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Integrating Quantum Communication with Machine Learning: a review

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Abstract

Quantum communication and machine learning convergence is one of the promising directions in the development of communication systems that could be secure, efficient, and scalable. The modern communication networks employ quantum communication technologies, such as quantum key distribution (QKD), entanglement, and teleportation, that can ensure high security and allow the transmission of reliable data. Combined with machine learning, these technologies can be used to process data better, provide better security, and perform better in many applications, including the Internet of Things (IoT), intelligent communication networks, health care, and artificial intelligence. This paper will provide a review of the key principles of quantum communication and the application of machine learning in communication systems, and how the two concepts can be applied to advantage. Besides that, the paper discusses critical technical problems, such as scalability, system integration, and the unavailability of standardization, that constrain the present application of hybrid quantum-classical systems. In addition, the future research directions are mentioned, specifically quantum-enhanced federated learning and the construction of a quantum internet. In general, this paper offers an analytical and systematic review of the field, highlighting the existing challenges, as well as the opportunities that may be explored in the future to establish next-generation intelligent communication systems.

Keywords: machine learning; quantum communication; QKD; data privacy; healthcare applications; Internet of Things (IoT).

1. Introduction

Quantum communication (QC) uses the concept of quantum mechanics so as to transform the process of transmitting data and it makes a giant leap in regards to security, speed, and efficiency [1, 2]. Basically, QC involves the use of quantum entanglement, quantum key distribution (QKD) and quantum teleportation. Quantum entanglement causes particles that are related to each other to become related in such a way that the state of one particle can become affected by the state of the other immediately even when the two are separated. This aspect allows near-real time transmission of communications over a long distance and this may significantly reduce latency in communication networks. In quantum mechanics, quantum key distribution plays a major role in proposing security to establish an in vulcanized communication channel. QKD allows any communication with the key being transmitted to be detected because of the characteristics of quantum measurement that would disrupt the quantum state and warn the parties. Moreover, quantum teleportation is also applied in transporting quantum information, in a given location, to another remote location, but not the physical data itself, with respect to the entangled states of the particles in order to recreate the quantum information itself. Such quantum communication technologies are much superior to the classical communication methods inherently based on providing secure communication as well as high-speed transmission hence leading to the future secure digital communication systems [2, 3].

Machine Learning (ML), which is a subfield of artificial intelligence, is changing the way data is processed and analyzed because it provides systems with the capacity of learning without being programmed. ML processing provides systems with the capability to detect patterns and make decisions according to the input of information and become more accurate the more information they are exposed to. Communication systems have also extensively relied on machine learning in order to maximize signal processing, network traffic control, error detection, and resource management processes. Modern-day communication networks are the most sensitive to these processes, which need to handle larger and more complex data sets. ML allows a communication system to be faster, efficient, and responsive, because it allows it to compress data and detect errors in real-time, and can control the network intelligently. As data keeps increasing rapidly, there is a need to integrate machine learning method in processing, controlling, and relaying data in an efficient way over communication networks. Models based on machine learning find application in telecommunication, health, autonomous vehicles, and financial technology to improve the effectiveness as well as reliability of communication networks [4-6].

ML in combination with QC is a probable way of the next generation of effective and secure communications system. The use of QC can be significant in increasing the performance of machine learning models through increased speed, security, and safety in the transmission of data. Reducing latency and enabling high-bandwidth, secure communication is an essential feature of QC, which is essential to ML systems, especially when they have to transfer very large quantities of data in low time, such as distributed machine learning or federated learning [7-10].

Figure 1 includes a full conceptual framework to offer a better insight into the connection between quantum communication and machine learning and demonstrates how core QC technologies, i.e., quantum key distribution (QKD) [11], entanglement, and teleportation are interplayed with the current sophisticated machine-learning-based applications to establish hybrid quantum-classical systems.

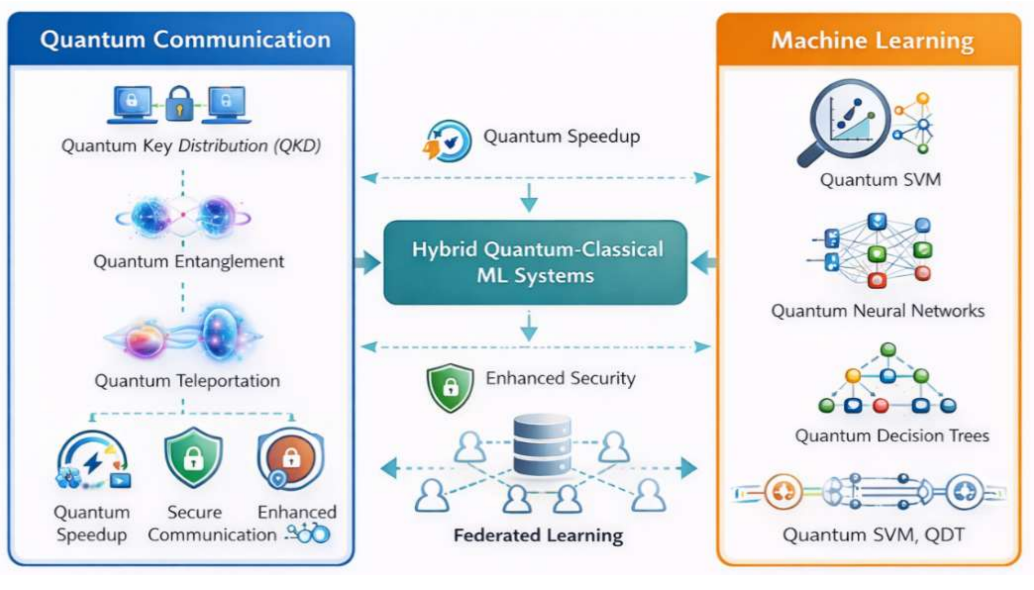

Figure 1. Theoretical context of the joint interaction between ML and QC.

The significance of quantum communication in this integration is quantum communication being utilized in boosting computational velocity, safeguarding data transmission, and facilitating distributed learning [12].

As shown in Figure 1, QC and ML intersection create a cohesive architecture that to a great extent improves the computational performance and data safety. With QC, it offers a safe and low-latency transmission layer which machine learning models use to offer effective data processing and decision-making [13]. This synergy is of great importance in distributed settings with federated learning, where a secure and effective sharing of data between two or more nodes is crucial. It follows that it is likely that hybrid quantum-classical systems will be central in facilitating the next generation intelligent communication networks [13].

The quantum encryption protocols such as QKD may as well play a major role in the protection of sensitive data along the path in the course of the ML training exercises to guarantee privacy and integrity and prevent unauthorized accessibility or manipulation. One of the most critical issues in the large ML implementation is privacy of information, particularly when sensitive data like medical history or financial information is involved. Through QC, it is possible to design ML networks that will work in an extremely secure environment with communications among network nodes always tamper proof and resistant to eavesdropping.

Moreover, quantum communication speed can provide faster processing and training of ML models by taking less time to transmit data across distant areas, thus, hastening the entire learning process. Such a combination of QC and ML can result in the creation of quantum-assisted ML models, which are faster and more secure and also more successful in tackling tricky problems that today classical systems cannot handle. Under these convergent technologies we can anticipate huge advancements in fields like artificial intelligence, cyber security and autonomous systems where computing capacity and data protection play a critical role [14, 15 and 16].

This paper has made the following contributions:

- Giving a full overview of QC technologies, such as quantum entanglement, quantum key distribution (QKD), and quantum teleportation.
- The role of ML in communication systems, especially signal processing, error correction and network optimization.
- Emphasizing the role of QC and ML integration, and explaining how the two can be used to improve the security, efficiency, and scalability of the contemporary communication systems. Determining significant technical issues, such as latency, security, and privacy concerns, in quantum-classical communication settings of hybrid environments.
- Providing future research directions and gaps on how to come up with secure, efficient, and scalable next-generation communication networks.

The next part will be dedicated to the background description of the problem of QC. The following part 3 shows Machine Learning (ML) and Its Role in communication systems. Part 4 is a description of the Effect of QC on ML. 5 Hybrid Quantum-Classical ML Models. Section 6 challenges and future directions. These last notes are listed in the last section of this paper.

2. Background of Quantum Communication

The concept of QC is based on several principles that distinguish it from classical communication systems [17]. These principles include quantum entanglement, QKD (quantum key distribution), and quantum teleportation, all of which are essential for enabling secure and efficient information exchange. Quantum entanglement allows correlated particles to share states regardless of distance, forming the basis for intrinsically secure links, while QKD leverages the laws of quantum mechanics to generate encryption keys that are resistant to eavesdropping. Quantum teleportation, on the other hand, enables the transfer of quantum states between distant nodes without physically transmitting the particles themselves. Together, these mechanisms, as depicted in Figure 2, form the foundation of QC technology and open the path toward the development of next-generation communication networks with enhanced security, reliability, and resistance to emerging cyber threats.

Figure 2. Basic principles of Quantum Communication

2.1 Basic principles

2.1.1 Quantum Entanglement

In quantum mechanics quantum entanglement is the interaction of two or more particles to where the state of one particle is correlated with the state of the rest, even though the particles may be separated by a long distance. Nevertheless, despite the strong correlations produced by entanglement between particles, faster-than-light transmission and instantaneous transmission of usable classical information is not possible. The measuring of one of the particles of an entangled pair correlates the state of the other particle, but cannot be used alone to provide direct communication without a classical communication channel. In spite of this drawback, entanglement is at the core of QC protocols and can be used to implement techniques like quantum key distribution and quantum teleportation that can improve the security and efficiency of communication in a contemporary communication system [17, 18].

2.1.2 Quantum Key Distribution (QKD)

QKD is an encryption technique, which relies on the principles of quantum mechanics to ensure a secure communication. QKD exploits quantum entanglement and quantum vagueness of quantum particles to transmit cryptography keys. Among other privileges, being the special privilege, QKD is such that the communication will be distorted in the event of someone trying to get into it, he or she will be informed of the presence of the intruder. This is what renders QKD both theoretically unbreakable, and its degree of security incomparable to the level of security that can be achieved with classical cryptographic systems. The presence of QKD in the communication networks can guarantee data confidentiality and integrity and is therefore a very important element in making sensitive information secure in many areas such as the banking, health and government communication [11, 19].

2.1.3 Quantum Teleportation

Quantum teleportation is a process to measure the quantum state of a particle and transmit it to another distant particle without transmission of the particle. Quantum entanglement is applied in this process along with a classical communication channel to recreate the quantum state at the destination. It should be noted that in quantum teleportation matter is not transferred, but quantum information is. More so, it involves classical communication and thus it does not support faster-than-light communication. Quantum teleportation has a significant role in quantum communication systems, allowing quantum information to be transmitted securely and allowing more complex communication protocols. It however does not substitute but rather complements classical communication technologies [20].

2.2 Existing Quantum Communication technologies

New developments in QC have led to the possibility of a quantum internet becoming a reality. The quantum repeater is one of the most important technologies that have made it possible to use quantum communication over long distance by storing and resenting quantum states, which reduces the loss and decoherence of signals, thus increasing the range of communication. Furthermore, QC via satellites has received a lot of interest. As an example, the quantum satellite Micius in China has been shown to do long-range quantum key distribution with a distance of thousands of kilometers [21]. The possibility of global quantum communication networks is suggested by such developments. Though full-fledged quantum internet is still in the development stage, there is current research to create secure communication systems that utilize quantum laws like entanglement and quantum teleportation. These technologies can greatly improve the security of communication, but they cannot provide total protection against interception, but only allow detecting any eavesdropping attempts and providing better data security [21, 22].

QC, quantum computing and quantum machine learning, should be distinguished. QC deals with the safe transmission of information based on quantum principles whereas quantum computing is interested in making computations with quantum bits. Quantum machine learning is an application of quantum computing with learning algorithms to improve the processing of data. These areas are interconnected and yet, they deal with dissimilar issues of smart communication systems.

2.3 Issues in Quantum Communication (QC)

Although QC has a very high potential, there are several challenges that it faces which still need to be overcome before it can be what it can be. Quantum decoherence or quantum information loss due to the interaction with the surrounding is one of the most essential problems. This makes it difficult to preserve the delicacy of the quantum states which are required to enable long-distance communication. Loss of transmission is another problem, in which the quantum information is lost in the transfer of entangled particles especially in long distance or light fibers. More challenging is scaling quantum systems to be on par with real-world communications networks due to such enormous technical challenges as stability, a low error rate requirement, and scaling the reliability and practicality of quantum devices to large scale. These are the hindrances that ought to be shattered to realize successful application of QC system in the future [23, 24].

3. Review methodology

The review has a systematic approach to identifying, choosing, and reviewing the existing literature on the combination of quantum communication and machine learning. The major scientific databases, such as IEEE Xplore, ScienceDirect, Springer, and Google Scholar were also searched to retrieve relevant studies. Selection criteria were:

- Journal and conference articles.
- Publications from 2015 to 2025
- Research on quantum communication, quantum machine learning and hybrid quantum-classical systems.

Exclusion criteria involved:

- Duplicate studies Articles that were not directly related to quantum communication and machine learning.
- Works that are not peer reviewed or are incomplete.

It was determined that the chosen literature was focused on the main aspects, such as methodology, field of application, contribution to the performance, and the significance to the next-generation communication systems. It is necessary to mention this work is a review paper and does not entail original simulations and optimization experiments. Rather, the work is dedicated to the analysis and synthesis of the existing studies, such as optimization methods and performance gains identified in the literature in the field of quantum machine learning and quantum-classical systems.

4. Machine Learning (ML) and its role in communication systems

4.1 Applications of ML in communication systems

Machine learning (ML) has turned out to be an effective way of optimizing the communication system to tackle the most critical issues, including the management of data, correction of errors, and signal processing. ML methods allow communication networks to learn and dynamically adapt to data, enhancing the overall system performance [2528]. The comparison between the classical and quantum machine learning methods is given in detail in Table 1 in section 5.

1. Data compression is an important feature of the communication networks especially in limited bandwidth networks. ML-based data compression Data compression using ML, including using autoencoders, is commonly used to compress data efficiently. Autoencoders are neural networks that are applied to reduce the information in a low-dimensional space and consequently project it back into its original form. When autoencoders are trained on large data, they are able to detect patterns and redundancy which help to compress data without much information loss. This has led to better storage and transmission which places less strain on the communication channels and faster transmission of information.
2. Error correction communication systems need to be improved by making the error correction to guarantee the correctness of data being transported. There is an increase in the use of ML models to estimate and remedy errors in communication channels [27]. Classical methods of error correcting like Hamming codes or Reed-Solomon codes are based on pre-coded algorithms. Even though ML algorithms such as decision trees and neural networks can be trained to identify and rectify errors in real-time, they respond to the dynamic nature of the communication channel. They are also capable of determining the trends of noise, interference, and signal degradation to offer higher data transmission reliability in totality. ML-based error correction systems can also obtain an optimal tradeoff between redundancy and efficiency to become more adaptative to changing network conditions.
3. Signal processing is a significant component of communication systems, such that the quality of the received signal may be impaired by noise, interference and distortion. ML is applied in noise removal and optimization of data transmission to improve the quality of signals. As an illustration, MLs, including convolutional neural networks (CNNs), can eliminate noise on the received signals, and the data will be more precise and understandable. Moreover, the ML models can also be used to optimize the use of the network resources in any communication system by estimating the traffic flows, sending power and determining the optimal routing algorithms. This gives maximum use of bandwidth, minimum latency and overall improved system performance [28].

4.2 Challenges in integrating ML with QC

Although ML has demonstrated significant potential to ease the traditional communication systems, the transition of ML to QC has a number of challenges. The major drawbacks of the traditional communication systems are that they are based on the traditional mechanisms of data transmission which are not fast and are susceptible to attacks. ML is sealing such gaps by providing faster and more secure transmission of data by correcting errors and optimizing networks. But even traditional systems continue to exhibit limited bandwidth, excessive latency, and the lack of security through the possibility of eavesdropping and hacking [1,29].

Most of these problems could be resolved through QC that can provide the ability to exchange data with ultra-security using QKD and provide even instant communications using quantum entanglement. Quantum communication technology has the potential to minimize the latency and enhance the bandwidths because quantum states are used to transmit the data. Replacement of traditional communication with the use of ML in place of quantum communication is not without its own difficulties. Among the largest ones, there is the fact that quantum communication systems are based on entirely new principles unlike classical systems, and thus the ML models must learn to handle the unruly nature of quantum channels. In addition, QC is still in its early days and there are no large-scale quantum networks and infrastructure that can enable QC to be seamlessly integrated with ML-based systems [30].

Nevertheless, the application of ML and QC is highly promising despite such challenges in improving the shortcomings of a standard communication system [31]. Once quantum communication technologies start evolving, the ML models will be improved by means of even faster, more secure, and efficient data transmission. QC would offer a safer platform of applications of ML, particularly in fields where sensitive data communications are necessary (healthcare, finance, and autonomous systems).

5. Quantum Communication's impact on Machine Learning

QC coupled with ML brings an innovative model to increase the efficiency of the computations, the safety of data, and system scalability. ML systems can gain access to faster processing, enhanced safety of data transfer, and enhanced privacy protection by utilizing important quantum technologies, including QKD, entanglement, and teleportation [32]. All of these capabilities combined can make machine learning models work better, especially in a distributed and federated learning setting, as shown in Figure 3.

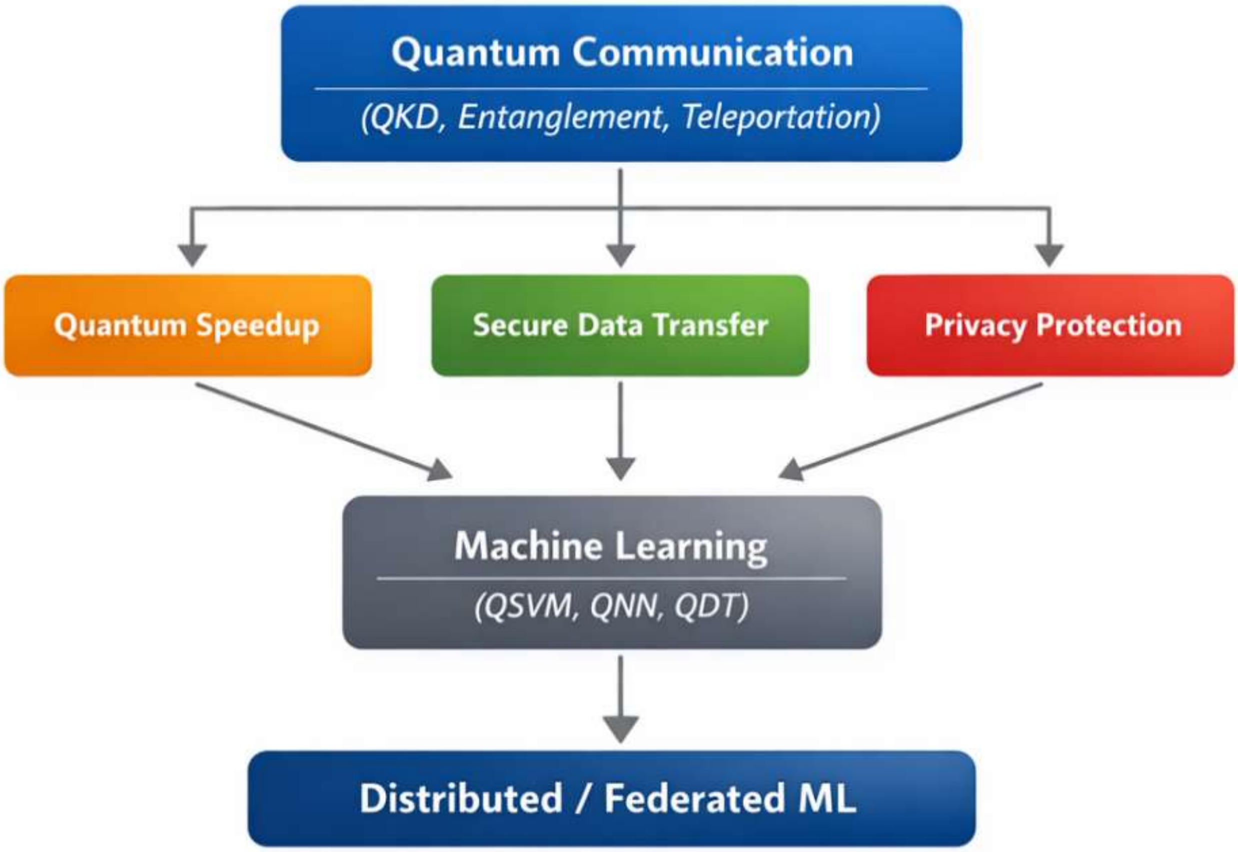

Figure 3. Effects of quantum communication on machine learning systems.

As illustrated in Figure 3, QC boosts machine learning systems in three basic dimensions, including computational acceleration, data exchange with security, and preserving privacy. Quantum speedup allows model training and optimization which is much faster especially with complex and high-dimensional problems. Simultaneously, secure transmission of data provides effective and efficient communication within distributed settings, which is critical to federated learning. Also, the protection mechanisms of privacy, which is made possible through QKD, are effective in protecting cases of breach of data and unauthorized access. In general, QC coupled with ML create a solid platform to construct the next generation intelligent systems that are efficient and by default secure [32, 33]. To further examine these advances, Table X compares classical with quantum machine learning methods.

Table 1. Performance, security and scalability Comparison of classical and quantum machine learning.

Aspect	Classical Machine Learning	Quantum Machine Learning
Computation Speed	Limited by classical processing	Potential quantum speedup
Data Security	Vulnerable to attacks	Enhanced security via QKD
Scalability	Limited for complex problems	Promising but hardware-limited
Data Processing	Sequential or parallel (limited)	Quantum parallelism
Maturity	Well-established	Emerging technology

As depicted in Table X, quantum machine learning has great potential benefits, especially when it comes to the speed of computation and security. Nevertheless, it is still restricted by the existing hardware limitations and scalability issues meaning that hybrid quantum-classical solutions are the most viable solution at the moment.

5.1 Quantum algorithms for Machine Learning

Quantum machine learning (QML) is a recent area of research which involves using the strengths of quantum computing and machine learning to enhance the performance, speed, and scalability of classic machine learning algorithms [34]. Some of the essential quantum algorithms, including the Quantum Support Vector Machine (QSVM), Quantum Neural Networks (QNN) and Quantum Decision Trees (QDT) provide novel breakthroughs over the classical versions. QSVM employs such quantum properties as superposition and entanglement to make the training and classification more efficient, especially in high-dimensional space. QNNs are also used to model neural networks using quantum circuits, which can be run at increased speed and possibly with greater accuracy using quantum parallelism. QDTs are quantum decision principles integrated with decision trees to enhance better classification activities and handling of huge data sets compared to traditional decision trees. The quantum algorithms can hasten the process of machine learning, resolving issues quicker and more proficiently by lessening the complexity of the training time and improving the capacity of the model to be extended [35, 36].

5.2 Enhancing communication efficiency in ML models

- Quantum speedup: Quantum computation and communication can accomplish a lot to help train machine learning model besides execute it faster. The traditional machine learning implementations, particularly those that use large data sets are associated with a heavy workload in terms of time spent in the training process besides the high processing costs. Quantum superposition and quantum entanglement are essential components in quantum computing which enables quantum speed up, fast data processing and less time to train complicated models. This accelerating is specifically applicable to optimization problems, in which quantum ness in the system can simultaneously explore multiple solutions and offer higher performance of convergence rates in algorithmic techniques such as gradient descent or support machine learning. As quantum hardware progresses, these features will enable ML models to be trained and deployed in a much shorter time, and it will be possible to develop real-time machine learning applications [37].
- Efficiency of data transmission: With distributed machine learning, such as federated learning, efficiency of data transmission is the key factor because there are multiple devices or nodes that collaborate to train a model with localized data. Such a decentralized model can be provided with ultra-high-speed and high-bandwidth communication by quantum communication. Potentially, the lack of latency can be mitigated by the capability to transmit data safely and in real time over a long path distance by utilizing quantum communication protocols in QKD to enhance data sharing efficiency among nodes. Quantum communication ensures that the models can send high volumes of datasets with high efficiency and safely without data degradation leading to successful distributed training processes [38].
- Privacy and security of data: The privacy and security of the information are paramount when dealing with machine learning activities, particularly when sharing sensitive information during the process of comparing the models. Privacy and security are guaranteed by quantum communication through the use of QKD, a method that is used to guarantee secure data transmission through the use of quantum

mechanics. Quantum channel eavesdropping is prevented because any such attempt to do this will be evident because it will affect the quantum state. This feature makes QKD especially federated learning and other applications of ML perfectly suited to scenarios in which several parties are sharing sensitive information. Quantum communication provides a reliable communication platform to provide the privacy of data throughout the training phase without unauthorized access to the data or manipulation of it. As the field of quantum communication technology evolves, privacy-aware and secure machine learning systems will become the future, and it will satisfy increasing demands of data security in industry, commerce, and defense [38, 39].

Overall, machine learning and quantum communication merge will transform each of the fields, improving the speed, efficiency, security, and scalability of machine learning algorithms, particularly in privacy-restricted and distributed settings. Quantum ML algorithms will open new possibilities to solve computationally intractable problems to classical computers, and quantum communication will allow a safe and efficient method of enjoying such benefits [39].

6. Hybrid Quantum-Classical Machine Learning models

6.1 Hybrid systems

Hybrid quantum-classical systems are quantum-computing systems that embrace the computational capabilities of quantum and classical computing to improve machine learning models. Quantum computers are employed in the running of particular tasks in these systems, such as optimization, feature selection, and sampling, whereas classical systems run more routine tasks, such as data preprocessing, model training, and validation. Quantum computers are able to execute gradient descent or support vectors machine (SVM) by utilizing the concept of quantum parallelism [45] to compute large volumes of data more efficiently.

Another instance of quantum-enhanced optimization that may be more effective than classical algorithms is the Quantum Approximate Optimization Algorithm (QAOA), a proposed quantum algorithm to solve combinatorial optimization problems [44]. The classical element is also important in data and model construction control, and quantum systems may not be yet beneficial.

These two paradigms in combination will enable the hybrid system to complement one another resulting in more efficient model that can be used to address the complex tasks which would not otherwise be addressable by classical systems only [40]. The mentioned mixed approach proves particularly useful since quantum hardware is still under development and can provide faster performance of some ML functions but not completely replace classical ones.

6.2 Quantum-inspired Machine Learning

Quantum-inspired machine learning (QIML) algorithms are supposed to be the quantum concepts used in the classical computing paradigms. By leveraging the properties of quantum mechanics such as parallelism and increased exploration of large solution spaces, these algorithms are used to improve classical machine learning models. An example is that, the Quantum Approximate Optimization Algorithm (QAOA) that was originally created to operate on quantum computers has inspired classical algorithms to solve optimization problems in machine learning [41]. Classical algorithms that implement quantum-inspired algorithms, like quantum annealing, have been shown to be much more useful than classical algorithms in optimization problems and reinforcement learning, with the quantum principles of superposition and entanglements making quantum-inspired algorithms more efficient at searching high-dimensional optimization problems [42].

QIML have also been used in reinforcement learning, where classical models can be improved using the quantum principles of superposition and entanglements to search high-dimensional optimization problems faster [43]. Such QIML constitute a bridge between classical and quantum computing, and provide new solutions to such problems as data classification, clustering, and predictive modeling, and provide scaling opportunities to quantum systems in the future as quantum hardware and algorithms scale. Table 2 gives a summary of the representative studies on hybrid quantum-classical machine learning models and their essential techniques and contributions to provide a structured overview of recent developments.

Table 2. Overview of critical sources on Hybrid quantum-classical machine learning models.

Ref	Name of Paper	Motivation	Year	Authors
[40]	Parameterized quantum circuits as machine learning models	This paper discusses the use of parameterized quantum circuits as ML models with emphasis on their application to QML problems.	2019	Benedetti, M., Lloyd, E., Sack, S., & Fiorentini, M.
[41]	A quantum approximate optimization algorithm	The article presents the Quantum Approximate Optimization Algorithm (QAOA) to solve optimization problems that can be used in the case of hybrid quantum-classical machine learning models.	2014	Farhi, E., Goldstone, J., & Gutmann, S.
[42]	Quantum Annealing and Related Optimization Methods	This paper gives a detailed overview of quantum annealing and optimization techniques that can be used in machine learning problems such as optimization.	2008	Das, A., & Chakrabarti, B. K.
[43]	Quantum machine learning in feature spaces	The article describes the application of QML in classical ML feature space, which provides possible optimization speed-ups.	2019	Schuld, M., & Killoran, N.
[44]	An initialization strategy for addressing barren plateaus in parameterized quantum circuits	This article discusses barren plateaus where parameterized quantum circuits are difficult to train, and a possible solution to this issue, namely an initialization strategy to beat it, to quantum machine learning.	2019	Grant, E., Benedetti, M., Wossnig, L., & Severini, S.
[45]	TensorFlow Quantum: A Software Framework for Quantum Machine Learning	The current paper opens the TensorFlow Quantum (TFQ) framework, which is a QML framework that integrates quantum computing and classical ML processes.	2020	Broughton, M., Verdon, G., McCourt, T., et al.

As indicated in Table 2, majority of the current strategies are aimed at exploiting parameterized quantum circuit and hybrid optimization methods to enhance learning. Nevertheless, the models continue to be limited by training issues, e.g. barren plateaus, and hardware constraints, suggesting that more robust and scalable solutions are required.

7. Real-World applications

Quantum communication technologies can revolutionize AI-driven communication technology by increasing the speed, safety, and productivity of several real-world applications.

7.1 Secure IoT systems

IoT is based on connected devices that constantly gather and transfer vast amounts of data, and these devices are likely to operate on possibly insecure networks. With the introduction of quantum encryption (especially QKD) into IOT, it is possible to protect devices in data transmission against eavesdropping and uncontrolled access (Bhatt et al. [46]; Adnan et al. [47]). Such capability is particularly important when it comes to applications that involve sensitive data, including personal data or industrial control signals.

Moreover, quantum cryptography allows detecting any attempts of interception, which is not possible when using the classical methods (Scarani et al. [48]; Primaatmaja et al. [49]). Also, the possibility of using QKD in the context of IoT has been explored, which proved to be effective in the exchange of keys securely and protection against eavesdropping in the contemporary communication systems (Chawla et al. [50]; Rahmayanti et al. [51]).

7.2 Intelligent Communication Networks

Quantum computing can greatly improve the performance of the communication networks because it helps to speed up the processes of making complicated decisions. The optimization problems that quantum processors are efficient in include resource allocation, routing, and traffic management, where they can manage the large-scales network dynamics faster than classical systems (Zeydan et al. [52]; Ali et al. [53]). An example is that next-generation (6G) networks are also under investigation using QML methods, allowing the optimization of elements in real-time, security, and smart-resource management (Bouchmal et al. [54]; Rodriguez-Diaz et al. [55]). Furthermore, QC systems like quantum internet designs are in active development to deliver very high-end communication networks that can withstand cyber attacks and offer more sophisticated AI-based services (Zeydan et al. [52]).

7.3 Healthcare systems

Healthcare industry requires a high speed and quality data transmissions especially when it comes to utilising the system in medical imaging, diagnostics and telemedicine. The machine learning based on quantum has shown promising potential in increasing the data analysis outcomes including classification, prediction, and pattern recognition of the complicated medical data (Gupta et al. [56]; Anand [57]). Meanwhile, QC protocols provide safe conveying delicate patient information among healthcare professionals, researchers, and patients. One of the suggested solutions has been quantum cryptography, especially QKD, which can provide a high level of security and privacy of medical data and guarantee secure information exchange within healthcare systems (Zhu et al. [58]).

Moreover, quantum-based communication systems will probably enable safe and high-speed data transfer in upcoming healthcare networks to carry out real-time diagnosis and enhanced patient care. According to the recent research, quantum computing could become an excellent solution to enhance the safety of healthcare data, the speed of medical operations, and the stability of systems, particularly when combined with cutting-edge communication systems (Jeyaraman et al. [59]; Lv et al. [60]).

8. Challenges and future directions

Although QC can be used to complement ML, a number of technical and practical issues will need to be resolved to facilitate its large-scale implementation. These problems cut across several dimensions and are issues of scalability, system integration, standardization and resource limitations. It is imperative to understand these limitations in order to come up with efficient and reliable hybrid quantum-classical systems. Table 3 presents a summary of the major challenges, their effects on machine learning systems, and possible solutions introduced to deal with them in the literature.

The integration of QC and ML systems as shown in Table 3 is undermined with several challenges interacting with each other making it impossible in real life. Scalability and noise sensitivity prove to be the problematic ones because they directly affect the reliability when transmitting quantum data and whether it is possible to implement large-scale distributed learning. In addition, the problem of QC being integrated with the existing classical machine learning infrastructures proves that there is a need to have efficient hybrid architectures that would guarantee the accruing of the advantages of both paradigms. The lack of standardized procedures is also a significant setback and this can ensure the quantum technologies are slower to implement it in different platforms and application fields.

Despite these limitations, the potential solutions offered in Table 3 demonstrate that there is a certain research direction to resolve these problems. The developments of quantum repeaters, error correcting algorithms, and quantum/classical systems should prove to be of great aid as far as the delivery of scalable and secure communication systems are concerned. All together, in a bid to achieve the ultimate potential of quantum-enhanced ML, challenges must be addressed and this will be followed by the next generation of intelligent communication systems that is not only efficient but also secure.

Table 3. Challenges and potential solutions in QC for ML systems

Challenge	Description	Impact on ML Systems	Potential Solutions
Scalability	Noise and decoherence are very sensitive to quantum systems, which restricts the long-range transmission and mass implementation.	Limits distributed ML and large-scale data processing	Analysis of quantum repeater performance, error correction designs as well as architectures of quantum networks on a scale.
Integration	The challenge in integrating QC and classic ML systems.	Difficulties with deploying hybrid quantum-classical ML models.	Development of hybrid frameworks, quantum classical interfaces, and middleware platforms
Standardization & Interoperability	Absence of standardized procedures and guidelines of QC systems.	Lack of intra-platform and inter-platform compatibility.	Development of global standards (ETSI, ITU), unified communication protocols, and interoperable architectures
Noise & Decoherence	Quantum states are delicate and they are sensitive to disturbances in the environment.	Decreases accuracy of transmitting data to ML training.	State-of-the-art quantum error correction and noise resilient communications.
Security Implementation Complexity	The application of quantum cryptography in practice is not an easy task.	Slacks adoption in ML-based applications.	Simplified QKD protocols and integration with frameworks of classical security
Resource Constraints	High computational and hardware requirements for quantum systems	Limits real-time ML deployment	Optimization of quantum algorithms and use of hybrid quantum-classical processing

8.1 Technical Challenges

- Scalability: The ability to scale the QC systems to support ML applications of large scale has remained a challenge. QC is based on sensitive quantum states which are very susceptible to noise and interference. Quantum information is hard to channel over long distances and still the integrity of data remains intact. Moreover, the sheer amount of computational resources used to serve the models of ML on scale and particularly the processing of big data and complex algorithms introduces new scalability problems. Researchers need to design better quantum communication tools and quantum repeaters that can provide the assurance of communication across the vast networks [61].
- Integration: The other issues of importance include scaling the integration of QC with existing classical ML infrastructures. The existing ML models strongly depend on classical computer resources to train, inference, and optimization. The classical systems should be compatible with quantum systems in order to produce hybrid architecture. This integration cannot be achieved only through hardware compatibility but also software frameworks that will be able to integrate quantum and classical systems seamlessly so that practitioners can freely leverage both technologies without having to have expertise in quantum mechanics [62].

- Standardization and Interoperability: There is a lack of industry standards on QC protocols, which is a problem in quantum communication technologies, which are still being developed. A globally accepted collection of protocols and standards with which the quantum and classical systems can be interoperable must be in place to ensure that QC is universally accepted in the applications of quantum in ML. These are also meant to solve problems concerning quantum encryption protocol, data structure, and data transmission security as a way of facilitating the exchange of information among different platforms and devices [63].

8.2 Future research directions

- Quantum Internet and ML: Construction of a quantum internet has the potential of transforming the communication system into machine learning tasks. A quantum internet would offer the most secure channels of communication and has the capacity to pass large quantities of information at record speeds. The new infrastructure could accelerate the execution of distributed machine learning models, especially in those applications where real-time sharing of the data and high security are paramount which include application in the field of healthcare and finance. In the future, the research will require the development of the quantum internet backbone, the construction of quantum data transmission protocols, and the issues of quantum routing and error fixing [64].
- Quantum-enhanced Federated Learning Federated learning, where machine learning models can be trained on decentralized data, can be significantly increased with quantum communication. Through quantum encryption techniques such as QKD, federated learning systems would be able to provide more security to sensitive information, including financial or healthcare information, that is exchanged between different parties. Also, QC would allow transferring data between devices more quickly, and as such, federated learning systems would be more efficient and faster. In this case, the research should focus on the development of quantum-amplified federated learning systems that embrace the benefits of quantum communication in terms of speed and security to improve the scalability and performance of distributed ML models [65, 66 and 67].

Although there is a potential of integrating QC with ML, there are a number of limitations. The existing quantum systems are still limited by hardware and noise, as well as scalability, that can limit their practical application. Moreover, QC needs to be integrated with classical ML models, which adds complexity to the design of systems and compatibility. Additionally, the absence of standardized procedures and developed infrastructure restricts the use of large-scale hybrid quantum-classical systems. Such constraints demonstrate the disunity between theoretical developments and practice.

9. Conclusions

The effectiveness of communication systems today can be transformed by QC and ML since they can enhance efficiency, security, and scalability of communication channels. QC technologies e.g. QKD and quantum entanglement are used to offer secure and high-speed data transmission that is essential in coping with the increasing amount of data in ML applications. With QC and ML we will be able to make systems more efficient, protect data better, and process a large amount of data faster. This intersection has the potential to have a more quickly and secure way of communication and an improved machine learning model specifically in the distributed setting and privacy sensitive setting. The convergence of these two spheres in the future will have colossal opportunities in most of the industries, including telecommunication, medicine and artificial intelligence, where convergence can simplify the data transfer process, accelerate decision-making, and offer a more powerful machine learning framework. To realize these benefits, however, quantum physicists, machine learning experts and communication engineers must collaborate on an interdisciplinary level. We will be able to fully realize the potential of quantum-enhanced machine learning and transform how we process and communicate data in the future by solving technical problems, scaling quantum systems and creating standardized protocols.

References

1. Mahmud and A. Abdelhadi, "Artificial intelligence in quantum communications: A comprehensive survey," IEEE Access, 2025.
2. Z.-Z. Sun, Y.-B. Cheng, D. Ruan, D. Pan, F.-H. Zhang, and G.-L. Long, "Quantum communication network routing with circuit and packet switching strategies," IEEE journal on selected areas in communications, 2025.
3. J. S. Sidhu, S. K. Joshi, M. Gündoğan, T. Brougham, D. Lowndes, L. Mazzarella, et al., "Advances in space quantum communications," IET Quantum Communication, vol. 2, pp. 182-217, 2021.
4. D. D. M. Rius, "Foundations of artificial intelligence and machine learning," in Artificial Intelligence in Finance, ed: Edward Elgar Publishing, 2023, pp. 2-18.
5. N. Dixit, R. Arora, V. Sharma, M. Sihare, S. Khule, and B. Ojha, "Developing artificial intelligence applications in manufacturing using digital twin-driven machine learning technology," in Transforming Industries, Empowering Societies, ed: Elsevier, 2026, pp. 199-210.
6. S. Palit, P. Madanan, S. Srivastava, G. R. Patil, M. Tiwari, and M. E. Lourens, "Quantum Machine Intelligence: A Framework for the Convergence of Quantum Computing, AI, and ML," in Emerging Hybrid Models for Neuromorphic AI and Quantum Computing, ed: IGI Global Scientific Publishing, 2026, pp. 33-66.
7. S. J. Nawaz, S. K. Sharma, S. Wyne, M. N. Patwary, and M. Asaduzzaman, "Quantum machine learning for 6G communication networks: State-of-the-art and vision for the future," IEEE access, vol. 7, pp. 46317-46350, 2019.
8. J. Wallnöfer, A. A. Melnikov, W. Dür, and H. J. Briegel, "Machine learning for long-distance quantum communication," PRX quantum, vol. 1, p. 010301, 2020.
9. X. Zhou, A. Shen, S. Hu, W. Ni, X. Wang, and E. Hossain, "Towards quantum-native communication systems: State-of-the-art, trends, and challenges," IEEE Communications Surveys & Tutorials, 2025.
10. Y. Alexeev, M. H. Farag, T. L. Patti, M. E. Wolf, N. Ares, A. Aspuru-Guzik, et al., "Artificial intelligence for quantum computing," Nature Communications, vol. 16, p. 10829, 2025.
11. A. I. Nurhadi and N. R. Syambas, "Quantum key distribution (QKD) protocols: A survey," in 2018 4th International Conference on Wireless and Telematics (ICWT), 2018, pp. 1-5.
12. Q. Zhang, F. Xu, Y.-A. Chen, C.-Z. Peng, and J.-W. Pan, "Large scale quantum key distribution: challenges and solutions," Optics express, vol. 26, pp. 24260-24273, 2018.
13. S. Sharma, K. Deka, and D. Dixit, "Introduction to Next-Generation Communications," in Next-Generation Wireless Systems: Fundamentals and Applications, ed: Springer, 2025, pp. 1-13.
14. C. R. Garcia, A. C. Aguilera, C. Stan, J. J. Vegas, S. Rommel, and I. T. Monroy, "Enhanced network security protocols for the quantum era: Combining classical and post-quantum cryptography, and quantum key distribution," IEEE Journal on Selected Areas in Communications, 2025.
15. A. I. Saiyed, "Optimizing quantum key distribution (QKD) protocols for secure communication in noisy quantum networks," Annals of Applied Sciences, vol. 6, 2025.
16. T. R. Akash, N. J. Sany, L. Akter, and S. A. Sarna, "Privacy-Preserving Technique in Cybersecurity: Balancing Data Protection and User Rights," Journal of Computer Science and Technology Studies, vol. 7, pp. 248-263, 2025.
17. Z. Yang, Y. Deng, J. Su, K. Chen, H. Song, Y. Huang, et al., "From micro-optical to quantum-enhanced gyroscopes: A comprehensive review," Laser & Photonics Reviews, vol. 19, p. 2402065, 2025.
18. X. Liu, C. Zeng, and J. Wang, "Generation of quantum entanglement in superposed diamond spacetime," The European Physical Journal C, vol. 85, p. 539, 2025.
19. E. Dervisevic, A. Tankovic, E. Fazel, R. Kompella, P. Fazio, M. Voznak, et al., "Quantum key distribution networks-key management: A survey," ACM Computing Surveys, vol. 57, pp. 1-36, 2025.
20. S. Pirandola, J. Eisert, C. Weedbrook, A. Furusawa, and S. L. Braunstein, "Advances in quantum teleportation," Nature photonics, vol. 9, pp. 641-652, 2015.

21. P. Jianwei, "Progress of the quantum experiment science satellite (QUESS) Micius Project," 空间科学学报, vol. 40, pp. 643-647, 2020.
22. S. K. Singh, A. El Azzaoui, and M. M. Salim, "Quantum Communication Technology for Future ICT--Review," Journal of Information Processing Systems, vol. 16, 2020.
23. R. Coates, D. Douglas, and M. Per, "AI and quantum computing ethics—same but different? Towards a new sub-field of computing ethics," Quantum Science and Technology, vol. 10, no. 3, p. 035030, 2025.
24. H. Dutta and A. K. Bhuyan, "Quantum communication: From fundamentals to recent trends, challenges and open problems," arXiv preprint arXiv:2406.04492, 2024.
25. O. Simeone, "A very brief introduction to machine learning with applications to communication systems," IEEE Transactions on Cognitive Communications and Networking, vol. 4, pp. 648-664, 2018.
26. I. Ahmad, S. Shahabuddin, H. Malik, E. Harjula, T. Leppänen, L. Loven, et al., "Machine learning meets communication networks: Current trends and future challenges," IEEE access, vol. 8, pp. 223418-223460, 2020.
27. T. C. Akinci, G. Erdemir, A. T. Zengin, S. Seker, and A. I. Idriss, "Machine learning-based error correction codes and communication protocols for power line communication: An overview," IEEE Access, vol. 11, pp. 124760-124781, 2023.
28. Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, "Application of machine learning in wireless networks: Key techniques and open issues," IEEE Communications Surveys & Tutorials, vol. 21, pp. 3072-3108, 2019.
29. M. Avramouli, I. Savvas, G. Garani, and A. Vasilaki, "Quantum machine learning: Current state and challenges," in Proc. 25th Pan-Hellenic Conf. Informatics (PCI), Nov. 2021, pp. 397–402.
30. T. O. Ogundare, A. P. Anyebe, F. O.-O. Alao, I. P. Idoko, and I. I. Odeh, "Role of Autonomous Systems in Overcoming Maritime Communication Bottlenecks through Quantum Computing and 6G Technologies."
31. G. G. Rozenman, N. K. Kundu, R. Liu, L. Zhang, A. Maslennikov, Y. Reches, et al., "The quantum internet: A synergy of quantum information technologies and 6G networks," IET Quantum Communication, vol. 4, pp. 147-166, 2023.
32. Y. Ismail, I. Sinayskiy, and F. Petruccione, "Integrating machine learning techniques in quantum communication to characterize the quantum channel," Journal of the Optical Society of America B, vol. 36, no. 3, pp. B116–B121, 2019.
33. A. Jaiswal, S. Kumar, O. Kaiwartya, P. K. Kashyap, E. Kanjo, N. Kumar, and H. Song, "Quantum learning-enabled green communication for next-generation wireless systems," IEEE Transactions on Green Communications and Networking, vol. 5, no. 3, pp. 1015–1028, 2021.
34. N. Schillo, "Quantum algorithms and quantum machine learning for differential equations," 2023.
35. P. Lamichhane and D. B. Rawat, "Quantum machine learning: Recent advances, challenges and perspectives," IEEE Access, 2025.
36. B. K. Behera, S. Al-Kuwari, and A. Farouk, "QSVM-QNN: Quantum support vector machine based quantum neural network learning algorithm for brain-computer interfacing systems," IEEE Transactions on Artificial Intelligence, 2025.
37. Z. Yang, M. Zolanvari, and R. Jain, "A survey of important issues in quantum computing and communications," IEEE Communications Surveys & Tutorials, vol. 25, no. 2, pp. 1059–1094, 2023.
38. A. Zaki et al., "Wireless communication channel scenarios: Machine-learning-based identification and performance enhancement," Electronics, vol. 11, no. 19, p. 3253, 2022.
39. G. Arun and V. Mishra, "A review on quantum computing and communication," in Proc. 2nd Int. Conf. Emerging Technology Trends in Electronics, Communication and Networking (ET2ECN), 2014.

40. M. Benedetti, S. Lloyd, and J. R. McClean, “Parameterized quantum circuits as machine learning models,” Quantum Science and Technology, vol. 4, no. 4, p. 043001, 2019, doi: 10.1088/2058-9565/ab31c2.
41. E. Farhi, J. Goldstone, and S. Gutmann, “A quantum approximate optimization algorithm,” arXiv preprint arXiv:1411.4028, 2014. [Online]. Available: https://arxiv.org/abs/1411.4028
42. A. Das and B. K. Chakrabarti, Quantum Annealing and Related Optimization Methods. Berlin, Germany: Springer-Verlag, 2008.
43. M. Schuld and N. Killoran, “Quantum machine learning in feature Hilbert spaces,” Physical Review Letters, vol. 122, no. 4, p. 040504, 2019, doi: 10.1103/PhysRevLett.122.040504.
44. E. Grant, M. Benedetti, L. Wossnig, and S. Severini, “An initialization strategy for addressing barren plateaus in parameterized quantum circuits,” Quantum, vol. 3, p. 214, 2019, doi: 10.22331/q-2019-12-09-214.
45. M. Broughton et al., “TensorFlow quantum: A software framework for quantum machine learning,” arXiv preprint arXiv:2003.02989, 2020.
46. A. P. Bhatt and A. Sharma, "Quantum cryptography for internet of things security," Journal of Electronic Science and Technology, vol. 17, pp. 213-220, 2019.
47. M. H. Adnan, Z. Ahmad Zukarnain, and N. Z. Harun, "Quantum key distribution for 5g networks: A review, state of art and future directions," Future Internet, vol. 14, p. 73, 2022.
48. V. Scarani, H. Bechmann-Pasquinucci, N. J. Cerf, M. Dušek, N. Lütkenhaus, and M. Peev, "The security of practical quantum key distribution," Reviews of modern physics, vol. 81, pp. 1301-1350, 2009.
49. I. W. Primaatmaja, K. T. Goh, E. Y.-Z. Tan, J. T.-F. Khoo, S. Ghorai, and C. C.-W. Lim, "Security of device-independent quantum key distribution protocols: a review," Quantum, vol. 7, p. 932, 2023.
50. D. Chawla and P. S. Mehra, "A survey on quantum computing for internet of things security," Procedia Computer Science, vol. 218, pp. 2191-2200, 2023.
51. D. Rahmayanti, "Quantum Key Distribution (QKD) as a Wireless Telecommu-nications Security Solution," 2025.
52. E. Zeydan, C. De Alwis, R. Khan, Y. Turk, A. Aydeger, T. R. Gadekallu, et al., "Quantum technologies for beyond 5G and 6G networks: Applications, opportunities, and challenges," IEEE Open Journal of the Communications Society, 2025.
53. M. Z. Ali, A. Abohmra, M. Usman, A. Zahid, H. Heidari, M. A. Imran, et al., "Quantum for 6G communication: A perspective," IET Quantum Communication, vol. 4, pp. 112-124, 2023.
54. O. Bouchmal, B. Cimoli, R. Stabile, J. J. Vegas Olmos, and I. Tafur Monroy, "From classical to quantum machine learning: Survey on routing optimization in 6G software defined networking," Frontiers in Communications and Networks, vol. 4, p. 1220227, 2023.
55. F. Rodríguez-Díaz, D. Gutiérrez-Avilés, A. Troncoso, and F. Martínez-Álvarez, "A survey of quantum machine learning: Foundations, algorithms, frameworks, data and applications," ACM Computing Surveys, vol. 58, pp. 1-35, 2025.
56. R. S. Gupta, C. E. Wood, T. Engstrom, J. D. Pole, and S. Shrapnel, "A systematic review of quantum machine learning for digital health," npj Digital Medicine, vol. 8, p. 237, 2025.
57. S. Anand, "Quantum Computing for Large-Scale Healthcare Data Processing: Potential and Challenges," International Journal of Emerging Trends in Computer Science and Information Technology, vol. 4, pp. 49-59, 2023.
58. D. Zhu, H. Zhou, Z. Zhou, J. Wu, and J. Zhao, "Quantum key-based medical privacy protection and sharing scheme on blockchain," Scientific Reports, vol. 15, p. 27983, 2025.
59. N. Jeyaraman, M. Jeyaraman, S. Yadav, S. Ramasubramanian, and S. Balaji, "Revolutionizing healthcare: the emerging role of quantum computing in enhancing medical technology and treatment," Cureus, vol. 16, 2024.

60. X. Lv, S. Rani, S. Manimurugan, A. Slowik, and Y. Feng, "Quantum-inspired sensitive data measurement and secure transmission in 5G-enabled healthcare systems," Tsinghua Science and Technology, vol. 30, pp. 456-478, 2024.
61. S. Pirandola et al., "Advances in quantum cryptography," Advances in Optics and Photonics, vol. 12, no. 4, pp. 1012–1236, 2020.
62. M. Schuld and F. Petruccione, Supervised Learning with Quantum Computers, vol. 17. Berlin, Germany: Springer, 2018.
63. C. J. Chunnilall et al., "Quantum Key Distribution (QKD); components and internal interfaces," ETSI Group Report QKD 003, Mar. 2018.
64. S. Wehner, D. Elkouss, and R. Hanson, "Quantum internet: A vision for the road ahead," Science, vol. 362, no. 6412, p. eaam9288, 2018.
65. P. Kairouz and H. B. McMahan, "Advances and open problems in federated learning," Foundations and Trends in Machine Learning, vol. 14, no. 1–2, pp. 1–210, 2021.
66. A. Mathur, A. Gupta, and S. K. Das, "When federated learning meets quantum computing: Survey and research opportunities," IEEE Communications Surveys & Tutorials, vol. 28, pp. 1351–1380, 2025.
67. N. Sivamangai, R. Naveenkumar, N. M. Kishore, C. Lingesh, A. Napolean, and U. Annamalai, "Quantum Computing Transforming Machine Learning: An Overview," *Quantum Computing,* pp. 19-54, 2026.

Appendix I

Abbreviations	Description
AI	Artificial Intelligence
ML	Machine Learning
QML	Quantum Machine Learning
QC	Quantum Communication
QKD	Quantum Key Distribution
QSVM	Quantum Support Vector Machine
QNN	Quantum Neural Network
QDT	Quantum Decision Tree
FL	Federated Learning
IoT	Internet of Things
DL	Deep Learning
QAOA	Quantum Approximate Optimization Algorithm
QIML	Quantum-inspired machine learning
TFQ	TensorFlow Quantum