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Review

Quantum Computing and Machine Learning in Medical Decision-Making: A Comprehensive Review

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Abstract: Medical decision-making is increasingly integrating quantum computing (QC) and machine learning (ML) to analyze complex datasets, improve diagnostics, and enable personalized treatments. While QC holds the potential to accelerate optimization, drug discovery, and genomic analysis as hardware capabilities advance, current implementations remain limited compared to classical computing in many practical applications. Meanwhile, ML has already demonstrated significant success in medical imaging, predictive modeling, and decision support. Their convergence, particularly through quantum machine learning (QML), presents opportunities for future advancements in processing high-dimensional healthcare data and improving clinical outcomes. This review examines the foundational concepts, key applications, and challenges of these technologies in healthcare, explores their potential synergy in solving clinical problems, and outlines future directions for quantum-enhanced ML in medical decision-making.

Keywords: quantum computing; machine learning; medical decision-making; healthcare AI; personalized medicine; quantum machine learning; medical chatbot

1. Introduction

Medical decision-making is a cornerstone of modern healthcare, encompassing processes that guide diagnosis, treatment planning, and patient management. Accurate and timely decisions are critical to improving patient outcomes, optimizing resource allocation, and enhancing the overall efficiency of healthcare systems [1]. However, the increasing complexity of medical data, driven by advancements in imaging, genomics, and electronic health records, presents significant challenges for clinicians. This data-rich environment necessitates innovative computational tools to extract actionable insights and support clinical decision-making [2].

Advanced computational techniques have emerged as indispensable in addressing these challenges. Among them, machine learning (ML) has demonstrated remarkable capabilities in processing and analyzing large volumes of heterogeneous medical data [3,4]. ML algorithms excel in tasks such as pattern recognition, predictive modeling, and anomaly detection, making them invaluable in fields like medical imaging, drug discovery, and personalized medicine [5]. However, as datasets grow in size and complexity, classical computational approaches often struggle to deliver the speed and efficiency required for real-time decision-making.

Quantum computing (QC) leverages the principles of quantum mechanics and holds the potential to outperform classical systems in certain optimization problems relevant to medical applications. However, their current implementations remain limited, and they

have yet to demonstrate a practical advantage over classical methods in processing large, complex datasets for real-world machine learning tasks [6]. While quantum speedup has been observed in specific, carefully designed problems, its applicability to broader medical computations is still an area of active research. Figure 1 shows the diverse applications of QC in medicine, showcasing its potential to transform areas such as drug design, genomics, medical diagnostics, AI-enhanced healthcare, and radiotherapy. QC's enhanced computational power and efficiency are poised to significantly advance these fields, improving both precision and speed in medical research and clinical practice. Each branch represents a key area where QC can make substantial contributions.

Figure 1. Schematic diagram illustrating the key applications of quantum computing (QC) in medicine. These include drug design and molecular simulation, genomics and personalized medicine, medical diagnostics, AI-enhanced healthcare, and Monte Carlo simulations in radiotherapy. QC's advanced computational capabilities have the potential to significantly improve accuracy, speed, and efficiency in these critical healthcare areas. Reproduced from reference [7] under the Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0/ (accessed on 24 January 2025)).

When integrated with ML, QC holds the potential to transform medical decision-making, enabling unprecedented precision and speed in analyzing complex medical datasets [8]. Applications range from optimizing treatment protocols to predicting disease progression and personalizing therapies. Figure 2 presents a comparison of quantum computing paradigms and classical computing approaches, highlighting their respective strengths, limitations, and potential applications. While the figure is reproduced from a previous review [6], its claims have been critically assessed. Notably, the term "suitability for routine and complex processing" requires further QC work to support it, as many advanced computational challenges, such as protein folding, have been successfully addressed using classical computing. Unlike conventional computers that use bits, quan-

tum computers operate with quantum bits, or "qubits", which can represent both '1' and '0' simultaneously.
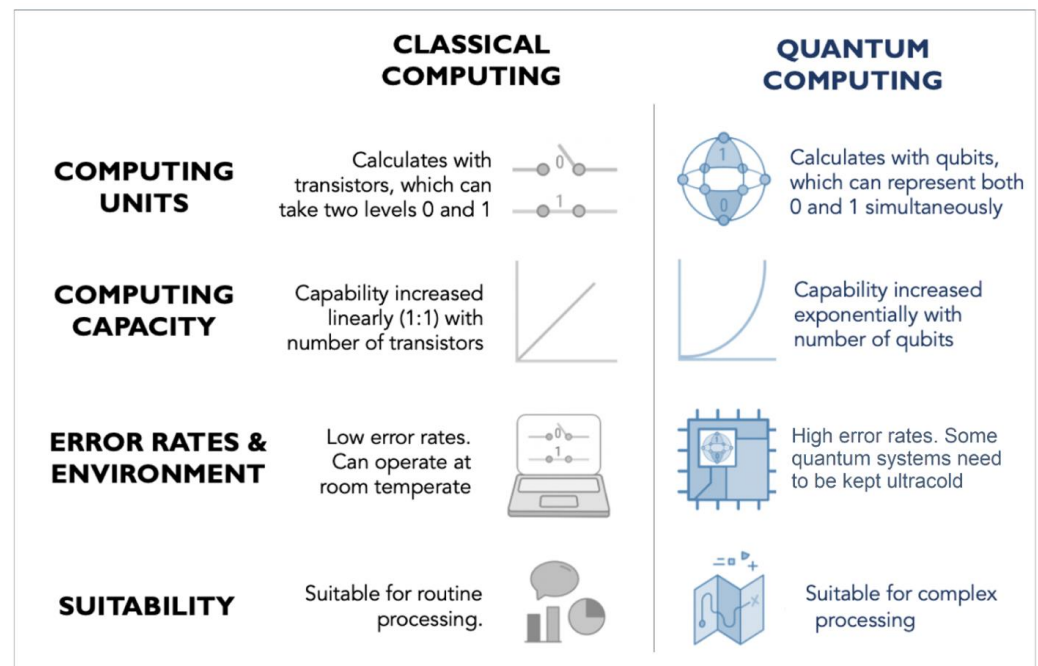

Figure 2. Comparison of classical computing vs. quantum computing: Classical computing uses bits (0 or 1) and is ideal for everyday tasks with low error rates. Quantum computing, utilizing qubits (0, 1, or both), offers potential exponential increases in computing power for complex problems but currently faces high error rates. Reproduced from reference [6] under the Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0/ (accessed on 24 January 2025)).

This review paper aims to explore the synergy between QC and ML in the context of medical decision-making. It provides a comprehensive analysis of the current state of research, key technological advancements, and existing challenges in integrating these transformative tools into healthcare. The paper is structured as follows: Section 2 reviews foundational concepts in QC and ML, while Section 3 examines their applications in medical decision-making. Section 4 discusses challenges and limitations, and Section 5 outlines future directions and opportunities in this emerging field. By presenting a holistic overview, this paper seeks to highlight the potential of QC and ML in shaping the future of medical decision-making.

2. Foundational Concepts

2.1. Quantum Computing

QC represents a paradigm shift in computation, leveraging the principles of quantum mechanics to process information in fundamentally new ways. Unlike classical computing, which relies on binary bits that exist in a state of 0 or 1, QC uses quantum bits, or qubits, that can exist in superpositions of states, enabling significantly enhanced computational power [9].

Qubits are the fundamental units of quantum information. Unlike classical bits, which are restricted to a binary state (0 or 1), qubits can exist in a superposition, representing multiple states simultaneously [10]. This property allows quantum computers to perform many calculations in parallel, offering exponential speedup for certain problems. Entanglement is a quantum phenomenon where the states of two or more qubits become intrinsically linked, such that the state of one qubit directly influences the state of the others,

regardless of distance [11]. This property enables highly efficient information sharing and parallel processing, which are key to the power of QC. Quantum gates are the building blocks of quantum circuits, analogous to logic gates in classical computing [12]. These gates manipulate qubits through operations that preserve quantum coherence, enabling complex transformations of quantum states. Common gates include the Hadamard gate (for creating superpositions), the CNOT gate (for generating entanglement), and the Pauli gates (for state rotations) [13,14].

QC differs from classical computing in speed, complexity, and problem-solving capacity. Classical computers process information sequentially, limiting their efficiency for problems involving vast datasets or complex optimizations. Quantum computers, on the other hand, leverage superposition and entanglement to perform multiple computations simultaneously, significantly reducing the time required for tasks such as factorization, searching unsorted databases, and solving differential equations [15]. For instance, a classical computer searching an unsorted database requires $O(N)$ operations, where N is the number of entries. Grover's algorithm, a quantum search algorithm, reduces this to $O(\sqrt{N})$, showcasing a quadratic speedup [16]. Similarly, Shor's algorithm, designed for integer factorization, achieves exponential speedup by solving problems in polynomial time that are infeasible for classical computers [17].

Grover's algorithm is designed for searching unsorted datasets. In medical decision-making, this algorithm could expedite searches through massive databases of patient records, genomic data, or drug libraries [18]. Shor's algorithm efficiently factors large integers, underpinning advancements in cryptography and data security. Its relevance in healthcare lies in safeguarding sensitive medical data during processing and transmission [19]. The Quantum Approximate Optimization Algorithm (QAOA) is used to solve combinatorial optimization problems [20]. Applications include optimizing treatment plans, scheduling surgeries, or resource allocation in hospitals.

While QC offers potential advantages, it also faces significant challenges that hinder its practical deployment. One of the most pressing issues is quantum decoherence, where qubits lose their quantum state due to interactions with their environment, leading to loss of information and computational errors [21]. Current superconducting and trapped-ion qubit systems exhibit coherence times ranging from microseconds to milliseconds, which severely limit the depth and complexity of quantum circuits that can be executed reliably. Quantum error correction (QEC) aims to mitigate these errors by encoding logical qubits across multiple physical qubits; however, implementing fault-tolerant QEC requires a massive overhead—potentially thousands of physical qubits per logical qubit—far beyond the capabilities of existing hardware. Scalability remains another key challenge, as present-day quantum processors, such as those developed by IBM, Google, and Rigetti, can only manage tens to a few hundred noisy qubits, whereas practical quantum advantage for machine learning applications likely demands thousands or even millions of high-fidelity qubits. Moreover, many quantum algorithms have yet to demonstrate a significant advantage over classical ML approaches, which have already solved numerous real-world problems with well-established frameworks. Individual quantum computations are often slower than their classical counterparts due to hardware limitations, and the high cost, fragility, and complexity of quantum hardware further complicate its widespread adoption. These challenges highlight the need for a balanced and realistic comparison between QC and classical ML, recognizing both the current limitations and the future potential of quantum-enhanced computation [22].

2.2. Machine Learning

ML encompasses a variety of techniques and methodologies aimed at enabling computers to learn from data without explicit programming. These techniques are broadly classified into three categories: supervised learning, unsupervised learning, and reinforcement learning (RL).

Supervised learning involves training a model on a labeled dataset, where the correct output is already known. The model learns to map inputs to their corresponding outputs by minimizing the error between predicted and actual values. This method is widely used in applications such as medical diagnosis, where labeled data (e.g., patient symptoms and diagnostic results) are used to train predictive models [23].

Unsupervised learning, on the other hand, deals with datasets that are not labeled. Here, the goal is to identify underlying structures or patterns in the data, such as clustering similar data points or reducing the dimensionality of large datasets. In the medical field, unsupervised learning is often used for discovering novel patterns in medical imaging data or genomic sequences, where labels are not readily available [24].

RL is a type of ML where an agent learns to make decisions by interacting with its environment. Through trial and error, it receives feedback in the form of rewards or penalties, which it uses to adjust its actions. This approach is increasingly applied in robotics and personalized medicine, where adaptive systems can optimize treatment plans or assist in surgical procedures [25].

Deep Learning: Deep learning, a subset of ML, leverages neural networks with multiple layers to model complex patterns in large datasets. In the medical field, deep learning algorithms have shown remarkable success in tasks such as medical image analysis, where convolutional neural networks (CNNs) can automatically detect tumors or abnormalities in radiographs and MRI scans [26].

Despite its successes, traditional ML faces several key challenges. Scalability remains an issue, as many ML models require large amounts of data and computational resources, making them difficult to apply to larger-scale datasets or real-time applications. Interpretability is another challenge, especially in deep learning models, where the decision-making process can be opaque. This lack of transparency makes it difficult for clinicians to trust or understand the reasoning behind machine-generated recommendations, which is critical in high-stakes fields like healthcare [27]. Addressing these challenges is essential for the widespread adoption of ML in medical decision-making and practice.

2.3. Data Analytics in Healthcare

The application of data analytics in healthcare has transformed the way medical professionals make clinical decisions, offering new insights and improving patient outcomes. Healthcare data are vast and diverse, encompassing a variety of types, each contributing to different aspects of patient care and medical research.

Imaging data is one of the most critical types of healthcare data, particularly in diagnostics. Medical imaging techniques, such as X-rays, CT scans, MRIs, and ultrasounds, generate visual representations of the interior of a patient's body. These images are essential for diagnosing a wide range of conditions, from broken bones to tumors, and are often used in conjunction with other data sources to make more accurate assessments. Data analytics plays a crucial role in processing and analyzing imaging data, enabling tools like automated image segmentation and anomaly detection, which can enhance the speed and accuracy of diagnoses [28,29]. For example, Figure 3 illustrates various ML algorithms, including classification, object detection, and segmentation, used to identify spleen injuries from CT images. These algorithms aim to determine whether the organ is injured, detect the target lesion, and perform voxel-level classification.
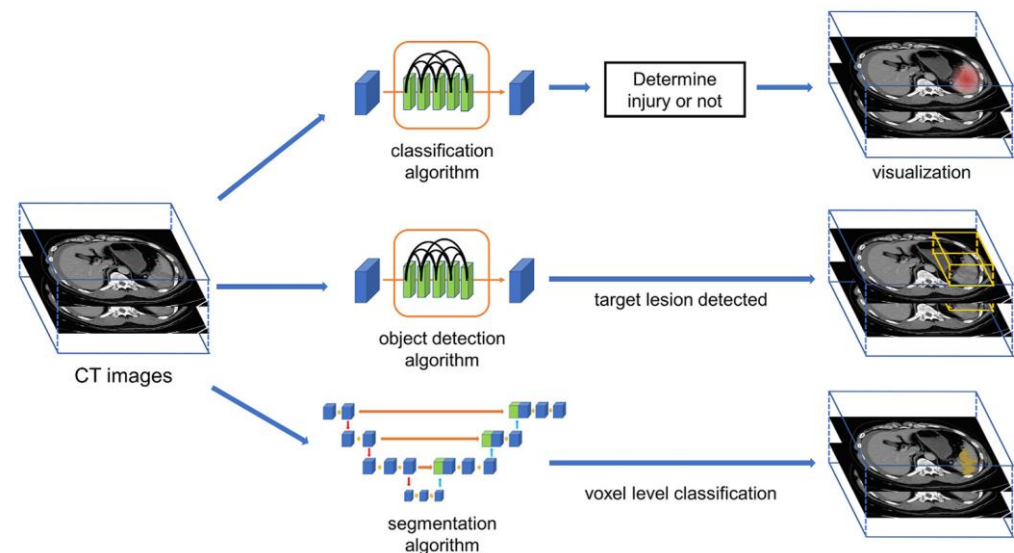
Figure 3. Illustration of machine learning algorithms applied to CT images for spleen injury detection. The algorithms include classification, object detection, and segmentation, focusing on determining the presence of injury, identifying the target lesion, and performing voxel-level classification. Reproduced from reference [29] under the Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0/ (accessed on 24 January 2025)).

Genomic data refer to information derived from an individual's genetic material. With the advent of genomic sequencing technologies, vast amounts of genetic data are now available, enabling researchers and clinicians to better understand the genetic basis of diseases and tailor treatments accordingly. Analyzing genomic data allows for the identification of genetic mutations or variations that influence disease development, drug responses, and the effectiveness of treatments. Data analytics techniques, such as ML, are used to analyze and interpret complex genomic datasets, allowing for the identification of biomarkers and more personalized approaches to treatment [30,31].

Electronic Health Records (EHRs) are another critical data source in healthcare. EHRs contain detailed information about a patient's medical history, diagnoses, treatments, medications, allergies, lab results, and more. This data are stored digitally, enabling healthcare providers to access patient information quickly and efficiently. Analyzing EHRs through data analytics can identify trends in patient health, predict potential risks, and improve care coordination. EHR analysis also helps in clinical decision-making, providing healthcare professionals with insights that guide treatment plans and interventions [32].

The importance of accurate and efficient data analysis in clinical decision-making cannot be overstated. With the increasing volume and complexity of healthcare data, clinicians face the challenge of processing and interpreting large datasets in a timely manner. Accurate data analysis is crucial for ensuring that clinical decisions are based on the best available information, whether that involves diagnosing a disease, selecting an appropriate treatment, or predicting patient outcomes. Effective data analysis can lead to better diagnosis accuracy, personalized treatment plans, and improved patient safety. However, for data analytics to be most effective, it must be coupled with high-quality data, robust analytical methods, and appropriate interpretation by healthcare professionals.

3. Applications in Medical Decision-Making

3.1. QC Applications

QC can enhance drug discovery by enabling simulations of complex molecular interactions at the quantum level [33]. Traditional computational methods often struggle

to model the behavior of large molecules accurately, especially in the context of drug design. Quantum simulations, however, can calculate the precise interactions between drug molecules and their targets, helping researchers design drugs that are more effective and have fewer adverse effects. This could drastically reduce the time required for preclinical drug development and allow for the discovery of novel therapeutic agents that otherwise are missed [34].

In radiotherapy, the challenge lies in accurately delivering radiation to the tumor while minimizing damage to surrounding healthy tissues. QC excels at solving optimization problems, which is crucial for radiotherapy treatment planning [35]. By leveraging quantum algorithms, healthcare providers can optimize the distribution of radiation doses across the tumor and surrounding tissue, improving treatment efficacy and minimizing side effects. This capability holds the potential to significantly improve outcomes in cancer treatment, making radiation therapy more precise and personalized for each patient [36].

Genomic data analysis involves processing vast amounts of information, such as DNA sequences and gene expression data, to identify patterns and make predictions about disease risk and treatment responses [37]. Classical computers are often limited in their ability to process such large datasets efficiently. QC, with its parallel processing power, has the potential to modernize genomic data analysis by enabling faster processing and more accurate predictions. This could lead to breakthroughs in understanding complex genetic diseases and more personalized treatment options based on a patient's genetic makeup [38].

3.2. ML Applications

ML algorithms are increasingly used in medical imaging and pathology to assist in diagnosing diseases with higher accuracy and speed. In medical imaging, techniques such as CNNs are widely employed to analyze images from X-rays, CT scans, MRIs, and other modalities [39]. These algorithms can automatically detect and classify abnormalities, such as tumors or lesions, which helps radiologists and clinicians make quicker, more informed decisions [40]. By training on large datasets of annotated images, ML models can identify patterns that might be overlooked by the human eye, leading to earlier detection and improved outcomes for patients.

In digital pathology, ML algorithms are applied to analyze histopathological slides of tissue samples, helping pathologists identify disease markers, cancerous cells, and other abnormalities [41]. These AI-powered diagnostic systems can assist pathologists by highlighting areas of concern and providing quantitative insights, such as tumor grading, which are essential for determining the severity of a disease and making treatment decisions. Moreover, ML can be used to detect rare conditions or atypical patterns in tissue samples, improving the sensitivity and specificity of diagnostic tests [42].

One of the most significant advantages of ML in healthcare is its ability to predict patient outcomes and track disease progression. By analyzing large datasets, such as patient records, laboratory results, and clinical data, ML models can identify risk factors and predict the likelihood of disease progression or recurrence [43]. These predictive models are invaluable in fields like oncology, where understanding the progression of cancer and the likelihood of metastasis is critical for developing effective treatment plans [44].

For example, in oncology, ML algorithms can predict how patients will respond to specific cancer treatments based on their medical history, genetic data, and tumor characteristics. By integrating clinical data with genomic information, ML can help identify the most effective therapies for individual patients, improving survival rates and minimizing the risk of unnecessary side effects [45]. Furthermore, predictive modeling can assist in

the early detection of complications such as sepsis or organ failure, allowing clinicians to intervene early and prevent adverse outcomes [46].

ML has also become a key component in personalized medicine, where treatment plans are tailored to the individual characteristics of each patient [47]. AI-based decision support systems analyze patient data, including genetic, demographic, and clinical information, to recommend the most effective treatment strategies. These systems can provide clinicians with evidence-based treatment options that are personalized for each patient's unique needs, leading to more precise and effective interventions. In precision oncology, for example, ML algorithms can analyze genetic mutations and molecular profiles of tumors to recommend targeted therapies that are more likely to succeed [48]. By integrating data from clinical trials, real-world patient outcomes, and genetic databases, AI-based systems can continuously update and refine treatment recommendations, ensuring that patients receive the best possible care based on the latest research and their specific condition. Moreover, AI-driven decision support tools are increasingly used in other specialties, such as cardiology, neurology, and endocrinology, to help clinicians make data-driven decisions that optimize treatment outcomes [49,50]. Figure 4 shows the iterative workflow of a RL approach to precision oncology. It begins with multimodal data from genetic assays, laboratory tests, radiographic images, and electronic health records, which serve as input for the RL framework. This framework, depicted as a deep neural network, selects treatment decisions based on its policy. These decisions impact tumor response and toxicity, ultimately influencing long-term patient outcomes. The resulting outcomes generate a reward signal for the RL agent, prompting a policy update and initiating a new cycle with updated inputs and treatment decisions, thereby closing the loop.
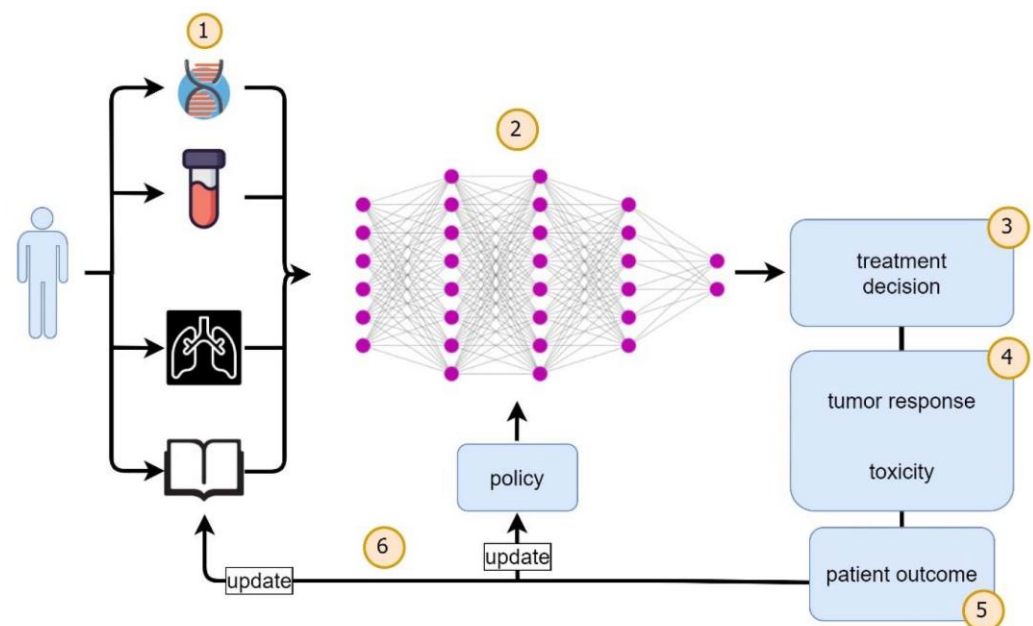

Figure 4. Iterative workflow of a reinforcement learning (RL) approach to precision oncology. Multimodal data (1) from genetic assays, lab tests, radiographic images, and electronic health records serve as input for an RL framework (2). The RL framework selects a treatment decision (3) that affects tumor response and toxicity (4), influencing long-term patient outcomes (5). This outcome generates a reward signal for the RL agent, leading to a policy update (6). The patient's state changes, initiating a new cycle with updated inputs and treatment decisions, closing the loop. Reproduced from reference [48] under the Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0/ (accessed on 24 January 2025)).

3.3. Synergy of QC and ML

The integration of QC with ML is a rapidly evolving field that holds immense promise for advancing medical decision-making. By combining the computational power of quantum algorithms with the data-driven capabilities of ML, this synergy has the potential to transform healthcare, particularly in areas requiring large-scale data analysis, complex optimization, and advanced predictive modeling. Below, we explore how QC enhances traditional ML, the role of hybrid quantum-classical models, and some potential use cases in healthcare decision-making.

Quantum ML (QML) refers to the application of QC to enhance traditional ML algorithms [51]. QC offers advantages in processing large datasets and solving computational problems more efficiently than classical computers. By leveraging quantum properties such as superposition and entanglement, QML can potentially perform certain ML tasks exponentially faster than classical methods. For instance, quantum algorithms can speed up matrix operations, a key component of many ML techniques, including principal component analysis (PCA) and clustering [52]. Quantum versions of popular ML algorithms, such as support vector machines (SVMs) [53] and neural networks [54], show promise for improving the efficiency of training models, particularly when dealing with high-dimensional data. In healthcare, where datasets are large and complex, QML could significantly accelerate tasks such as drug discovery, genomics, and medical imaging analysis [55,56]. Furthermore, quantum algorithms improve the optimization processes in ML, enabling more accurate and timely predictions that could improve patient care [57].

While QC holds significant potential, current quantum hardware is still in its nascent stage, with limitations in qubit coherence times and error rates. As a result, researchers are exploring hybrid quantum-classical models, where quantum algorithms are integrated with classical ML methods to leverage the strengths of both approaches [58]. In these models, QC is used for specific tasks that benefit from quantum speedup (such as optimization and linear algebra operations), while classical computing handles tasks that are better suited to classical methods. In medical decision-making, hybrid quantum-classical models are particularly promising for complex optimization problems like treatment planning, personalized medicine, and drug discovery. For example, quantum computers could optimize the allocation of radiation doses in cancer treatment planning, considering various patient-specific factors, while classical systems could handle patient data analysis and clinical decision support [59]. By using quantum-classical hybrids, healthcare providers can harness the advantages of both quantum speed and classical reliability to improve treatment accuracy and efficiency.

There are several promising use cases for the synergy between QC and ML in healthcare decision-making. For example, QML can accelerate drug discovery by simulating complex molecular interactions more efficiently than classical computers [60]. By combining quantum simulations with ML algorithms, researchers can more quickly identify promising drug candidates and predict their interactions with biological targets. This approach could significantly shorten the time required for drug development, reducing costs and improving the availability of new treatments. Moreover, QML can be used to develop more accurate predictive models for personalized medicine [61]. By analyzing vast datasets, including genomic data, clinical records, and medical imaging, quantum-classical hybrid models could help predict patient responses to specific treatments. For example, in oncology, QML could improve the accuracy of predicting cancer recurrence or response to chemotherapy, enabling more tailored treatment plans that optimize patient outcomes [62]. In addition, QML has the potential to transform medical imaging by improving the speed and accuracy of image analysis [63]. Hybrid quantum-classical models could enhance medical imaging by combining quantum algorithms for image processing with classical

ML techniques for disease detection, potentially improving early diagnosis in fields like radiology and pathology [64]. However, clinical implementation remains at least a decade away due to hardware limitations, error rates, and scalability challenges. In the next 5 years, progress will be limited to small-scale experiments and simulations, while in 10 years, early clinical testing may emerge as quantum hardware improves. Widespread adoption will require fault-tolerant quantum systems, regulatory approval, and clear advantages over classical methods, making large-scale clinical deployment a long-term goal. QML can also be applied to optimize radiotherapy treatment plans, where quantum algorithms can handle the computationally intensive optimization of radiation dose distribution, while classical models process patient data and medical history. This synergy could lead to more precise and effective radiation therapy, minimizing side effects and improving patient outcomes [65].

3.4. Large Language Model-Based Chatbots in Healthcare

The application of large language models (LLMs), such as GPT (Generative Pretrained Transformer) and BERT (Bidirectional Encoder Representations from Transformers), as conversational agents is transforming the landscape of healthcare [66,67]. LLMs are capable of processing vast amounts of textual data, generating human-like responses, and engaging in meaningful conversations. This has led to their increasing use in various healthcare settings, from patient education and symptom checking to clinical decision support [68]. LLMs like GPT and BERT [69] are deep learning-based models designed to understand and generate human language. GPT, a generative model, can create coherent and contextually appropriate text based on a given input, making it ideal for tasks such as dialogue generation and content creation [70]. BERT, on the other hand, is a transformer model that excels in understanding the context of words within sentences, making it particularly useful for tasks that require comprehension, such as question answering and sentiment analysis. In healthcare, these models serve as conversational agents, capable of interacting with users in natural, human-like conversations. By processing large datasets of the medical literature, clinical guidelines, and patient information, LLMs can generate relevant and accurate responses to healthcare-related queries [71]. These capabilities make LLM-based chatbots powerful tools for enhancing patient engagement, supporting clinical workflows, and improving healthcare accessibility.

LLM-based chatbots are increasingly being used in patient education, providing individuals with personalized, accessible information about their conditions, treatments, and medications. These chatbots can answer patients' questions about symptoms, procedures, and preventive care, helping them better understand their health and treatment options [72]. The ability to access healthcare information in real-time enhances patient empowerment, reduces anxiety, and promotes informed decision-making. Another significant application of LLM-based chatbots is in symptom checking. By asking patients a series of questions about their symptoms, these chatbots can assess potential conditions and offer recommendations on next steps, such as scheduling an appointment or seeking emergency care [73]. These chatbots are trained on medical databases and clinical guidelines to provide accurate assessments, acting as a first point of contact for individuals seeking guidance about their health. However, it is crucial to note that these systems are not intended to replace healthcare professionals but rather to supplement them by triaging patients and providing initial advice [74]. In clinical decision support, LLM-based chatbots can assist healthcare providers by offering evidence-based recommendations, assisting in diagnostic processes, and providing treatment suggestions [75]. These chatbots can review patient records, clinical guidelines, and research the literature to offer clinicians up-to-date and relevant information. By integrating with EHRs, chatbots can analyze patient data to sug-

gest potential diagnoses or flag concerns, helping clinicians make more informed decisions quickly and efficiently [76].

One of the key advantages of LLM-based chatbots is their ability to integrate with other ML models for personalized responses and diagnostics. By incorporating patient-specific data, such as medical history, demographics, and previous health conditions, these chatbots can generate responses tailored to the individual. For example, if a patient queries about a treatment option, the chatbot can factor in their specific health conditions, comorbidities, and preferences to offer a personalized recommendation [77]. Furthermore, when integrated with diagnostic algorithms, LLM-based chatbots can help healthcare professionals by providing clinical insights based on the patient's symptoms, lab results, and medical history. These systems leverage ML models that have been trained on large datasets of medical records and outcomes, allowing them to provide accurate diagnostics and assist clinicians in making data-driven decisions. Figure 5 shows an example of the retrospective assessment of patients enrolled in the University of California, Los Angeles (UCLA) Center for IBD electronic care management platform (UCLA eIBD). The UCLA eIBD platform (ver. 1.4) is a software-as-a-service solution that provides a web-based interface for providers, featuring treatment decision support, business intelligence, messaging functionality, and performance improvement tools. For patients, the platform includes a mobile app offering care management insights, educational modules, surveys, and messaging capabilities [78].
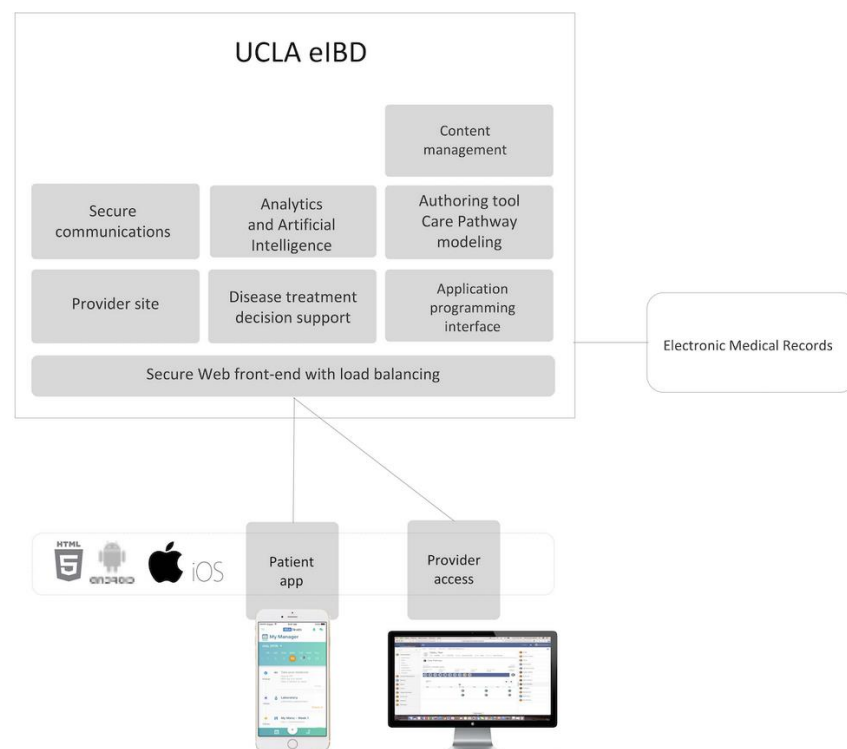

Figure 5. Overview of the UCLA eIBD platform. AI: artificial intelligence; API: application programming interface. All patients. Reproduced from reference [78] under the Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0/ (accessed on 24 January 2025)).

Several examples of LLM-based chatbot applications in healthcare demonstrate their growing utility in clinical settings:

Buoy Health is an AI-powered chatbot used for symptom checking [79]. It allows users to input their symptoms and receive a preliminary assessment of their condition. The chatbot uses natural language processing to ask follow-up questions and guide users to the

appropriate next steps, whether it is suggesting self-care, seeking urgent care, or consulting a healthcare professional. Buoy Health has been integrated into various healthcare systems, helping to reduce the burden on healthcare providers by offering patients immediate advice [80]. Babylon Health's chatbot provides virtual consultations by combining AI with human medical professionals [81]. The chatbot helps patients with symptom checking, health monitoring, and medical advice, using ML models to assess patient inputs and determine the likelihood of various conditions. It also integrates with telemedicine services, allowing patients to connect with healthcare providers for further consultation. IBM Watson has developed AI-driven chatbots for healthcare that assist both patients and clinicians [82]. Watson for Health is capable of engaging in conversations, reviewing patient records, and providing evidence-based recommendations to healthcare providers. The system can also assist patients by providing tailored health information, answering medical questions, and supporting chronic disease management [83]. The Mayo Clinic has developed a chatbot that interacts with patients to provide health information, including advice on conditions, symptoms, and treatments [84,85]. It also helps with appointment scheduling and medication reminders. The chatbot integrates with the Mayo Clinic's database, allowing it to provide accurate and up-to-date information tailored to individual patient needs. Table 1 shows a comprehensive summary of various applications in medical decision-making, highlighting the integration of QC and ML technologies. Each application is described along with its potential impact on healthcare, ranging from drug discovery and radiotherapy to genomic data analysis and personalized medicine.

Table 1. Summary of applications in medical decision-making.

Application	Description	Reference
Drug Discovery	QC can enhance drug discovery by enabling simulations of complex molecular interactions at the quantum level.	[34]
Radiotherapy	QC excels at solving optimization problems, which is crucial for radiotherapy treatment planning.	[35]
Genomic Data Analysis	QC has the potential to innovate genomic data analysis by enabling faster processing and more accurate predictions.	[37]
Medical Imaging	ML algorithms are increasingly used in medical imaging and pathology to assist in diagnosing diseases with higher accuracy and speed.	[39]
Digital Pathology	ML algorithms are applied to analyze histopathological slides of tissue samples, helping pathologists identify disease markers, cancerous cells, and other abnormalities.	[41]
Predictive Modeling	ML models can identify risk factors and predict the likelihood of disease progression or recurrence.	[43]
Personalized Medicine	ML algorithms can analyze genetic mutations and molecular profiles of tumors to recommend targeted therapies.	[47]
Quantum ML (QML)	QML refers to the application of QC to enhance traditional ML algorithms.	[51]
Hybrid Quantum-Classical Models	Researchers are exploring hybrid quantum-classical models, where quantum algorithms are integrated with classical ML methods.	[58]
LLM-based Chatbots	LLM-based chatbots are increasingly being used in patient education, providing individuals with personalized, accessible information about their conditions, treatments, and medications.	[72]

4. Challenges and Limitations

4.1. QC Challenges

QC holds immense promise for transforming medical research, but several challenges remain that must be addressed to fully realize its potential [86]. One of the most significant

barriers is the current state of quantum hardware. Scalability remains a critical issue; while existing quantum computers are capable of executing specific algorithms, they are far from being powerful enough to handle the vast complexities of real-world medical datasets [87]. In addition, high error rates in quantum computations hinder accuracy and reliability. Quantum systems are inherently susceptible to noise, which can cause decoherence—the loss of quantum information due to interactions with the surrounding environment [88]. Overcoming these limitations requires advancements in qubit stability, error correction protocols, and the development of fault-tolerant quantum architectures. Another major challenge is the accessibility of QC resources for medical researchers [89]. Quantum computers are expensive and require specialized infrastructure, such as ultra-low-temperature environments, to operate. These requirements limit their availability to a few well-funded institutions and organizations. As a result, many medical researchers lack the opportunity to experiment with quantum techniques or develop applications tailored to their specific needs [90]. Furthermore, the steep learning curve associated with quantum programming languages and frameworks adds another layer of difficulty, creating a gap between theoretical possibilities and practical implementation in the medical field [91].

Quantum Simulators

Quantum simulators, such as IBM's Qiskit, play a crucial role in the development and evaluation of QML algorithms [92]. These simulators allow researchers to test QML approaches in a controlled environment before deploying them on actual quantum hardware, which is currently constrained by factors such as limited qubit coherence times, gate errors, and noise. While Qiskit provides access to real quantum processors, most QML studies rely on simulations due to the practical challenges of running large-scale algorithms on existing hardware. Simulated results, although useful for benchmarking and exploring algorithmic behavior, do not fully capture the effects of hardware imperfections, such as decoherence and gate fidelity [21], which can significantly impact performance. In contrast, experiments conducted on real quantum devices provide insights into these physical limitations but are often restricted in scale and computational depth. Therefore, a clear distinction between simulated and hardware-based QML results is essential to accurately assess the feasibility and future potential of quantum computing in real-world applications [93]. Some widely used quantum simulators, including Qiskit Aer, Cirq, and PennyLane, further illustrate their importance in advancing QML research by enabling algorithm testing on larger datasets and increasing the complexity of problem-solving beyond what current quantum hardware can handle [94,95].

4.2. ML Challenges

While ML has demonstrated significant potential in advancing healthcare, several challenges must be addressed to ensure its effective and ethical implementation. ML models rely heavily on high-quality data, but medical datasets often contain inconsistencies, missing values, and errors that can compromise model performance. Additionally, ensuring patient privacy is a critical concern, as healthcare data are highly sensitive and subject to strict regulations [96]. Techniques such as data anonymization and federated learning are being explored to mitigate these concerns, but they are not yet universally adopted. Bias in data is another pressing issue; if datasets are not representative of diverse patient populations, models produce inequitable outcomes, potentially exacerbating healthcare disparities [97]. The complexity of many ML models, particularly deep learning algorithms, poses challenges in explainability—the ability to understand and interpret model predictions. In healthcare, where decisions can have life-altering consequences, explainability is essential for building trust among clinicians and patients [98,99]. Regulatory compliance

adds another layer of difficulty, as healthcare applications must meet stringent standards set by organizations like the FDA or EMA [100]. Ensuring that models are transparent, interpretable, and compliant with these regulations is a complex and ongoing challenge.

4.3. Integration Challenges

The integration of QC and ML into clinical workflows presents unique challenges that must be addressed to ensure successful adoption and implementation. Integrating QC and ML in healthcare involves bridging two highly complex domains. Quantum algorithms and ML models operate on fundamentally different principles, requiring specialized expertise and tools to enable seamless interaction [101]. In addition, clinical workflows are often rigid and standardized, making it difficult to incorporate experimental technologies without disrupting existing systems. Ensuring interoperability between quantum systems, ML frameworks, and EHRs is another critical challenge that necessitates significant coordination and innovation [102]. The cost of implementing QC and ML in healthcare is prohibitive for many institutions. Quantum hardware is expensive to acquire and maintain, often requiring specialized environments such as cryogenic systems [103]. Similarly, the computational demands of advanced ML models necessitate substantial investment in high-performance computing infrastructure. These financial and logistical constraints limit the accessibility of these technologies to resource-rich organizations, creating a divide between institutions that can afford to innovate and those that cannot [104]. Table 2 outlines the challenges and limitations of applying QC and ML in medical decision-making, along with potential solutions.

Table 2. Summary of challenges and limitations in medical decision-making and potential solutions.

Challenge	Description	References	Potential Solutions
QC Challenges	Scalability, high error rates, and accessibility of quantum hardware.	[86–91]	Advancements in qubit stability, error correction, fault-tolerant architectures, and increased accessibility.
ML Challenges	Data quality, patient privacy, bias, explainability, and regulatory compliance.	[96–100]	Improved data curation, anonymization techniques, bias mitigation, explainable AI, and adherence to regulations.
Integration Challenges	Bridging QC and ML, rigid clinical workflows, interoperability, and high costs.	[101–104]	Specialized expertise, flexible workflows, interoperability standards, and investment in infrastructure.

5. Future Directions and Opportunities

5.1. Emerging Trends in Quantum Hardware and Algorithm Development

Continuous advancements in quantum hardware, including the development of more stable qubits and efficient error correction techniques, are paving the way for practical applications in medical research [105]. Simultaneously, the evolution of hybrid quantum-classical algorithms is enabling researchers to leverage QC for specific tasks while relying on classical systems for others [106]. These innovations hold the potential to tackle complex problems, such as simulating molecular interactions or optimizing treatment protocols.

5.2. Role of Explainable AI (XAI) in Medical Applications

Explainable AI is becoming increasingly important in medical applications, as it addresses the need for transparency and trust in ML models [107]. By providing clear and interpretable insights into how predictions are made, XAI can help clinicians understand the rationale behind recommendations, fostering confidence in AI-driven decision-making [108].

Integrating XAI with quantum-enhanced models further enhances its applicability by providing robust, interpretable solutions to intricate medical challenges [109,110].

5.3. Potential for Real-Time Decision-Making Using Quantum-Enhanced ML Models

The combination of QC and ML offers the potential for real-time decision-making in critical medical scenarios [111]. Quantum-enhanced ML models can process and analyze vast datasets at unprecedented speeds, enabling rapid diagnosis and personalized treatment planning. These capabilities could redefine fields such as emergency medicine and precision oncology, where timely interventions are crucial.

5.4. Ethical Implications and the Need for Cross-Disciplinary Collaboration

As these technologies evolve, addressing ethical implications becomes paramount. Ensuring fairness, mitigating bias, and safeguarding patient privacy are essential to prevent unintended consequences [112]. Cross-disciplinary collaboration between ethicists, clinicians, technologists, and policymakers will be vital to establish robust ethical guidelines and regulatory frameworks [113]. Such efforts will ensure that the integration of QC and ML aligns with societal values and promotes equitable access to advanced healthcare solutions.

6. Conclusions

QC and ML hold transformative potential for advancing medical decision-making, offering unprecedented capabilities in processing complex datasets, optimizing treatment strategies, and enabling real-time solutions. Their integration can innovate healthcare by addressing challenges in diagnosis, treatment personalization, and resource allocation. However, realizing this potential requires significant research and development to overcome current limitations in hardware, data quality, and integration workflows. Advancements in quantum hardware, explainable AI, and interdisciplinary collaboration are critical to ensuring these technologies are both effective and ethically implemented. As these fields continue to evolve, fostering cross-disciplinary efforts among researchers, clinicians, and policymakers will be essential to unlocking their full potential. By addressing the outlined challenges and seizing emerging opportunities, QC and ML can drive a paradigm shift in medical research and clinical care, ultimately improving patient outcomes and transforming global healthcare systems.

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