# Quantum Intelligence Networks: Integrating Communications into Learning

Bhaskara Narottama, *Member, IEEE,* Anal Paul, *Member, IEEE,* Keshav Singh, *Member, IEEE,* Simon L. Cotton, *Fellow, IEEE,* Hyundong Shin, *Fellow, IEEE,* Trung Q. Duong, *Fellow, IEEE*

***Abstract*—This article introduces quantum intelligence networks (QINs): large-scale, autonomous networks of quantum-enabled learning entities with varied architectures, interconnected through quantum communications, processing multiple types of data. While we witness unprecedented developments in quantum-enabled learning, most studies assume that each of the learning models works individually, overlooking the potential for collaboration through non-centralized information exchange. Furthermore, we strongly advocate that it should not rely exclusively on classical information exchange, due to the rising security concerns posed by quantum algorithms. To address this pressing need, this article calls for the development of QINs, first highlighting the importance of integrating quantum communications into learning, and then detailing the necessary quantum communication protocols. Subsequently, it discusses the realization of QINs, summarizing relevant practical approaches, and highlighting their feasibility. As the development of QINs gains prominence, collective efforts will be essential. To help catalyze this activity, we point out some prospective research directions.**

***Index Terms*—Quantum communications; quantum computing; quantum machine learning; secure communications.**

## I. Introduction

B. Narottama is with the Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, NL A1C 5S7, Canada (e-mail: bnarottama@mun.ca).

A. Paul is with the Department of Computer Science and Engineering, Yuan Ze University, Taoyuan 320315, Taiwan (e-mail: apaul@saturn.yzu.edu.tw).

K. Singh is with the Institute of Communications Engineering, National Sun Yat-sen University, Kaohsiung 804, Taiwan (e-mail: keshav.singh@mail.nsysu.edu.tw).

S. L. Cotton is with the Centre of Wireless Innovation (CWI), School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, Belfast, U.K (e-mail: simon.cotton@qub.ac.uk).

H. Shin is with the Department of Electronics and Information Convergence Engineering, Kyung Hee University, 1732 Deogyeong-daero, Giheung-gu, Yongin-si, Gyeonggi-do 17104, Republic of Korea (e-mail: hshin@khu.ac.kr).

T. Q. Duong is with the Faculty of Engineering and Applied Science, Memorial University, St. John's, NL A1C 5S7, Canada, and with the Centre of Wireless Innovation (CWI), School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, Belfast, U.K, and also with the Department of Electronic Engineering, Kyung Hee University, Yongin-si, Gyeonggi-do 17104, South Korea (e-mail: tduong@mun.ca).

The work of T. Q. Duong was supported in part by the Canada Excellence Research Chair (CERC) Program CERC-2022-00109, in part by the Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery Grant Program RGPIN-2025-04941, and in part by the NSERC CREATE program (Grant number 596205-2025). The work of S. L. Cotton was supported by the U.K. Engineering and Physical Sciences Research Council (EPSRC) through the EPSRC Hub on All Spectrum Connectivity under Grant EP/X040569/1 and Grant EP/Y037197/1. The work of H. Shin was supported in part by National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (RS-2025-00556064).

Corresponding authors are Trung Q. Duong and Hyundong Shin.

RECENT years have witnessed rapid advancements in quantum computing, as reflected in the growing number of logical qubits, and quantum computing servers all around the globe. These developments have driven the practical utilization of quantum computing and, in tandem with the widespread use of artificial intelligence (AI), facilitated quantum-enabled learning, giving rise to emerging learning categories such as hybrid quantum-classical learning and quantum reinforcement learning. i) *Hybrid quantum-classical learning.* Notably, quantum-enabled learning is comprised of not only pure quantum learning models, but also hybrid quantum-classical architectures, benefiting from the computational potential of quantum models and the practicality of classical models, supported by extensive software libraries, such as those used in large language models (LLMs). It is possible to leverage classical models, such as graph neural networks, to extract inherent features from datasets, and subsequently use quantum learning models, such as variational quantum circuits, to perform classification tasks. Such hybrid architectures are gaining prominence, especially in wireless communications, where they are employed to optimize communication systems, improving their performance, e.g., reducing block error rates. Thus, these architectures alleviate the constraints of early quantum processing systems, including the limited number of logical qubits. Of note, [1] employs classical dense layers for reducing data dimensionality, and subsequently, utilizes variational quantum circuits to process the multi-modal relations between different information aspects, particularly visuals and acoustics, aiming to detect emotional sentiments, such as sarcasm. ii) *Quantum reinforcement learning.* Quantum reinforcement learning comprises agents which learn through iterative interactions with their respective environments, executing sets of actions, and receiving rewards as feedback. In this sense, it employs quantum learning models for different purposes, such as representing learning agents, in which outputs can be directly translated into action spaces. They can also optimize reward functions, as used in quantum inverse reinforcement learning. Although designing reward functions is typically done manually, this approach might prove ineffective when the behavior of the complex environment is only partially known, as in the case of strategic market bidding [2].

While the aforementioned categories mostly deal with the architectures and learning paradigms of quantum-enabled learning, we are convinced that the next generation of quantum-enabled learning must move beyond isolated learning models, as the collaborations between them offer significant benefits such as enhanced learning convergence and data privacy. This leads us to the third category: iii) *Quantum-enabled collaborative learning.* Multiple quantum and classical learning models have been used within quantum-enabled collaborative learning frameworks. Such collaborations prominently revolve around model or data aggregation, with approaches such as quantum federated and ensemble learning being advocated, as well as the interplay between quantum learning models and evolutionary algorithms. For instance, the work in [3] highlights the use of evolutionary algorithms to optimize quantum gate arrangements, which in turn affect the circuit depth of quantum learning models. Not to mention, this notion can be extended to meta-learning settings, in which evolutionary algorithms, such as multi-objective quantum genetic algorithms [4], optimize the hyper-parameters of multiple quantum neural network models, especially regarding their number of layers. While most studies on quantum-enabled collaborative learning focus on the algorithms, recent studies now account for the communication exchanges within it.

### A. Challenges and Opportunities in Quantum-Enabled Collaborative Learning

*1) Information Exchange Between Different Quantum Learning Models:* There is growing interest in developing different types of information or knowledge to be exchanged within quantum-enabled collaborative learning, as now multiple learning units are used, instead of solely relying on a centralized learning unit. In addition to widely-studied scenarios, such as federated learning, the merits of quantum collaborative learning are apparent in knowledge distillation. In a quantum-enabled collaborative learning system with multiple learning models, it is conceivable to have learning models with differing computational capabilities. The models with augmented prediction capabilities, characterized with a higher number of quantum gates and qubits, tend to be computationally taxing and, thereby, take longer to be trained, contributing to training latencies. On the other hand, models with lower computational capabilities are ideal for tactile and time-sensitive predictions, as the lower training latencies compensate for the accuracy trade-offs. During the training, models of the former type (known as the "teachers") assist the models of the latter type (known as the "students"), facilitating knowledge distillations. This notion can subsequently be broadened. Knowledge distillations can be used to optimize distinct optimization variables, and even to address multi-objective optimizations.

As illustrated in Fig. 1, a less complex model, used to optimize a particular variable, facilitates the training of a more complex model, optimizing two variables. In this particular context, a trained learning model responsible for a static base station, assists in training another model responsible for a moving base station, where the latter's movements need to be optimized as well. It is likewise feasible to apply knowledge distillation to multiple student models, wherein aggregate operations, akin to those of federated learning, serve to combine the outputs of multiple student models. In the context of quantum intelligence networks (QINs), a network with trained models and hyper-parameters, e.g., the maximum number of qubits used for communications, may, in turn, train other networks. Among other scenarios, user positioning in particular would benefit from this approach, as one model-processing transmitter node may "teach" another to identify user positions within its own area [5].

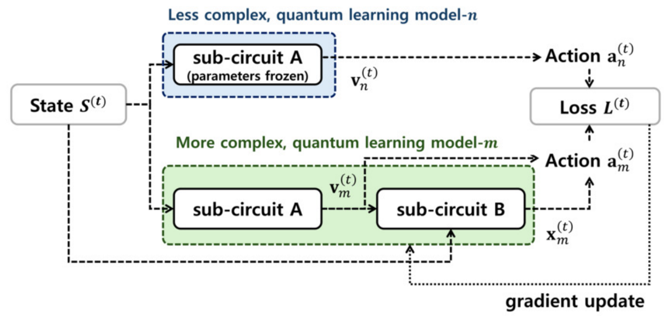


Fig. 1: A proposition for employing knowledge distillation across multiple optimization variables. We assume two distinct learning models, each computed by different quantum processors. The less complex model yields the first variable $\mathbf{v}_n^{(t)}$, while the more complex model is tasked with optimizing both the first and the second variables, $\mathbf{v}_m^{(t)}$ and $\mathbf{x}_m^{(t)}$, respectively.

*2) Security Vulnerabilities:* Nevertheless, current developments in quantum-enabled collaborative learning mostly center on what information to exchange or distill (for instance, either the models' gradients or output responses) rather than on the medium and the method of sharing. Consequently, developments in quantum-enabled collaborative learning remain largely dependent on classical communication for information exchange, bringing forth tangible security risks, as identified next.

i) *Model extractions.* There exist possibilities for adversaries to illegitimately extract information about learning models, such as the model parameters, the operations used, and the depth of the models, thereby attempting to construct imitations of the originals, and replicating their responses. Such risks are particularly apparent in classical federated learning, where centralized servers typically aggregate the gradients from the distributed, locally-positioned learning units. To illustrate, at each learning iteration, the aggregated gradient can be calculated as a weighted average of the gradients sent by a number of distributed units, with each unit's contribution being determined by its corresponding weight coefficient. The server sends the global model as feedback to the distributed units, possibly via widely-used transport layer protocols, such as TCP. From this process, the eavesdropper may attempt to gain information about the global model, exploiting the training effort to mimic its outputs. In fact, when we consider trained models as an intellectual property (IP), owing to their capacity to generate proprietary content, as in large language models (LLMs), such attempts may be directed towards stealing the ownership of federated learning models. Unfortunately, current quantum federated learning frameworks remain exposed to these attacks, as model information exchanges are typically done through classical channels.

ii) *Model and data poisoning.* Attackers may impersonate legitimate distributed units, or manipulate them, subsequently feeding malicious training data for the distributed learning frameworks. In federated learning, they may also send false gradients to the server, sabotaging the learning process, and ultimately rendering the trained model worthless ineffective. While the impact of such attacks may be alleviated by methods such as label outlier detections, their implementation becomes increasingly computationally demanding, particularly when dealing with a larger number of attackers and extensive non-independent and identically distributed (non-IID) datasets. Such datasets can be generated via learning processes, particularly Bayesian optimizations, aimed at diminishing the performance of a target model. From an attacker's perspective, they strive to maximize the training loss pertinent to the legitimate node's model, leveraging the adversarial model. As the majority of their datasets consist of classical values, current quantum learning models are not immune to poisoning attacks, motivating the use of quantum data.

### B. *QINs and Key Takeaways*

Considering the evident limitations of classical information exchange, it is quite surprising that quantum communications remain underexplored for connecting both quantum and classical models. In response to this, we envisage the emergence of QINs, where seamless quantum information exchanges occur between learning models. We define QIN as a system of connected nodes capable of processing quantum-based computations (for instance, implementing quantum gates and circuits) and participating in quantum communication protocols (for example, distributing and/or receiving entanglement pairs). Such a network may assign distinct roles for different nodes, such as acting as the orchestrator or operating the fusion model, as illustrated later in Fig. 5. In this regard, a QIN can govern both its learning and communication processes to satisfy KPIs while respecting constraints. For instance, when the end-to-end latency increases due to the arrival of new devices, the network can reduce the frequency of learning updates to maintain low-latency communication. Thus, QINs address both the networking and learning aspects, functioning as unifying structures in which ad-hoc, distributed quantum-enabled learning workflows are incorporated. QINs also allow closed-loop quantum information exchange between learning nodes. In contrast, current distributed quantum-enabled learning workflows typically assume classical information exchange, which possibly requires measurements, and thereby leads to collapse of superposition and lose of entanglement. Departing from typical distributed architectures, where groups of learning entities operate independently, QINs connect different distributed computing systems. Integrating multiple architectures into a cooperative environment, a QIN facilitates i) transfer learning to other sets of nodes, and ii) access to diverse data modalities that support model generalization.

To this end, this article charts the developments of QINs, as a novel research direction, offering the following key takeaways. First, it provides *a concise guide to integrate quantum communications and learning.* In Section II, key quantum communication protocols are discussed, curated based on their potential to facilitate secure information exchange between models in quantum-enabled learning. It also elaborates on important approaches pertinent to connecting quantum and classical learning models, in Section III. Second, it discusses *the realizations of QINs.* In particular, Section IV highlights some the milestones which must be hit along the way towards self-managed QINs. Finally, it provides some prospective research directions in Section V.

## II. Utilizing Quantum Communication Protocols

Quantum communication represents a transformative shift in secure communication, exploiting the fundamental principles of quantum mechanics. It enables the development of communication protocols offering unprecedented security, particularly against the potential threats posed by quantum computing.

### A. *A Recap on Quantum Technologies*

Quantum technologies exploit quantum mechanical phenomena such as superposition, entanglement, and quantum coherence to improve computational and communication capabilities. Ongoing projects in integrated photonics, superconducting circuits, and ion-trap platforms illustrate the diverse approaches undertaken to achieve robust and scalable quantum devices.

*1) Quantum Bits and Superpositions:* Unlike classical bits, which exist exclusively in binary states of 0 or 1, quantum bits, or qubits, can simultaneously exist in a superposition of these states. The property of superposition enables quantum computers to encode and process exponentially more information compared to classical systems. This benefit is further accentuated in many-body systems, where multiple qubits can be entangled and collectively manipulated.

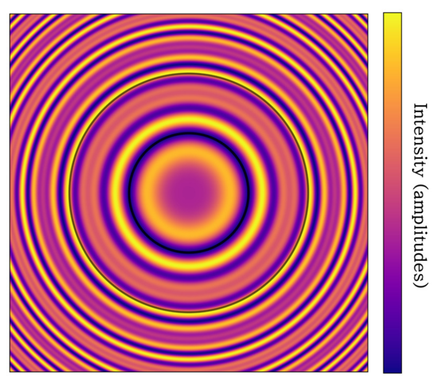


Fig. 2: A two-dimensional interference pattern generated from sine and cosine waves, illustrating quantum superposition, with the color bar mapping the wave's intensity, transitioning from negative to positive amplitudes, ranging from purple to yellow.

In Fig. 2, two wave components (one sine-based and one cosine-based) combine to form concentric rings, representing regions of constructive and destructive interference. This interplay mirrors the behavior of quantum superposition, where a qubit can be in a state that is a linear combination of its basis states. A qubit state is often written in terms of sine

"$\sin(\cdot)$" and cosine "$\cos(\cdot)$" functions, corresponding to the complex probability amplitudes of the basis states $|0\rangle$ and $|1\rangle$, with the relative phase $\phi$ and the angle $\theta$, as in $\cos\left(\frac{\theta}{2}\right)|0\rangle$ and $e^{i\phi}\sin\left(\frac{\theta}{2}\right)|1\rangle$. The interference between these amplitudes, akin to the combination of our sine and cosine waves, gives rise to the complex patterns observed, in Fig. 2. The color bar to the right, which spans from negative (purple) to positive (yellow) amplitudes, provides a quantitative mapping of the wave's intensity. The black circles mark shells of equal radius, evoking layers of constant amplitude similar to radial probability distributions in quantum systems. Besides capturing the core idea of quantum superposition, this visualization also illustrates how qubits can encode exponentially more information than classical bits.

*2) Quantum Gates:* Quantum gates are fundamental units for manipulating qubits and orchestrating quantum computations by precisely transforming quantum states. Prominent examples along with their use include: the Hadamard (H) gate, used to create and undo superposition; the controlled-*NOT* (CNOT) gate, essential for creating and managing entanglement; the Pauli-X (NOT) gate, used to flip the state of a single qubit, mirroring the classical *NOT* operation; and the Pauli-Z (phase flip) gate, used to impart a phase shift of $\pi$ to the $|1\rangle$ state, without altering $|1\rangle$. These gates form the building blocks of quantum circuits, enabling the execution of complex algorithms.

*3) Quantum Measurement:* Quantum measurement is the process by which a qubit's quantum state collapses from a superposition into a definite outcome, typically one of the standard basis states. Consider a qubit initially prepared in a superposition of the states $\alpha|0\rangle$ and $\beta|1\rangle$: If we measure this qubit in the computational (Z) basis, $\{|0\rangle, |1\rangle\}$, the measurement outcome would be randomly observed as "0," with probability $|\alpha|^2$, or "1" with probability $|\beta|^2$. Accordingly, the post-measurement state of the qubit collapses to $|0\rangle$, if the measurement outcome is "0," or to $|1\rangle$, if the outcome is "1." Consequently, the original superposition of the qubit is irreversibly lost. In more concrete terms, suppose a particular qubit is in the superposition of the states $\frac{1}{\sqrt{2}}|0\rangle$ and $\frac{1}{\sqrt{2}}|1\rangle$; measuring it in the computational basis implies there is a 50% chance of observing the readout as "0," and a 50% chance of detecting "1." Once the measurement is done, the qubit collapses to whichever state was observed, losing the balanced superposition. Consequently, if a third party (which, in this case, is an eavesdropper) intercepts and measures qubits sent over a quantum channel, they would inevitably disturb this state. In a typical quantum key distribution scenario, this disturbance manifests as detectable anomalies in the measured error rates.

*4) Quantum Entanglement-Based Protocols:* In entanglement-based approaches, two parties share an Einstein-Podolsky-Rosen (EPR) pair, a special class of correlated quantum states, enabling advanced functionalities such as quantum teleportation and secure key generation. When one qubit in an entangled pair is measured, the joint state collapses, instantly affecting the potential outcomes of the other qubit. This characteristic facilitates robust intrusion detection: any adversarial measurement modifies the expected correlations, thereby alerting legitimate users to the presence of an eavesdropper.

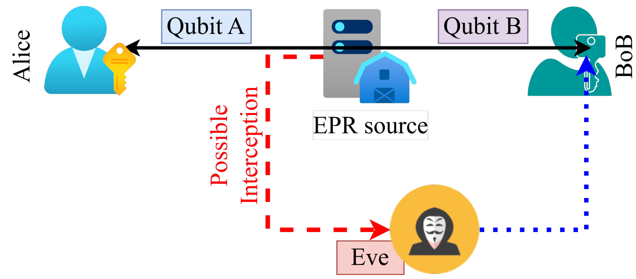


Fig. 3: An EPR source producing two correlated qubits, A and B. Alice receives qubit A, and Bob receives qubit B. Any interception by Eve disrupts the entanglement, enabling the detection of the eavesdropping activity.

*An Illustrative Example:* Let us suppose that Alice and Bob share a Bell state, which is in the superposition of the states $\frac{1}{\sqrt{2}}|00\rangle$ and $\frac{1}{\sqrt{2}}|11\rangle$. Here, neither qubit A (held by Alice) nor qubit B (held by Bob) individually resides in a definite basis state. Instead, both are perfectly correlated. If Alice measures her qubit in the computational (Z) basis and observes $|0\rangle$, the total wavefunction collapses, forcing Bob's qubit to be $|0\rangle$. Conversely, if her measurement yields $|1\rangle$, Bob's qubit is projected into $|1\rangle$.

Figure 3 illustrates an eavesdropping activity, where an eavesdropper (Eve) intercepts Bob's qubit and performs an unauthorized measurement. The entangled pair is unavoidably disturbed, introducing anomalies in the measured correlations. During subsequent reconciliation over a classical channel, Alice and Bob detect these discrepancies, deducing the presence of Eve.

### *B. Different Quantum Communication Protocols*

Quantum communication protocols employ the core properties of quantum mechanics, such as superposition, entanglement, and the no-cloning principle, to facilitate secure and efficient information transmission. They are broadly categorized by their specific operational goals, ranging from direct quantum state transfers, e.g., as in quantum teleportation, to secure key generations, e.g., as in quantum key distributions (QKDs), and, eventually, to large-scale networking via quantum repeaters. Substantial progress in experimental demonstrations, including fiber-based and satellite-based implementations, has validated the feasibility of such protocols over increasing distance [6].

*1) Quantum Teleportation:* Quantum teleportation provides a powerful method for transmitting an unknown quantum state between distant parties, given a pre-shared entanglement pair and classical communication channels. Suppose Alice and Bob each hold one half of an entangled pair, typically in a Bell state conveyed as the superposition of the states $\frac{1}{\sqrt{2}}|00\rangle$ and $\frac{1}{\sqrt{2}}|11\rangle$. Alice performs a joint Bell measurement on the quantum state she wishes to teleport and her portion of the entangled pair, collapsing these two qubits into one of four possible Bell states. She then sends the corresponding two classical bits to Bob, who applies a unitary operation to his qubit to recover the original state.

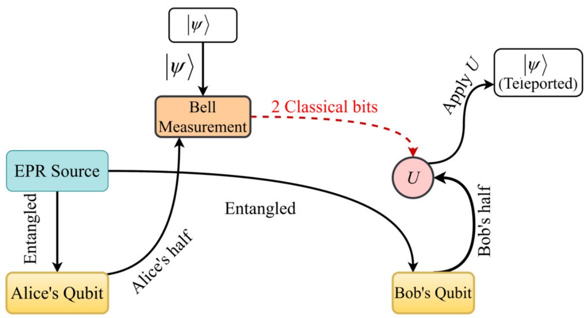


Fig. 4: Illustration of quantum teleportation. An EPR source provides two entangled qubits, one for Alice and one for Bob. Alice performs a Bell measurement on the qubit she wishes to teleport, denoted as $|\psi\rangle$, along with her share of the entangled pair, then transmits two classical bits of measurement information to Bob. Using these bits, Bob then applies an appropriate unitary $U$ to his qubit, to recover the original state $|\psi\rangle$, previously unknown to him.

In Fig. 4, an EPR source produces two entangled qubits, with Alice and Bob each receiving one. Alice has a separate, unknown qubit $|\psi\rangle$ that she wishes to transfer to Bob. She performs a Bell measurement on her entangled qubit and the unknown qubit, collapsing both into one of four possible Bell states. The outcome of this measurement, encoded in two classical bits, is sent to Bob through a standard communication channel. Bob then applies the corresponding unitary operation $U$, which can, for example, be a combination of Pauli $X$ and $Z$ gates, to his qubit, thus reconstructing the original state $|\psi\rangle$ perfectly. Alice's measurement simultaneously destroys her copy of $|\psi\rangle$, consistent with the no-cloning theorem, thereby ensuring that the state has, in effect, been "teleported" from her location to Bob's. This method eliminates the need to physically transport the quantum system itself, relying instead on entanglement and minimal classical communications.

*2) Quantum Key Distribution:* QKD is dedicated to creating cryptographic keys with security rooted in physical laws rather than computational complexity. Protocols like BB84 [7] exploit superposition to encode bits in different polarization or phase bases. Any eavesdropper's (Eve's) attempt to intercept qubits causes a detectable disturbance due to the measurement-induced collapse, thus alerting Alice and Bob of potential intrusion. In this context, the quantum bit error rate (QBER), which is generally calculated as the number of errors against the count of the transmitted qubits, serves as a practical metric for quantifying such disturbances. In particular, when the QBER remains below a prescribed threshold, Alice and Bob can apply error correction and privacy amplification procedures to extract a shared secret key with provably high-security levels. Moreover, field implementations in various countries demonstrate the practicality of metropolitan-scale QKD networks. Furthermore, in larger networks, multiple nodes can share entangled resources to perform multi-party tasks such as conference key agreement, secure voting, or distributed quantum computation. Free-space and satellite channels further extend coverage, overcoming the terrestrial limitation of fiber-based links and enabling truly intercontinental quantum networks.

### C. Security Aspects of Quantum Communications

Quantum communication inherently provides robust security guarantees far superior to classical cryptographic techniques, primarily owing to fundamental quantum mechanical properties. Notably, any attempt to measure or replicate quantum states without authorization directly impinges on their delicate superposed or entangled natures, instigating detectable disturbances. As quantum technologies mature, these built-in defense mechanisms become increasingly vital in safeguarding sensitive data, ranging from financial transactions to government communications and beyond.

*1) No-Cloning Theorem:* The no-cloning theorem, a cornerstone of quantum mechanics, establishes that unknown quantum states cannot be duplicated precisely. This crucial quantum property ensures that any illicit interception and copying of quantum information inevitably introduces detectable anomalies, providing an intrinsic mechanism for safeguarding communication confidentiality against eavesdropping attempts. Violations of this principle would compromise quantum security, but are forbidden by the laws of quantum mechanics. This principle underpins the security of QKD and other quantum communication protocols, since any adversarial intervention leaves a traceable footprint in the communication channel's measurement statistics.

*2) Post-Quantum Cryptography:* While quantum communication protocols inherently resist quantum computational attacks, practical deployment demands complementary security measures. Post-quantum cryptography explores cryptographic methods anticipated to withstand quantum computational threats, effectively integrating classical and quantum security paradigms. Techniques employed include lattice-based cryptography, code-based cryptography, and multivariate cryptography, each tailored to resist quantum-enabled adversaries and to fortify future-proof secure communication infrastructures.

## III. Approaches to Connecting Quantum and Classical Learning Models

*The use of quantum data.* While post-quantum cryptography may enhance the security of classical-valued data exchanges, they remain vulnerable to attacks like data poisoning, as discussed in Sub-subsection I-A2. Accordingly, studies have discussed the use of quantum data for training, opening possibilities for further computational benefits. Notably, [8] demonstrates how quantum data, generated through quantum clusters, can be useful for federated learning. Furthermore, complex information from quantum devices, such as those used for quantum sensing and metrology, can be processed directly as quantum data. When using quantum data is not possible (due to the challenges in data storage, among other factors) one alternative is to encode classical data using quantum computing before transmitting it through classical channels. This notion is likewise applicable in quantum federated learning, as shown in [9], in which classical datasets are

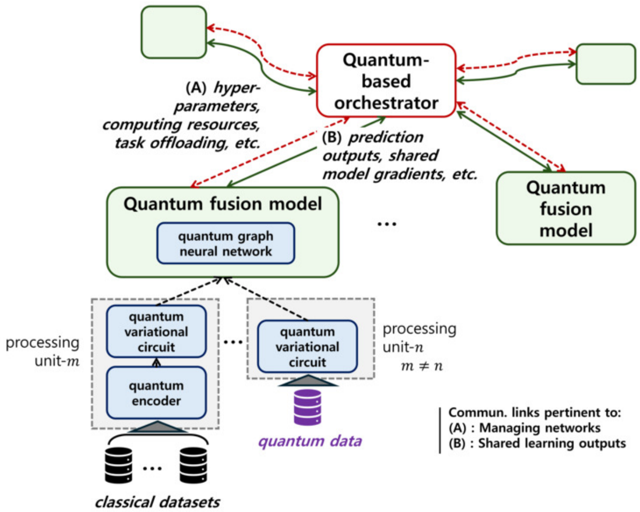


Fig. 5: A portrayal of QINs, where a quantum-based orchestrator oversees several model aggregators, blending the outputs of several processing units. Note that either classical or quantum data can be used in the learning processes: The orchestrators initiate the learning tasks, and manage the computing and communication resources. The aggregators then share the learning outcomes, including prediction results and aggregated gradients.

first mapped to Hilbert spaces using locally processed quantum encoding operations.

*Distinct quantum models with differing roles.* The rapid developments of various quantum learning models offer the possibility to integrate differing functions within QINs, as illustrated in Fig. 5. First, sourcing both classical data, e.g., from internet-of-things sensors, and quantum data, e.g., from quantum sensing, opens the possibility of using different sets of data from different domains to improve prediction. This allows us leverage quantum graph neural networks for fusion models, acting as aggregators that extract the inherent relationship between data features. Second, quantum-enabled orchestrators can (A) manage the aggregators, optimizing their hyper-parameters as in meta-learning, and (B) share the prediction outputs between them. For such tasks, the orchestrator may utilize quantum inverse reinforcement learning, aiming to optimize its reward functions according to the aggregators' learning progressions. In practice, employing quantum-enabled orchestrators affords the model-processing nodes to optimize the task and communication load (such as the number of training episodes and the size of datasets, respectively) based on the pertaining metrics such as buffer size, current average latency, and even the possible presence of eavesdroppers.

*Employing multiple quantum communication channels.* Different communication channels can be used for distinct communication purposes, using different channels for (A) managing the aggregators and (B) sharing the prediction outputs. To support such tactile quantum communications, protocols (primarily those based on multipartite entanglements) must be designed to address specific layers and functions: for instance, communication synchronizations are ensured using one-way and two-way time protocols [10], whereas those of the quantum link layer, can handle entanglement generations and fidelity, facilitating quantum communications.

## IV. Beyond Quantum Internet

It is worth highlighting that the notion of interconnected quantum communication nodes, referred to as the quantum internet, has garnered considerable advocacy. While the standardization of quantum communications is yet to be achieved, we contend that progression through the following stages will be essential for realizing QINs. i) We are currently at the first stage, wherein quantum communication protocols operate between a single sender and a single receiver. While this offers enhanced security, among other attributes, prominent studies strongly encourage advancing beyond one-to-one (or peer-to-peer) quantum communications. ii) The second stage requires advancing interconnected quantum communication nodes, shifting toward the quantum internet. As the natural transition from one-to-one quantum communications, this stage will see multiple nodes interconnected, allowing broader transmission scenarios such as broadcasting. This stage shall witness the development of a range of quantum communication equipment and protocols, such as quantum repeaters and quantum routing. iii) The third stage is expected to usher in QINs, marked by rapid developments in quantum processing units, potentially scaled to reduce footprints, allowing for placement closer to the end user, akin to edge processing units of current classical communication networks. The use of entangled quantum data, shall facilitate reductions in training latencies. As discussed in Section III, QINs can facilitate the exchange of quantum data via multiple quantum communication channels, potentially preserving properties such as superposition and entanglement, instead of sending them as classical information. Beyond conventional distributed architectures, QINs' offers self-orchestration capabilities that support challenging functions such as i) optimizing number of qubits utilization in non-centralized workflow and ii) managing parameter updates in hybrid quantum-classical learning. iv) We anticipate self-managed QINs at the fourth stage. At this later stage, QINs shall eventually be managed and maintained by quantum-enabled learning entities, facilitating tactile decision-making and seamless operations. Such networks will also benefit from developments in quantum actuators, receiving feedback in quantum-based information, allowing coherent quantum systems. As illustrated in Fig. 5, quantum-based actuators manage the QINs. Common security threats present in any communication networks can also be addressed in QIN using known approaches. For instance, distributed denial-of-service (DDoS) attacks may be mitigated by data rate throttling, while model poisoning may be addressed by authenticating and verifying parameter updates via key distribution protocols, ensuring that models can only be modified by trusted nodes. Such security improvements are increasingly important as i) current quantum-classical learning workflows exploit classical datasets and parameter optimization algorithms, and ii) circuit model parameters are typically stored as classical values.

The growing prominence of hybrid quantum-classical learning (recall Section I), requires seamless information exchanges

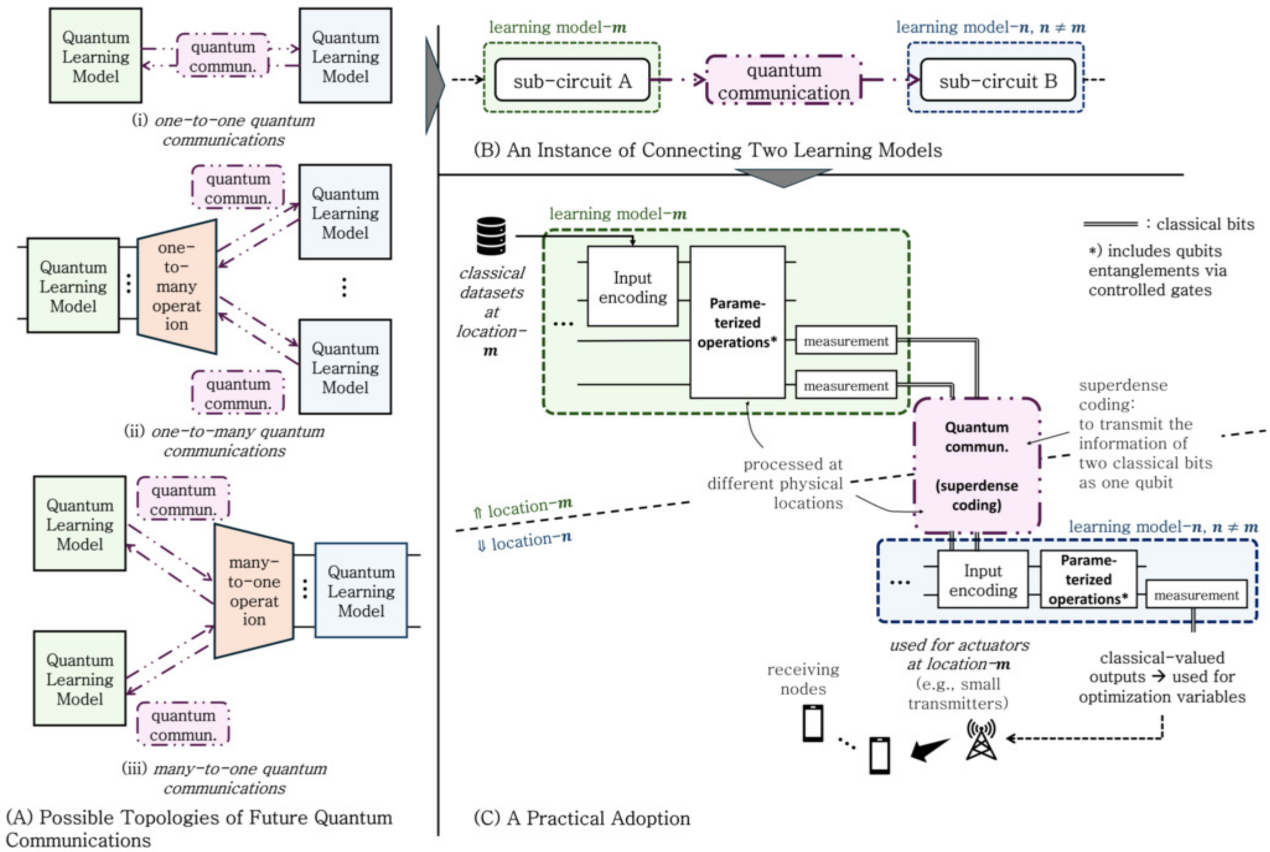


Fig. 6: Possible quantum communication topologies for QINs include i) one-to-one communications between two learning models, ii) one-to-many operations, where a supplemental operation distributes the outputs or the parameters of a quantum learning models, and iii) many-to-one communications, in which the outputs or parameters of several quantum learning models are aggregated into a singular model. In support of this, (B) illustrates the notion of employing quantum communications to connect two quantum circuits, each of which corresponds to a learning model. This is specified in (C), where superdense coding connects two learning models computed in different locations, allowing the datasets stored in one site to be used to optimize the variables of the actuators placed away.

between multiple quantum and classical processing units. The inclusion of classical learning models allows legacy nodes (i.e., those that can only process classical information) to store classical datasets, and make predictions based on them, while considering measures relevant to both quantum and classical platforms, such as model trainability, expressibility, and learning latency. Consequently, QINs must effectively handle classical and quantum information flows. In support of this, several routing protocols, especially Chiral quantum routing [11], have been developed. Similar to classical-processing nodes, computational loads can be managed between quantum-processing nodes handling similar learning tasks, mitigating bottleneck and thus minimizing latency, by employing methods akin to user association and clustering [12].

In the future, this calls for the readiness of the quantum communication physical layer, including essential devices, such as repeaters and routers, while tripartite quantum entanglement can be considered for facilitating multi-node quantum communications. These models can be interconnected in different topologies, including one-to-many and many-to-one configurations, as illustrated in Fig. 6. Ideally, QINs would operate on nodes that are able to fulfill the roles of entanglement distributors, routing controllers, learning model processors, parameter trainers, and hyperparameter tuners. Furthermore, to add an extra layer of security, mainly on the side of classical processing units, post-quantum security can be improved by developing encryption methods that are not potentially vulnerable to quantum algorithms. In this regard, non-commutative cryptography methods, such as those using braid groups, can be accounted as viable approaches [13].

## V. Conclusion and Prospects

Through this article, we advance the realization of QINs, by discussing possible quantum communication protocols and quantum-enabled learning approaches that drive their realizations. Subsequently, we show that self-managed QINs are indeed the ideal technology to strive for, as they facilitate autonomous operations. We then present important research directions to stimulate the collaborations that will be needed between fields, to make QINs a reality. In the future, QINs will be able to facilitate the formation of private networks, which will be attractive to government, allowing them to control access to data lakes and nodes, akin to today's private 5G networks. Moreover, QINs will benefit from incorporating learning models processed by low-earth orbit satellites as well, which will be vital for managing non-terrestrial networks, meteorology, and military purposes, e.g., surveillance. Regarding network security, the availability of quantum-classical links will facilitate the development of quantum-classical cryptographic methods, such as in hybrid key distribution protocols [14]. Such a direction will enrich emerging directions such as symbiotic blockhain consensus [15]. These consensus may particularly include both classical-processing and quantum-processing blockchain nodes, where information are distributed among quantum nodes using QKD, and among classical nodes leveraging post-quantum encryption methods, such as those based on lattice constructions. As a final point, it is imperative that directives facilitating the quantum technologies pertinent to QINs, towards materializing the stages outlined in Section IV, are pursued. We assert that standardization efforts, such as IEEE's P1913: Software-Defined Quantum Communication, are vital for the commercialization of QINs, and as such, we encourage the formation of working groups dedicated to them, especially those relevant to quantum communications, electronics, and computing architectures.

## References


[1] A. Phukan, S. Pal, and A. Ekbal, "Hybrid quantum-classical neural network for multimodal multitask sarcasm, emotion, and sentiment analysis," *IEEE Trans. Comput. Social Sys.*, vol. 11, no. 5, pp. 5740–5750, Oct. 2024.

[2] H. Guo, Q. Chen, Q. Xia, and C. Kang, "Deep inverse reinforcement learning for objective function identification in bidding models," *IEEE Trans. Power Sys.*, vol. 36, no. 6, pp. 5684–5696, Nov. 2021.

[3] J. Ur Rehman, M. S. Ulum, A. W. Shaffar, A. A. Hakim, Mujirin, Z. Abdullah, H. Al-Hraishawi, S. Chatzinotas, and H. Shin, "Evolutionary algorithms and quantum computing: Recent advances, opportunities, and challenges," *IEEE Access*, vol. 13, pp. 16 649–16 670, Jan. 2025, DOI: 10.1109/ACCESS.2025.3530952.

[4] L. He and W. Wang, "Design optimization of public building envelope based on multi-objective quantum genetic algorithm," *J. Building Eng.*, vol. 91, p. 109714, Aug. 2024.

[5] X. Zhang, H. Zhang, L. Liu, Z. Han, H. V. Poor, and B. Di, "Target detection and positioning aided by reconfigurable surfaces: Reflective or holographic?" *IEEE Trans. Wireless Commun.*, vol. 23, no. 12, pp. 19 215–19 230, Dec. 2024.

[6] S.-K. Liao, W.-Q. Cai, W.-Y. Liu, L. Zhang, Y. Li, J.-G. Ren, J. Yin, Q. Shen, Y. Cao, Z.-P. Li *et al.*, "Satellite-to-ground quantum key distribution," *Nature*, vol. 549, no. 7670, pp. 43–47, Sep. 2017.

[7] C. H. Bennett and G. Brassard, "Quantum cryptography: Public key distribution and coin tossing," *Theoretical Comput. Sci.*, vol. 560, pp. 7–11, Dec. 2014.

[8] M. Chehimi and W. Saad, "Quantum federated learning with quantum data," in *Proc. IEEE Int. Conf. Acoustics, Speech, Sig. Process.*, 2022, pp. 8617–8621.

[9] R. Huang, X. Tan, and Q. Xu, "Quantum federated learning with decentralized data," *IEEE J. Sel. Topics Quantum Electron.*, vol. 28, no. 4, pp. 6 500 110–6 500 110, Jul. 2022.

[10] N. S. Azahari, N. Z. Harun, C. Chai Wen, S. N. Ramli, and Z. Ahmad Zukarnain, "Review of clock synchronization in quantum communications," in *Proc. Int. Conf. Software, Comput. App.*, 2024, pp. 350–356.

[11] S. Cavazzoni, G. Ragazzi, P. Bordone, and M. G. Paris, "Perfect chiral quantum routing," *Phys. Review A*, vol. 111, no. 3, p. 032439, Mar. 2025.

[12] M. Dai, G. Sun, H. Yu, S. Wang, and D. Niyato, "User association and channel allocation in 5G mobile asymmetric multi-band heterogeneous networks," *IEEE Trans. Mobile Computing*, vol. 24, no. 4, pp. 3092–3109, Apr. 2025.

[13] M. A. Khan, S. Javaid, S. A. H. Mohsan, M. Tanveer, and I. Ullah, "Future-proofing security for UAVs with post-quantum cryptography: A review," *IEEE Open J. Commun. Soc.*, vol. 5, pp. 6849–6871, Oct. 2024.

[14] S. Ricci, P. Dobias, L. Malina, J. Hajny, and P. Jedlicka, "Hybrid keys in practice: Combining classical, quantum and post-quantum cryptography," *IEEE Access*, vol. 12, pp. 23 206–23 219, Feb. 2024, DOI: 10.1109/ACCESS.2024.3364520.

[15] H. Luo, Q. Zhang, G. Sun, H. Yu, and D. Niyato, "Symbiotic blockchain consensus: Cognitive backscatter communications-enabled wireless blockchain consensus," *IEEE/ACM Trans. Netw.*, vol. 32, no. 6, pp. 5372–5387, Dec. 2024.