2024). Quantum neural networks are also being explored for healthcare data generation. The Quantum Conditional GAN (QCGAN-ECG) has been utilized to generate realistic synthetic ECG data, enhancing the training of cardiovascular diagnostic models and ensuring robustness against signal distortions (Qu et al., 2023).

III Quantum Computing for Data Security and Telemedicine—With the increasing digitalization of healthcare, information security is a top priority. Quantum cryptography, particularly Quantum Key Distribution (QKD), is strengthening the protection of digital medical records and sensitive healthcare data, mitigating vulnerabilities to cyber threats (Awan et al., 2022). Additionally, the application of quantum photonics in telemedicine has enhanced data security in e-health systems, ensuring secure and private communication between patients and healthcare providers (Irfan et al., 2024).

IV Optimization of Clinical Processes and Computational Biology—The use of quantum computing in clinical trials enables the simulation of complex scenarios, optimization of patient selection, and improved prediction of drug responses. Quantum variational algorithms (VQA) and quantum annealing allow for the reduction of time and costs in clinical research, enhancing medical studies' efficiency (Doga et al., 2024). At the same time, computational biology is benefiting from the integration of quantum computing with multi-scale models. The combined use of Quantum Eigensolver and Quantum Phase Estimation (QPE) enhances macromolecular modeling and the simulation of gene regulatory networks, paving the way for new hybrid quantum-classical approaches (Marchetti et al., 2022). Furthermore, emerging classifications for quantum bioinformatics, including Q-Bioinformatics, QCt-Bioinformatics, QCg-Bioinformatics, and QCr-Bioinformatics, structure the integration of quantum algorithms into biological and genomic analysis (Mokhtari et al., 2024).

4.5.3 Artificial intelligence and neuromorphic computing

The convergence of Artificial Intelligence (AI), Neuromorphic Computing, and Quantum Computing is progressively reshaping biomedical research and healthcare, enabling new paradigms in disease detection, personalized treatment, and computational medicine. Quantum computing is emerging as a key enabler in enhancing AI capabilities through quantum-inspired optimization, hybrid modeling, and exponentially faster processing, especially in data-intensive clinical scenarios.

Artificial Intelligence (AI) and Neuromorphic Computing are revolutionizing the healthcare sector, biomedical research, and computational biology, driving advancements in disease detection, personalized treatments, and healthcare infrastructure. The combination of AI-driven models and neuromorphic architectures is enhancing biomolecular simulations, predictive modeling, and medical education while addressing challenges related to AI governance in healthcare systems. These technologies also address critical challenges related to AI governance in healthcare systems, especially when considered in light of future quantum integration. The integration of AI with big data analysis plays a crucial role in supporting the Sustainable Development Goals (SDGs), particularly in healthcare, sustainable energy, and infrastructure. AI applications are improving disease monitoring, precision medicine, and predictive analytics, contributing to more resilient healthcare systems. However, ethical concerns such as data privacy, security, and algorithmic bias must be reconsidered considering emerging quantum risks, which are expected to impact encryption standards and data protection strategies (Nedungadi et al., 2024). Generative Artificial Intelligence (GAI) is transforming the personalization of medical education, enabling adaptive learning experiences tailored to the specific needs of healthcare professionals. Large Language Models (LLMs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs) allow real-time content adaptation, improving surgical training and precision medicine programs. The anticipated future incorporation of quantum-enhanced models into these generative systems will likely further accelerate the customization of surgical training and clinical simulations. Ethical considerations, such as bias in AI-based educational tools, highlight the importance of developing regulatory frameworks that ensure fairness and inclusivity in AI applications for medical education (Almansour and Alfhaid, 2024). The adoption of AI in public healthcare systems is influenced by governance structures, macroeconomic conditions, and the availability of AI specialists. Studies conducted in EU member states reveal that brain drain negatively affects AI readiness, leading to skill shortages and a slower adoption of AI innovations in healthcare. Addressing these challenges requires policy interventions aimed at retaining talent and promoting international collaboration in AI research and healthcare applications (Socol and Iuga, 2024). In biomolecular research, neuromorphic computing and high-performance computing (HPC) are accelerating molecular dynamics simulations and enabling real-time biomedical analysis. The integration of AI with quantum computing is already improving protein folding simulations, drug discovery processes, and the modeling of complex biological interactions. The potential of neuromorphic architectures in reducing computational energy consumption further strengthens their applicability in biomedical research. Modular supercomputing frameworks that incorporate AI, quantum computing, and neuromorphic computing represent a transformative factor in large-scale computational biology (Diaz-Pier and Carloni, 2024). In oncology, Quantum Machine Learning (QML) is demonstrating superior performance in cancer diagnostics and treatment planning. Applications include noise reduction in medical imaging, enhanced edge detection in breast cancer screening tests, and advanced clinical decision support for radiotherapy. Studies confirm that QML outperforms classical machine learning models, offering greater accuracy in cancer classification and personalized treatment strategies. The development of hybrid AI-quantum models is set to further improve precision oncology by enabling more accurate predictions and individualized treatment plans (Rahimi and Asadi, 2023). As AI and quantum computing continue to evolve, their role in large-scale biomolecular simulations is becoming increasingly relevant. Exascale computing, combined with AI-driven predictive modeling, is optimizing protein-ligand interactions, genomic analysis, and in silico drug discovery. Even in the intermediate era of Noisy, Intermediate-Scale Quantum (NISQ) computers, quantum algorithms are demonstrating significant potential in biomedical applications. These advancements mark a shift toward more efficient and precise computational methodologies in molecular biology and pharmaceutical research (Pyzer-Knapp and Curioni, 2024). This intersection of AI, neuromorphic systems, and quantum computing marks a transformative phase in medicine. Moving forward, the development of hybrid AI-quantum frameworks will be essential to unlock new levels of precision, efficiency, and ethical intelligence in healthcare applications. By integrating these technologies, the medical field is poised to achieve new breakthroughs in disease diagnostics, personalized treatments, and biomedical research, leading to more intelligent and efficient healthcare systems.

5 Experimental extension: development and evaluation of a predictive model

This section, as an experimental extension of the study, introduces a predictive model to analyze the three main topics identified in quantum computing for healthcare. The goal is to provide a practical and quantitative response to the previously posed research questions, offering a deeper understanding of the interconnections between different areas of study. To ensure an accurate and targeted classification, the model is based on three binary variables, identified as transversal factors present across the analyzed studies. The first, Biomedical/Life Sciences Application, identifies studies that apply quantum computing to biomedicine, genomics, healthcare, or biosecurity, highlighting its impact in the medical and biological sectors. The second, Blockchain/Distributed Systems Use, highlights the integration of these technologies, emphasizing their role in data security, information integrity, and decentralized healthcare solutions. The third, Ethical & Legal Aspects, evaluates studies that address regulatory, ethical, and legal implications of quantum computing in healthcare, emphasizing compliance, policy considerations, and responsible implementation. The analysis of these variables, recognized as transversal elements within the reviewed literature, enables the classification of studies into the three main research areas, offering a structured perspective on research trends and contributing to a better understanding of the intersections between quantum computing and healthcare.

5.1 Dataset classification and feature analysis in quantum computing for healthcare

The dataset created for the classification model has been designed to accurately identify research trends and priorities in the application of quantum computing in healthcare. To ensure an effective classification of studies into the two main topics—Quantum Computing & Security in Healthcare, AI & Quantum Computing for Healthcare—three key variables have been selected, expressed in a binary format. A value of 1 indicates the presence of the characteristic in the analyzed study, while a value of 0 denotes its absence. The first variable, Biomedical/Life Sciences Application, assesses whether the study focuses on quantum computing applications in biomedicine, genomics, healthcare, or biosecurity. This characteristic is present in 55.56% of studies, while 44.44% do not address this aspect. The second variable, Blockchain/Distributed Systems Use, evaluates whether the study incorporates blockchain or distributed system technologies. 17.46% of studies include these aspects, while 82.54% do not focus on them. The third variable, Ethical & Legal Aspects, identifies research centered on system design, infrastructure optimization, or quantum-enhanced engineering applications. 69.84% of studies demonstrate this focus, while 30.16% do not. Table 3 summarizes the distribution of the selected features within the dataset, providing an overview of their presence across the analyzed studies.

The analysis of feature distribution provides a clear picture of current research directions. Biomedical and life sciences applications remain a significant area of focus, with more than half of the studies addressing this topic. However, a substantial portion of the research still explores other domains. Blockchain and distributed systems are the least frequently addressed aspect, indicating that their integration in quantum computing research is still developing. Ethical and legal aspects, system design, and infrastructure optimization emerge as a major theme, reflecting efforts to enhance system performance and scalability.

5.2 Machine learning model for quantum computing classification in healthcare

Machine learning techniques have proven to be essential in deriving valuable insights and constructing accurate predictive models from intricate datasets across various domains. Previous research has demonstrated their effectiveness in diverse applications, including the prediction of neurological developmental disorders in children (Toki et al., 2024) and the development of AI-driven IoT-based diagnostic models for cardiovascular diseases (Marengo et al., 2024). Likewise, their relevance is further underscored in studies examining hospital facility efficiency, public health impact, and patient health mobility, reinforcing their potential to optimize healthcare systems (Santamato et al., 2023; Santamato et al., 2024; Santamato et al., 2024). Moreover, the combination of systematic reviews and machine learning techniques has been shown to be effective in studying the impact of artificial intelligence on healthcare management (Santamato et al., 2024). Recently, the application of advanced machine learning techniques has led to significant improvements in the security and efficiency of healthcare data management. For instance, the adoption of deep learning-based models has ensured secure and sustainable access to data in industrial wireless sensor networks (IWSN),

TABLE 3 Feature distribution in the dataset.

Feature	Present (1)	% of Total	Absent (0)	% of Total
Biomedical/Life Sciences Application	35	55.56	28	44.44
Blockchain/Distributed Systems Use	11	14.46	52	82.54
Ethical & Legal Aspects	44	69.84	19	30.16

addressing issues related to security and energy consumption (Alzubi, 2022). Similarly, the implementation of blockchain and artificial intelligence approaches has enhanced the secure transmission of medical data within the Internet of Things (IoT), increasing diagnostic accuracy (Alzubi et al., 2021). Furthermore, the combined use of blockchain and federated learning has helped preserve the privacy of electronic health records (EHR) in the context of the Industrial Internet of Things (IIoT), ensuring the integrity and confidentiality of healthcare data (Alzubi et al., 2023). Finally, the adoption of advanced optimizers has improved feature selection in medical diagnosis, as evidenced in real cases of COVID-19, contributing to increased diagnostic accuracy and the efficiency of predictive models (Braik et al., 2023).

In this study, it was implemented and evaluated a diverse set of predictive models, encompassing Logistic Regression, Neural Networks, Support Vector Machines (SVM), Random Forest, Gradient Boosting, Naïve Bayes and Stochastic Gradient Descent (SGD). This systematic comparison enabled us to determine the most effective model for the specific application, ensuring a comprehensive and rigorous assessment of the available predictive methodologies. The selection of the predictive model was carried out through a structured computational approach, utilizing Python scripts to implement advanced machine learning techniques that ensured both automation and interpretability. The workflow was designed to maintain methodological rigor while optimizing performance. Data preparation began with dataset partitioning using *train_test_split*, assigning 70% of the data for training and 30% for testing. This configuration preserved a substantial portion for model learning while reserving an independent set for evaluating generalization. The partitioning strategy aimed to maximize predictive accuracy while preventing overfitting. Following the preprocessing phase, eight predictive models were implemented. A stratified 10-fold cross-validation approach was applied to enhance the reliability of performance evaluation across different dataset splits. To further refine the models, hyperparameter tuning was performed using *GridSearchCV*, systematically identifying the most effective configuration for each model. To address the slight class imbalance present in the dataset, models that support weighting, such as Logistic Regression, SVM, Random Forest, and SGD, were configured with class weight balancing to improve classification performance. This adjustment helped mitigate bias toward the majority class, ensuring a more robust evaluation of the minority class. For model selection, AUC (Area Under the Curve) was chosen as the primary evaluation metric, as it measures the model's ability to distinguish between classes, making it particularly suitable for applications where sensitivity and specificity are crucial. Table 4 presents a comparative analysis of the optimized predictive models, summarizing their classification performance and highlighting the most effective approach for the given dataset.

The comparative analysis of Machine Learning models showed that Gradient Boosting, Neural Networks, Random Forest, Logistic Regression, SVM, and SGD all achieved the highest AUC (0.875), indicating strong discriminative capability. However, since AUC was the primary selection metric, additional performance measures were considered in case of ties. Among these models, Gradient Boosting emerged as the best-performing due to its highest values in Accuracy (0.842), Precision (0.889), Recall (0.842), F1-score (0.845), and MCC (0.725), ensuring the best balance between predictive power and model stability. In contrast, Neural Networks (Accuracy 0.684, F1-score 0.679, MCC 0.519) and Random Forest (Accuracy 0.632, F1-score 0.617) demonstrated weaker overall classification performance. Logistic Regression, SVM, and SGD, despite sharing the same AUC (0.875), performed even worse (Accuracy 0.526), while Naïve Bayes (AUC 0.792) had the lowest performance. Given its superior performance across all key metrics, Gradient Boosting was selected as the most effective model for analyzing quantum computing applications in healthcare.

To ensure methodological transparency and facilitate reproducibility, the final hyperparameters selected through GridSearchCV are reported as follows. For the Gradient Boosting classifier, which achieved the best performance, the model was optimized with n_estimators = 200 and learning_rate = 0.1. Other optimized models included Neural Networks (hidden_layer_sizes = (100, 50)), SVM (C = 1, kernel = 'rbf'), Random Forest (n_estimators = 200, max_depth = 20), Logistic Regression (C = 1), and SGD (alpha = 0.001). The Naïve Bayes classifier was used with its default configuration, as it does not rely on tunable hyperparameters. All hyperparameter selections were based on 10-fold stratified cross-validation, using AUC as the primary optimization criterion.

To further enhance methodological transparency and performance interpretation, class-specific metrics were also computed for the best-performing model (Gradient Boosting). These include precision, recall, and F1-score for each class, along with macro and weighted averages. The model achieved perfect scores (1.0) across all metrics for the Quantum Computing & Security in Healthcare class. For the AI & Quantum Computing for Healthcare class, it recorded a precision of 0.70, recall of 0.64, and F1-score of 0.67, demonstrating strong discriminative power despite class imbalance. The macro-average F1-score was 0.835, reflecting a high level of classification quality across both classes. To mitigate the effects of class imbalance,

TABLE 4 Comparison of predictive model performance post-optimization.

Model	AUC	Accuracy	Precision	Recall	F1	MCC
Gradient Boosting	0.875	0.842	0.889	0.842	0.845	0.725
Neural Networks	0.875	0.684	0.830	0.684	0.679	0.519
Random Forest	0.875	0.632	0.816	0.632	0.617	0.456
Logistic Regression	0.875	0.526	0.793	0.526	0.477	0.331
SVM	0.875	0.526	0.793	0.526	0.477	0.331
SGD	0.875	0.526	0.793	0.526	0.477	0.331
Naive Bayes	0.792	0.526	0.793	0.526	0.477	0.331

class weighting was applied in the models that support it, improving the recognition performance for the minority class.

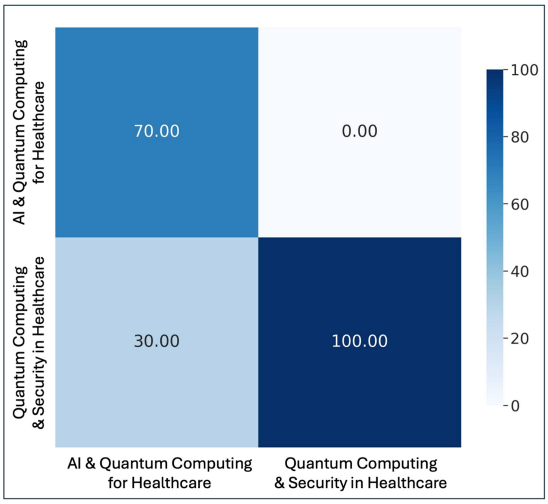

FIGURE 4
Confusion matrix (proportion of predictions)—Gradient Boosting model.

Figure 4 represents a confusion matrix, a fundamental tool for evaluating the performance of a classification model. This matrix illustrates the relationship between the model's predicted categories and the actual categories, showing the proportion of correctly classified instances.

The color intensity facilitates interpretation: darker blue shades indicate higher classification accuracy, while lighter shades represent lower values. In this case, the model demonstrates 100% accuracy in predicting the "Quantum Computing & Security in Healthcare" category, indicating perfect classification for this class. The "AI & Quantum Computing for Healthcare" category was classified with 70% accuracy, meaning that 30% of these instances were misclassified into the "Quantum Computing & Security in Healthcare" category. Notably, there are no false positives for "AI & Quantum Computing for Healthcare," as the model never misclassified an instance from the second category into the first. These results confirm the strong discriminative power of the Gradient Boosting model, particularly in recognizing the Quantum Computing & Security in Healthcare category with maximum precision, while some misclassifications occur within the AI & Quantum Computing for Healthcare category.

Figure 5 displays the Receiver Operating Characteristic (ROC) curve, which evaluates the classification model's ability to distinguish between the two analyzed categories. The X-axis represents the False Positive Rate (FPR), while the Y-axis indicates the True Positive Rate

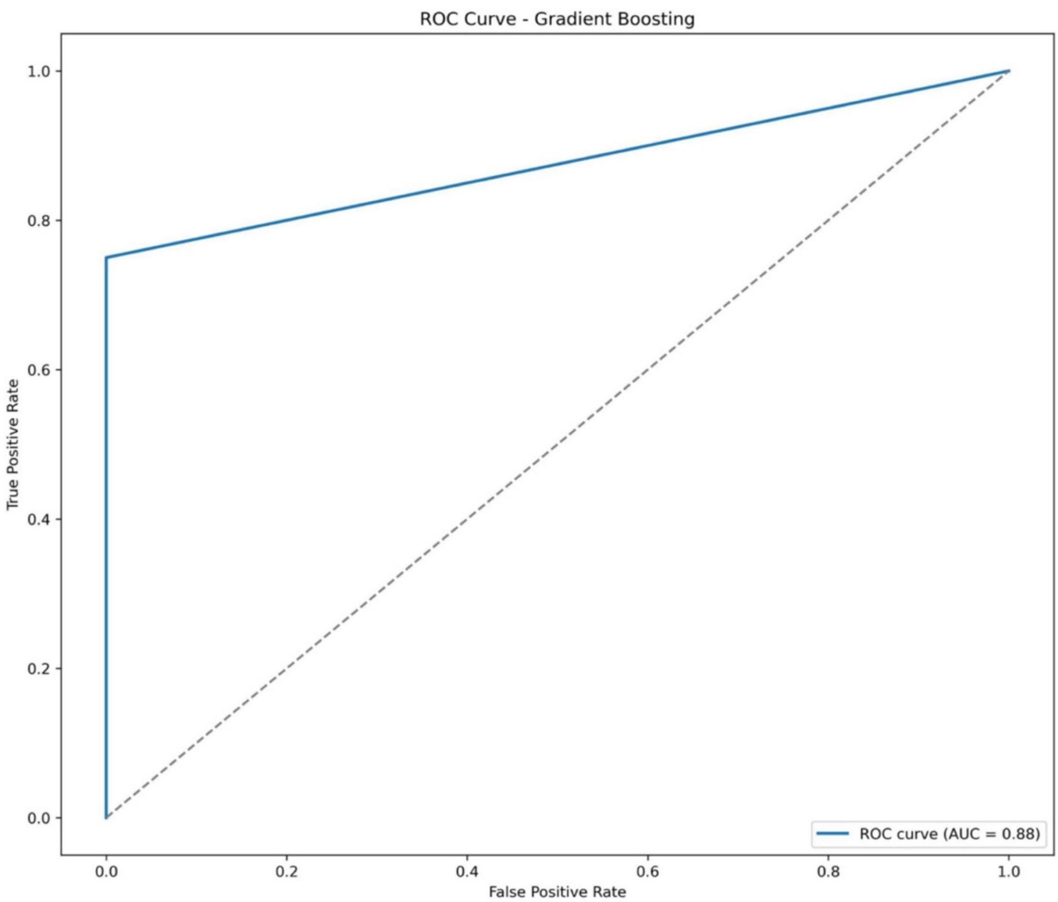

FIGURE 5
ROC curve for the Gradient Boosting model.

(TPR). The closer the curve is to the upper left corner, the better the model's discriminative ability. In this case, the solid blue curve represents the ROC for the Gradient Boosting model, achieving an AUC of 0.88, which indicates a strong overall classification performance. The dashed diagonal line represents a random classifier (AUC = 0.5), serving as a baseline for comparison. The model's ROC curve being well above this line confirms its superior predictive capability in distinguishing between the two categories.

The comparison between Figure 4 (confusion matrix) and Figure 5 (ROC curve) confirms the robust performance of the Gradient Boosting model. The confusion matrix highlights its strong classification accuracy, while the ROC curve further validates its discriminative power and balanced trade-off between sensitivity and specificity.

5.3 Model interpretation

To enhance the interpretability of the classification model and gain deeper insights into the decision-making process, LIME (Local Interpretable Model-agnostic Explanations) was employed in Python. The analysis was conducted using well-established libraries such as LIME, NumPy, and Pandas, which enabled the generation of local explanations for individual predictions. LIME approximates the behavior of complex machine learning models through simpler, interpretable models, providing a detailed analysis of the factors influencing classification decisions. This approach is particularly valuable in quantum computing applications, where model transparency is crucial for ensuring reliability and trust in automated decision-making systems. In healthcare, transparency is not merely a technical requirement but a fundamental ethical imperative. The integration of explainability techniques such as LIME enables clinicians and researchers to understand not only the outcome of a classification but also the rationale behind it. For instance, identifying which keywords or topic distributions most significantly influenced the model's assignment allows users to verify whether the system's logic aligns with domain knowledge or reveals potential biases. This is especially critical in sensitive healthcare domains, where incorrect or unexplainable predictions may have clinical or policy implications. By improving interpretability, these methods promote accountability, support informed decision-making, and enhance the credibility of AI-assisted analyses in biomedical contexts (Tjoa and Guan, 2021). The interpretability analysis focused on two classification categories: Quantum Computing & Security in Healthcare and AI & Quantum Computing for Healthcare. Figures 4, 5 illustrate the impact of key features on classification outcomes, using bar charts where positive contributions are represented in green and negative contributions in red. Positive values indicate a higher probability of assignment to a given category, while negative values suggest a lower probability.

Figure 4 illustrates the Feature Importance Analysis for the "Quantum Computing & Security in Healthcare" class using LIME, providing insight into the model's decision-making process. Among the key factors, Ethical & Legal Aspects had the most significant impact, with a value of −0.133, making it the strongest element reducing the probability of classification in this category. Similarly, Biomedical/Life Sciences Application also contributed negatively, though to a lesser extent, with an impact of −0.030. In contrast, Blockchain/Distributed Systems Use showed a positive influence, with a value of 0.016, slightly increasing the likelihood of classification. These results highlight the different roles that features play in shaping model predictions, confirming that while regulatory and biomedical considerations tend to push classifications away from this category, the presence of blockchain-related aspects provides a modest reinforcing effect.

Figure 5 presents the Feature Importance Analysis for the "AI & Quantum Computing for Healthcare" class using LIME, providing insights into how different features influence the model's classification decision. Among the key factors, Ethical & Legal Aspects had the most significant positive impact, with a value of 0.128, making it the strongest contributor to the classification of instances into this category. Biomedical/Life Sciences Application also played a reinforcing role, with an impact of 0.031, though to a lesser extent. Conversely, Blockchain/Distributed Systems Use exhibited a negative influence, with a value of −0.014, slightly reducing the likelihood of classification in this category. These findings highlight the model's reliance on Ethical & Legal Aspects and Biomedical/Life Sciences Application as primary indicators for assigning instances to the AI & Quantum Computing for Healthcare category, while blockchain-related factors appear to act as a limiting element in this classification.

The integration of explainable AI techniques such as LIME into quantum computing research has significant implications for interpretability, accountability, and the practical deployment of AI-driven quantum solutions. The findings demonstrate that feature importance analysis provides valuable insights into model decision-making, helping to validate classification boundaries, optimize fairness, and ensure that automated decision-making aligns with domain-specific priorities. A key takeaway from this analysis is that explainability enhances trust in AI models, particularly in domains like quantum computing and cybersecurity, where transparent, auditable, and robust decision-making processes are essential. As quantum computing advances, understanding how models differentiate between AI-driven healthcare applications and quantum security frameworks becomes critical to ensuring that these technologies align with ethical, regulatory, and scientific best practices (Figures 6, 7).

The results also highlight the necessity of domain-specific model training in quantum computing applications. The distinct thematic separation between AI & Quantum Computing for Healthcare and Quantum Computing & Security in Healthcare suggests that interdisciplinary AI models must be carefully curated to prevent feature misattributions and ensure clear category differentiation. This is particularly relevant in areas such as quantum-safe cryptography, quantum-enhanced AI, and blockchain applications, where classification precision directly impacts security, privacy, and computational efficiency. A closer examination of feature importance reveals compelling insights into how different factors shape classification decisions. Ethical & Legal Aspects emerge as a decisive influence, yet their impact varies across categories. Their strong positive contribution to AI & Quantum Computing for Healthcare suggests that ethical and regulatory considerations are paramount in AI-driven medical applications, where transparency, compliance, and data security are key. Conversely, their negative effect on Quantum Computing & Security in Healthcare implies that research in

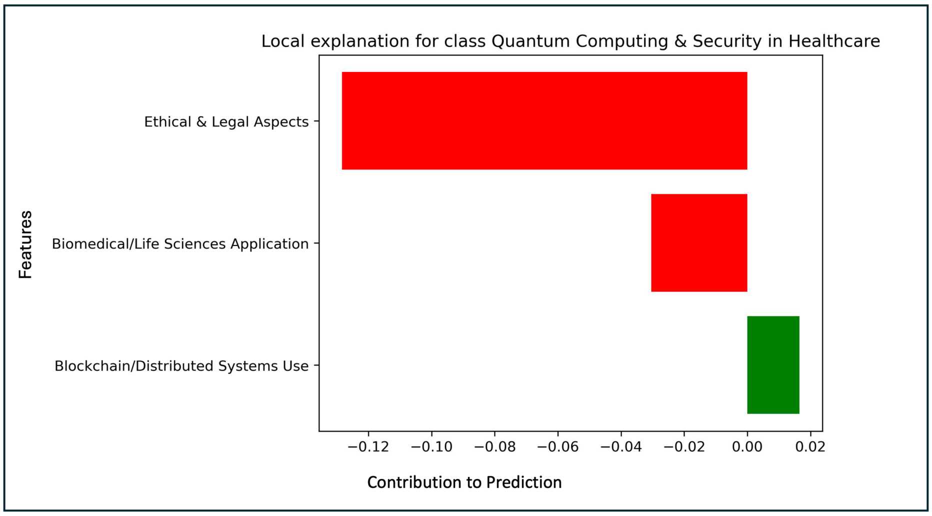

FIGURE 6
Feature importance analysis for the "Quantum Computing & Security in Healthcare" class using LIME.

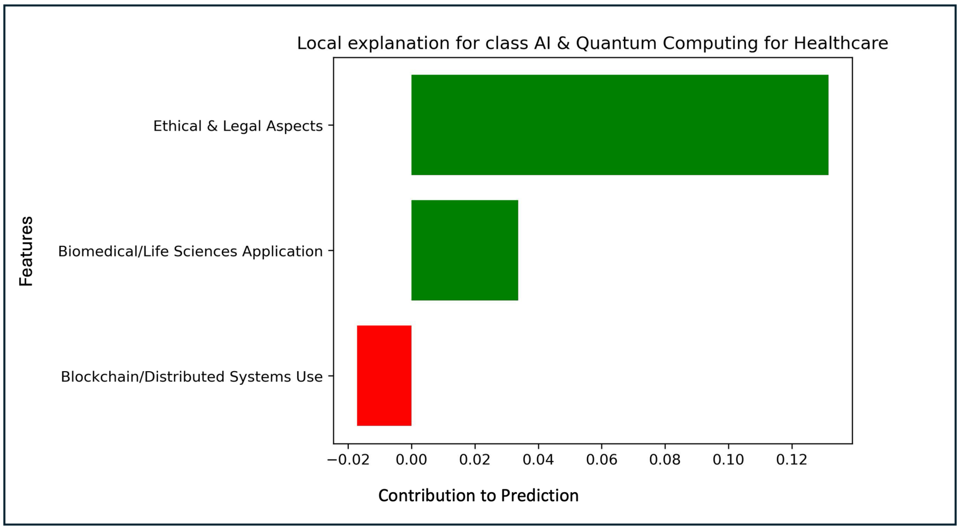

FIGURE 7
Feature importance analysis for the "AI & Quantum Computing for Healthcare" class using LIME.

quantum security prioritizes technical and infrastructural concerns over regulatory oversight. Biomedical/Life Sciences Application follows a similar pattern, reinforcing classification into the healthcare category while reducing the likelihood of classification in the security-focused category. This indicates a strong association between AI-driven quantum computing and biomedical research, whereas quantum security applications tend to focus more on computational architectures rather than medical advancements. In contrast, Blockchain/Distributed Systems Use has an inverse effect. Its positive contribution to Quantum Computing & Security in Healthcare underscores its role in strengthening quantum-safe cryptography and secure decentralized infrastructures. However, its negative impact on AI & Quantum Computing for Healthcare suggests that blockchain is not a dominant factor in AI-driven medical applications, potentially introducing complexities rather than enhancing predictive capabilities.

These findings not only validate the model's decision-making but also provide strategic insights into the evolving relationship between AI and quantum computing, emphasizing the need for precise and context-aware model training. Furthermore, the insights gained from LIME reinforce the importance of interpretability in hybrid AI-quantum computing frameworks, where the integration of classical and quantum computational paradigms requires models to be both powerful and explainable. As machine learning plays an increasing role in quantum-assisted optimizations, error correction, and hybrid neural network architectures, the ability to interpret classification outcomes at multiple levels will be essential for developing the next generation of quantum-aware AI models.

5.4 Research answers

The analyses conducted provide a clear and in-depth perspective on the potential of quantum computing and quantum technologies in the healthcare sector, offering strategic and innovative insights in response to the original research questions:

- *Q_1: How can quantum technologies enhance data security and ensure the integrity of healthcare information?*

  Quantum technologies introduce revolutionary advancements in data security, offering cutting-edge solutions to mitigate cybersecurity risks and protect healthcare information. Quantum Key Distribution (QKD) enables the establishment of ultra-secure communication channels, making eavesdropping on cryptographic key exchanges virtually impossible. Alongside this, Post-Quantum Cryptography (PQC) employs advanced algorithms that safeguard sensitive healthcare data against emerging quantum-enabled cyber threats. The integration of advanced authentication frameworks, such as PDAC-CoV, reinforces access control mechanisms, ensuring that only authorized personnel can modify or retrieve patient records. Moreover, blockchain solutions integrated with quantum security protocols, such as QUMA, enhance data immutability and traceability, preventing unauthorized alterations while ensuring long-term integrity verification. However, the findings indicate that the role of blockchain in AI-driven healthcare applications is not as pronounced as in security-focused quantum computing research, suggesting that its integration may introduce complexities rather than providing a clear advantage in predictive AI models. As the Internet of Medical Things (IoMT) expands, quantum sensor networks and secure data aggregation techniques are becoming pivotal in protecting medical data transmissions. In Hospital-at-Home (HaH) models, these technologies ensure the confidentiality, accuracy, and reliability of patient-generated health data, strengthening the foundation for remote healthcare ecosystems. Interpretable AI techniques, such as LIME, further validate the need for robust security frameworks, reinforcing the role of Ethical & Legal Aspects in defining security policies for quantum-driven healthcare systems. By integrating quantum-enhanced security solutions with explainable AI frameworks, the healthcare sector can ensure a resilient, scalable, and transparent digital infrastructure capable of safeguarding sensitive medical data while maintaining regulatory compliance.

- *Q_2: How can quantum computing improve medical diagnostics and AI-driven healthcare applications?*

  Quantum computing is redefining medical diagnostics and AI-driven clinical applications, unlocking the ability to process large-scale, high-dimensional healthcare datasets with unprecedented efficiency. Quantum Machine Learning (QML) advances medical image analysis, significantly improving anomaly detection and early disease identification compared to classical deep learning models. Quantum Artificial Intelligence (QAI) accelerates drug discovery and personalized treatment design, enabling quantum simulations of molecular interactions that predict patient responses with unparalleled accuracy. The findings suggest that Biomedical/Life Sciences Applications play a crucial role in shaping the classification of quantum healthcare research, reinforcing the alignment of AI-driven quantum computing with biomedical advancements. Conversely, Blockchain/Distributed Systems Use appears to play a more central role in security applications, highlighting the need for context-specific quantum AI models rather than a one-size-fits-all approach. The fusion of quantum computing and digital twin models allows for personalized patient monitoring and predictive healthcare, optimizing treatment strategies while minimizing adverse effects. Quantum Convolutional Neural Networks (QCNNs) enhance deep learning architectures, significantly accelerating training efficiency and improving the analysis of complex health data, such as mental health assessments and facial expression recognition. Additionally, the interplay between Federated Learning and Quantum Computing is set to revolutionize secure data sharing among healthcare institutions, fostering privacy-preserving AI models while enhancing the robustness and generalizability of predictive analytics. The explainability provided by LIME further strengthens the interpretability of these quantum-driven AI models, ensuring that classification outcomes align with clinical priorities and regulatory standards. This convergence of quantum computing, AI, and healthcare is ushering in a new era of precision medicine, AI-assisted diagnostics, and computationally secure healthcare infrastructures. However, ensuring the transparent and ethical deployment of quantum AI models will require strategic advancements in hybrid quantum-classical computing, as well as standardized protocols for explainability, reliability, and security in healthcare AI applications.

5.5 Limits and future directions

The adoption of quantum computing in the healthcare sector is still in its early stages and faces several challenges that limit its full implementation. One of the primary obstacles is technological maturity: qubit decoherence and current hardware limitations compromise computational reliability, making continuous investment in research essential to improve stability and scalability. Data security is another critical concern, as existing infrastructures are not designed to support advanced quantum technologies. Integrating quantum systems with legacy healthcare infrastructures requires solutions that ensure interoperability without compromising performance, while post-quantum cryptography emerges as a crucial research area to prevent vulnerabilities and safeguard sensitive information.

In addition to hardware constraints, current quantum algorithms themselves present significant limitations for clinical adoption. Many models remain fragile and sensitive to noise, requiring extensive error correction methods that are not yet ready for routine clinical use. Furthermore, most algorithms are designed and tested in idealized or simulated environments, making their translation to real-world clinical workflows highly challenging. These models often demand specialized knowledge and bespoke hardware, restricting their practical deployment to highly resourced institutions. Finally, a considerable gap persists between proof-of-concept quantum solutions and clinically validated tools, as very few have undergone trials or met regulatory approval. Bridging this gap will require coordinated efforts in translational research, standardization, and clinical validation.

At the same time, the lack of specialized expertise could slow the adoption of these technologies. The convergence of quantum physics, computer science, and medicine requires highly skilled professionals, who are currently scarce. Addressing this challenge calls for the development of interdisciplinary educational programs to train experts capable of leading the implementation of quantum computing in healthcare. Economic and infrastructural aspects also present barriers: the high cost of quantum hardware and research limits widespread deployment, making it essential to adopt a strategy that combines targeted investments, supportive policies, and incentives for experimentation in clinical applications. Another key direction for future research involves developing specialized algorithms tailored to the unique needs of the healthcare sector, from early disease detection to personalized treatment strategies. These algorithms must be scalable and seamlessly integrated into existing workflows to ensure tangible clinical impact. Advancing quantum healthcare also requires interdisciplinary collaboration, bringing together quantum physicists, computer engineers, and healthcare professionals to develop solutions aligned with real-world needs. Pilot projects and shared research platforms can accelerate this process, fostering experimentation and innovation.

From a regulatory standpoint, the lack of global standards for data security and interoperability between traditional and quantum systems is a major challenge. Establishing common guidelines is essential to facilitate a structured transition to these new technologies while ensuring transparency and compliance with existing regulations. Additionally, awareness and education among medical professionals and industry stakeholders will be crucial: disseminating knowledge about the practical advantages of quantum computing can encourage adoption and drive investment in this field. The integration of emerging technologies, such as blockchain and distributed systems, holds immense potential for improving security and reliability in healthcare infrastructures. However, their adoption within quantum computing frameworks remains limited. Research must explore how these technologies can enhance data protection, traceability, and information security in quantum-powered healthcare systems. Lastly, ethical and legal considerations must be carefully addressed to ensure the responsible implementation of quantum computing in healthcare. In the specific context of quantum AI applications in healthcare, ethical concerns acquire new dimensions. Quantum algorithms, when combined with machine learning models, may amplify biases present in clinical datasets due to the non-transparent and probabilistic nature of quantum processing. This raises concerns regarding fairness in decision-making, particularly in diagnostic or treatment recommendation systems. Moreover, the integration of quantum computing with sensitive health data introduces heightened privacy risks. For example, entangled systems and cloud-based quantum services may challenge current data localization and encryption standards. Regulatory frameworks such as GDPR or HIPAA may not yet account for the unique characteristics of quantum data processing, creating potential gaps in accountability, traceability, and informed consent. Addressing these concerns will require proactive ethical guidelines, updated legal frameworks, and the integration of explainable quantum AI models to ensure trust, transparency, and patient safety. AI models must be developed with transparency and fairness in mind, avoiding bias and ensuring clear differentiation between thematic categories analyzed. The integration of explainable AI techniques will be essential to enhance model interpretability and reliability in automated decision-making systems.

A further area requiring critical attention concerns the computational cost and practical feasibility of hybrid quantum-classical models in healthcare. While these models offer a promising bridge between current classical systems and quantum capabilities, their implementation often demands high-performance computing environments, specialized middleware, and precise synchronization between quantum and classical components. This significantly raises the infrastructural and operational requirements, particularly in clinical contexts where real-time processing, system reliability, and compatibility with legacy infrastructure are essential. Moreover, only a limited number of hybrid frameworks have demonstrated scalability outside controlled research environments. Future efforts must therefore evaluate not only the theoretical performance gains of these models, but also their sustainability, cost-effectiveness, and adaptability to real-world healthcare systems.

In summary, the future of quantum computing in healthcare will depend on overcoming technological, infrastructural, and ethical challenges while promoting cutting-edge research, security, interdisciplinary collaboration, and standardization. The goal is to transform quantum potential into practical, scalable, and seamlessly integrated solutions, ensuring long-term innovation and sustainability in healthcare.

6 Conclusion

This study highlights the emerging role and transformative potential of quantum computing in the healthcare sector, outlining both its most promising applications and the challenges that must be addressed. By combining a systematic literature review with a predictive model optimized through Latent Dirichlet Allocation (LDA) and Particle Swarm Optimization (PSO), this research categorizes existing studies into Quantum Computing & Security in Healthcare and AI & Quantum Computing for Healthcare, providing a comprehensive mapping of the state of the art and future research directions.

The findings confirm that quantum technologies have the potential to redefine data security, advanced diagnostics, and AI-driven healthcare applications. However, technological barriers such as qubit decoherence, quantum hardware scalability, and the lack of efficient error correction mechanisms remain major obstacles to large-scale adoption. At the same time, the integration of quantum computing into existing healthcare infrastructures presents interoperability challenges, requiring hybrid quantum-classical models to enable a secure and gradual transition to quantum-powered systems. From a security perspective, quantum computing presents both risks and opportunities. While Quantum Key Distribution (QKD) strengthens data transmission security, the emergence of quantum algorithms threatens classical cryptographic standards, making post-quantum cryptography (PQC) essential for long-term healthcare data protection. Blockchain technologies, particularly in security-focused quantum computing applications, reinforce data integrity, but findings suggest that their role in AI-driven healthcare remains secondary.

On the computational side, quantum computing holds great promise for machine learning optimization, significantly improving the ability to process complex healthcare datasets. The increasing interest in Quantum Neural Networks (QNNs), Quantum Machine Learning (QML), and Quantum Convolutional Neural Networks (QCNNs) underscores their potential to advance medical imaging diagnostics, precision medicine, and predictive disease modeling. However, explainability remains a challenge, making interpretable AI techniques like LIME essential for ensuring transparency and trust in quantum AI systems. The results highlight that Biomedical/Life Sciences Applications and Ethical & Legal Aspects play a key role in defining AI-driven quantum computing research, whereas blockchain is more relevant in quantum-enhanced security applications.

Another critical factor that emerged is the shortage of interdisciplinary expertise, which is crucial for accelerating the transition to a quantum-powered healthcare ecosystem. The convergence of quantum physics, artificial intelligence, and biomedical sciences necessitates the development of specialized educational programs to train professionals capable of bridging theoretical advancements with real-world applications. Additionally, economic and infrastructural barriers require targeted investments in quantum hardware and software research, supported by both public and private initiatives.

The future of quantum computing in healthcare will depend on the ability to address these challenges through a multidisciplinary and collaborative approach, involving academia, industry, regulatory bodies, and healthcare professionals. The establishment of global standards for data security, ethical AI practices, and quantum system interoperability will be crucial to enabling a structured and responsible adoption of these technologies.

In conclusion, this study provides a scientifically rigorous assessment of the current landscape and the emerging challenges in quantum computing for healthcare, offering a solid foundation for future research. Quantum computing is no longer a theoretical concept but an evolving technology transitioning toward real-world applications, with the potential to redefine digital healthcare through AI-driven innovations and enhanced security frameworks. However, ensuring tangible and sustainable impact will require targeted research strategies, hybrid computational models, regulatory alignment, and ethical AI frameworks, ultimately accelerating the integration of quantum computing into a secure and transparent healthcare ecosystem.

Author contributions

AM: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. VS: Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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