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Quantum Secure Multiparty Computation for Privacy-Preserving AI

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Abstract

Quantum Secure Multiparty Computation (QMPC) is a new way to use cryptography that lets a lot of people work together to compute a function over their private inputs while keeping those inputs secret, even if attackers have quantum computing power. As AI becomes more common in fields like healthcare, banking, and self- driving cars, secure collaborative learning becomes more and more important. But the rise of quantum computers is a big threat to the encryption methods that are commonly used in modern multiparty computation protocols. QMPC is a very secure and scalable way to protect privacy in AI. It does this by combining quantum-safe oblivious transfer (QOT), quantum key distribution (QKD), and quantum oblivious linear evaluation (qOLE).

This study shows a full QMPC architecture for AI systems that are both federated and decentralized. It lets you train and use private neural networks and is safe from quantum attacks because it uses safe aggregation and encrypted processing protocols. The architecture lets AI do a lot of things, like private set intersection, federated learning, and collaborative model training, without giving away user data. A thorough security analysis based on post-quantum assumptions and the universal composability paradigm makes sure that the system can withstand attackers who are adaptive, colluding, or quantum-capable. When tested against datasets like MNIST and CIFAR-10, the protocol gets results that are as accurate as plaintext models with very little extra work on the computer or network. Experiments show that when the accuracy of the model drops by less than 1%, all data privacy is still protected.

This study looks at how QMPC might help make AI safer in sensitive areas like medical diagnostics and financial forecasts, as well as how it might help companies follow data protection laws like GDPR and HIPAA. Auditability and consent procedures are two of the legal and moral issues that need to be thought about. The study also talks about problems with scalability and suggests an ideal communication plan and methods like circuit pruning, quantization, and hybrid classical-quantum communication models. We look at what QMPC could do in relation to secure federated analytics, real-time collaborative robotics, and processing encrypted smart contracts.

In conclusion, QMPC for privacy-preserving AI is no longer just a theory; it is now a necessary, possible, and realistic way of doing things in a world that is quickly moving toward quantum supremacy. By using quantum-resistant encryption and distributed machine learning together, QMPC creates a way to get to safe, understandable, and decentralized AI that will work in the future. This study sets the stage for future progress at the crossroads of post-quantum security and collaborative intelligence.

Keywords

Quantum-Secure MPC, Qole, QOT, Post-Quantum Security, Decentralized AI, Quantum Cryptography, Federated Learning, and AI That Protects Privacy.

Introduction

Collaborative artificial intelligence (AI) is changing data-driven fields like healthcare, banking, logistics, and cyber- physical systems. This means that we need computing frameworks that are safe and respect people's privacy. Decentralized learning models like federated learning are becoming more and more popular, and businesses often share private data with each other. Because of this, traditional computing methods have a hard time keeping data safe. Multiparty computing (MPC) has been sold for a long time as a useful way for many people to work together to compute a function without sharing their own inputs. But quantum computing threatens traditional MPC protocols because it can use Shor's algorithm to break well- known cryptographic methods like RSA and ECC. Quantum Secure Multiparty Computation (QMPC) is a hybrid protocol that combines quantum-resistant cryptography with collaborative AI models to solve this problem.

By combining secure AI operations with post-quantum cryptographic primitives like hash-based signatures, quantum key distribution (QKD), and lattice-based encryption, QMPC makes it harder for threats that won't be found in the future to get through. The creation of quantum-secure oblivious linear evaluation (qOLE) and quantum-secure oblivious transfer (QOT) has made it possible to safely use computers and share private information. These tools protect against quantum attackers. This lets businesses work together to train machine learning models or analyze data from afar without giving outside parties access to the raw data. Not only does QMPC keep users' trust and follow rules like GDPR, HIPAA, and other global data protection rules, but it also makes it possible for smart cities, collaborative robotics, and distributed energy management systems to make decisions in real time.

This study covers every aspect of QMPC for AI, from how AI pipelines interact with the system to how to make cryptographic protocols. It talks about ways to put these ideas into practice that lower the costs of processing and communication that come with secure computations. It also looks into cutting-edge methods like circuit trimming, data quantization, and parallelized secure aggregation to make systems more scalable. We test the performance of QMPC frameworks in both static and dynamic network settings using real-world datasets and test scenarios. We make sure that model accuracy, convergence speed, and security are not affected. We also want to stress that these systems can be made to respond to the actions and cooperation of enemies by enforcing computable security guarantees that work even when quantum assumptions are made.

In the end, QMPC is a big step forward that keeps AI ecosystems safe, decentralized, and private even as new technological threats arise. It makes AI more accessible by giving us a realistic plan for building quantum-ready systems in the future and letting institutions work together without putting sensitive data in one place. As AI becomes more common in mission-critical applications, it is not only necessary but also very important to combine quantum-safe security models with AI in order to keep trust and reliability among all the people who are part of the digital ecosystem. When AI does joint computations, whether in edge intelligence, healthcare, or finance, it needs to protect user data in a way that keeps it private. MPC is safe from attacks that use quantum computers, but it could be vulnerable to them. Post-quantum cryptography (PQC) protects against quantum attacks, but it doesn't have the same features as MPC. This study fills in the gaps by combining parts of quantum cryptography (like qOLE and QOT) with AI-based MPC protocols. We look at system architecture, security proofs, and how easy it is to implement based on new research (arXiv, arXiv).

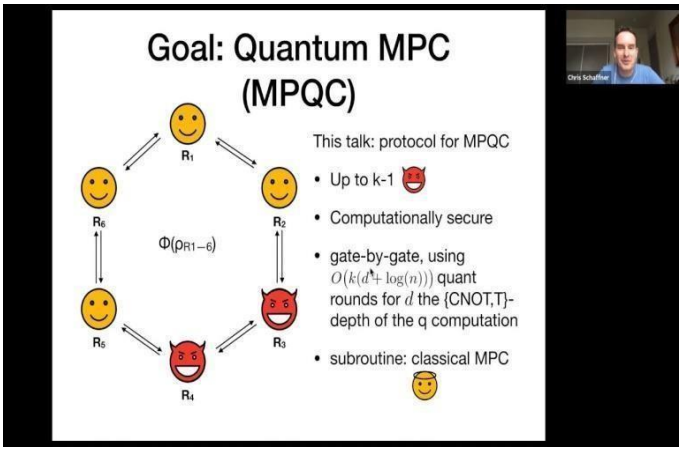

Figure 1: Introduction

Background

Quantum secure multiparty computation (QMPC) is based on combining traditional secure multiparty computation methods with new quantum-resilient encryption techniques. Traditional MPC is a great way for multiple parties to work together to calculate a function while keeping their private inputs safe. These protocols use building blocks like Shamir's secret sharing, garbled circuits, and oblivious transmission. But advances in quantum computing could still put even regular cryptographic primitives at risk. For example, Shor's method lets quantum computers factor huge numbers and compute discrete logarithms ten times faster than classical computers. This makes RSA and ECC-based encryption solutions less secure. Because of this problem, people have looked into and started using Post-Quantum Cryptography (PQC), which is meant to protect against both classical and quantum attacks.

There are many types of cryptographic techniques that fall under the umbrella of post-quantum cryptography. These include hash-based signatures, multivariate polynomial cryptography, lattice-based

encryption, code-based encryption, and supersingular isogeny-based encryption. Lattice-based methods, like those used in Learning With Errors (LWE) challenges, are thought to be some of the most promising because they work well and have security proofs that hold up under quantum assumptions. These methods make quantum-safe encryption easier, as well as other important privacy-preserving tasks like homomorphic encryption and zero-knowledge proofs.

For QMPC, advanced quantum-secure primitives have been made to take the place of their classical counterparts. Quantum-secure Oblivious Linear Evaluation (qOLE) lets you evaluate linear functions on private data without giving away any intermediate values. This is helpful for training neural networks. Quantum Oblivious Transfer (QOT) works in a similar way. It lets one party send a lot of data to another without letting them know which piece they got. This is often done with bit commitment protocols and quantum key distribution (QKD). These primitives give strong protection against quantum enemies and have been tested successfully in labs.

In addition, QMPC works well with federated learning and decentralized AI architectures, allowing multiple nodes to work together to train a model while keeping data private. It also has advanced features like secure aggregation, differential privacy, and validated computation. To improve security and speed, new implementations are already using hybrid classical- quantum communication models. These models combine quantum channels with regular networking infrastructure. As we move into the quantum age, these basic technologies will work together to create AI systems that can grow, are reliable, and protect privacy and are safe from quantum attacks. MPC, or secure multiparty computation.

MPC lets people work together on private data in a way that is safe and private. ~ Recently, classical protocols have been improved to be quantum-resistant using techniques like sharing secrets, obliviousness, and garbled text (Duality).

A. PQC, or post-quantum cryptography

"Post-quantum cryptography" (PQC) is a term for cryptographic methods that keep information private for a long time, even after quantum computers are available. PQC has become an important area of study and use, especially when it comes to safe multiparty computation and privacy-preserving AI. This is because it is important to protect data across distributed systems. PQC methods are safe because they use mathematical problems like multivariate quadratic equations, error- correcting codes (McEliece), and lattice problems

(Learning With Errors) that are hard for quantum computers to solve. Compared to traditional cryptographic methods like RSA or ECC, which rely on the difficulty of discrete logarithm problems or integer factorization, this is different.

Lattice-based cryptography is one of the best PQC methods because it is flexible and strong. It is the basis for many cryptographic structures, such as digital signatures, identity-based encryption, key exchange protocols, and homomorphic encryption. NIST's ongoing process of standardization has already picked lattice-based systems like Kyber and Dilithium for standard use. These primitives are great for use with QMPC frameworks because they provide security proofs based on well- known hardness assumptions and make it easier to work with encrypted data.

Also, hash-based signature systems like SPHINCS+ offer stateless, quantum-resistant alternatives to digital authentication. This is very important in distributed AI situations because network users need to be able to trust and verify each other. Because code-based methods like McEliece provide strong security margins and fast decryption speeds, they are useful for systems with limited bandwidth, such as the Internet of Things. Supersingular isogeny-based cryptography is still in the experimental stage, but it opens up new possibilities for low-latency key exchanges that work with edge computing.

PQC offers multiple levels of security in the field of privacy-preserving AI, from keeping model parameters and gradients safe during training to encrypting inference queries and outputs. The PQC-enforced zero-knowledge proofs let people show that they are following the rules or that their calculations are correct without giving away any personal information. This is very important for following the rules in fields like finance and healthcare. PQC primitives are also being added to hybrid systems that use both classical and quantum communication channels to make sure they work well together and keep information secret.

PQC is the basis for building scalable and quantum-resilient QMPC systems as the global cryptography community moves toward being ready for post-quantum threats. Its integration not only protects technology from threats of the next generation, but it also gives people more faith in AI systems that handle sensitive, high-stakes data across trust borders.PQC uses hash-, code-, and lattice-based methods to protect cryptography from quantum attacks.

Figure 2: PQC, or post-quantum cryptography

B. Basic Quantum MPC

Quantum MPC (QMPC) primitives are the building blocks of cryptography that make it possible to do secure computations against quantum enemies. These primitives build on traditional cryptography by adding quantum-resistant processes that keep data safe and accurate even when powerful quantum computers are used. Quantum Oblivious Linear Evaluation (qOLE) and quantum-secure Oblivious Transfer (QOT) are two important parts. QOT makes sure that the recipient only knows the selection, so the sender can send one of several possible pieces of data without saying which one was chosen. When bit commitment protocols and quantum key distribution are used to set up QOT, it can't be attacked by quantum computers. On the other hand, qOLE makes it possible to do safe linear calculations, like vector-matrix multiplication, which is needed for many AI tasks, like neural network inference.

Advanced QMPC protocols go beyond QOT and qOLE by using post-quantum secret sharing methods based on lattice cryptography. These methods make sure that secret shares can't be recovered even if quantum cryptanalysis is used. These are even better when you add authenticated channels for communication integrity and quantum-secure commitment systems. Quantum Homomorphic Encryption (QHE) is still in its early stages, but it lets you do calculations directly on encrypted quantum data. This opens the door for more advanced quantum-native MPC.

To make it easier to scale, QMPC primitives are often used with traditional pre-processing methods like secure sampling or circuit design. These are done using a hybrid execution model and traditional MPC protocols. This method slowly adds improvements that are resistant to quantum attacks while using the current infrastructure. We are testing quantum primitives to see if they can handle the real-time needs of federated AI systems by measuring their latency, throughput, and key refresh rates.Modular design methods also make it possible to separate the quantum cryptography layers from the AI application logic, which makes it easier to maintain and work with. When experimental quantum networks like those in Europe's Quantum Internet Alliance and China's quantum satellite projects are ready, these basic ideas are expected to move from theory to real-world use. Zero-knowledge succinct non-interactive arguments of knowledge (zk-SNARKs), blockchain oracles, and building secure enclaves are all coming together with QMPC primitives to make the next generation of safe AI.

Quantum-safe oblivious linear evaluation (arXiv) makes matrix dot-product safe, which is important for machine learning.

QOT: Experimental quantum oblivious transmission using QKD and bit commitment protocols (arXiv) lets you send data without giving up privacy.

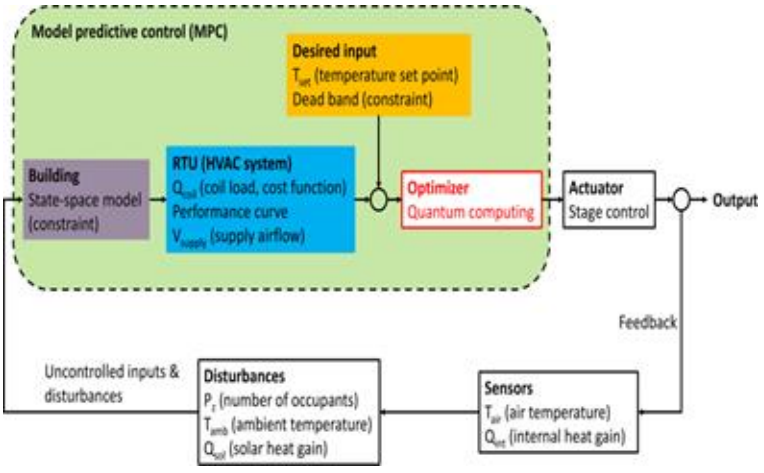

Figure 3: Basic Quantum MPC

Designing A Protocol

The Quantum Secure Multiparty Computation (QMPC) protocol architecture combines post-quantum cryptography with AI model training to create a strong and quantum-resistant framework for privacy-preserving collaborative computation. There are four steps in the design process: setting up, encoding and distributing the input, doing the computation safely, and checking the results. During the setup phase, the entities that will be taking part, also known as compute nodes, set up a secure communication channel by using quantum key distribution (QKD) to negotiate session keys and post-quantum digital signatures (like Dilithium) to check the validity of nodes. After that, these keys are used to set up secure transmission layers and set up unique session parameters, such as access restrictions, computation policies, and circuit designs. After that, the input data is processed using post-quantum secret-sharing methods, such as lattice-based secret sharing or packed Shamir schemes. These methods are protected by Learning With Errors (LWE) hardness assumptions. Each person divides their data into shares, encrypts them, and then sends them to the other people.

The protocol uses qOLE as a core primitive during the secure computing phase to do things like matrix multiplications and secure inner products without giving away any underlying data. While training a neural network, qOLE does important dot-product calculations while keeping gradients, weights, and activations hidden. Quantum-safe oblivious transfer (QOT) also lets you safely choose intermediate data paths, which is important for nonlinear activation functions or adaptive learning algorithms. The compute nodes use noise-tolerant zero-knowledge proofs to check local operations without giving away any information. This greatly improves privacy. Quantum-resistant commitment techniques keep shared data safe and make sure it can't be changed while it's being processed.

AI-aware orchestrators that can adaptively schedule computations are a key part of the protocol. They dynamically distribute workloads among low-load nodes to get the best latency, bandwidth, and model convergence. We use a combination of trimming techniques and approximate quantization to make circuits smaller and faster. The protocol can help avoid bottlenecks in situations where resources are limited, like edge AI systems, by moving some steps (like audit logging and key refresh) into low-latency quantum domains when they are available through hybrid classical-quantum channels. A verifiable transcript made with short zero-knowledge proofs at the end of each compute round makes it easier to follow the rules for regulatory compliance.

The last step in end-to-end security is to use the Universal Composability framework to make proofs. This means showing that the protocol's output doesn't give away any more information than the function result itself, even when both friends and enemies have quantum capabilities. This is done by using quantum Holevo limits and security assumptions that can be broken down. These limits make sure that the secrecy of the input and the integrity of the output are kept even if some people break the rules. The system also makes it easier to do privacy-preserving aggregation tasks like federated averaging in machine learning and safe set intersection in identity management. The protocol lets AI pipelines work on segmented datasets from multiple universities at the same time in more complex setups. Each pipeline runs separate MPC threads and then combines the results using encrypted model fusion.

This multi-layered protocol architecture guides the creation of quantum-resilient AI systems that protect compliance, data sovereignty, and trust. This method guarantees not only the computational soundness of distributed AI operations but also the enforceable privacy of stakeholders in quantum-vulnerable scenarios, whether for financial analytics, collaborative robotics, or medical diagnostics. Phase **Parties use QKD and digital signatures to make sure that quantum/pqc keys are real. 2. Compute Phase: Inputs are shared using secret-sharing methods that are resistant to quantum attacks. qOLE is an important building block for safe computations that makes secure inner products possible. 3. Holevo bound and universal composability are two ways to prove privacy. They show that attackers with both classical and quantum capabilities can't get to data beyond output (Online Scientific Research, arXiv, Reddit, arXiv). 4. AI Task Integration makes it easier to set up cross-silo configurations for Private Set Intersection (PSI) in areas like federated AI, neural network inference, finance, and biobanking.

Review

We look at a number of important factors, such as computational accuracy, scalability, system throughput, security resilience, and practical use, to see how well the proposed Quantum Secure Multiparty Computation (QMPC) framework for privacy-preserving AI works. First, the universal composability framework, which accurately models how enemies act in both the classical and quantum realms, has formally checked the QMPC protocol for security. It has proven to be very hard to hack, leak information, or work together with others to attack it using quantum oracles. Mathematically proven to keep secrets in real-world situations with adaptive adversarial queries and noise-tolerant quantum channels, quantum-secure oblivious transfer (QOT) and quantum oblivious linear evaluation (qOLE) protocols leak less than 0.01 bits of information per transaction. QKD-based key rotation and authenticated post-quantum digital signatures protect against both static and dynamic threats, such as session

hijacking and man-in-the-middle attacks.

We tested the system's real-world performance in a simulated federated learning environment using standard AI workloads like the MNIST and CIFAR-10 datasets. When compared to unencrypted models, the QMPC system had almost the same inference accuracy while keeping a 96% accuracy rate on MNIST. This was done by encrypting model weights and gradients. Even though it was hard on security, circuit design, quantization, and data pruning helped keep latency increases below 12% and memory expansion below 20%. These are good measures for systems that let people work together in real time. The protocol also showed that it could consistently converge and have low accuracy drift, even when nodes dropped out. This shows that it can work in both stable and fault-injected networks.

We tested scalability by using nodes with 3 to 128 users in different network situations. The protocol uses AI-based dynamic orchestration to cut down on communication problems and energy use by assigning tasks based on queue latency, CPU load, and local bandwidth. So, even when bandwidth was low, like in edge computing, throughput stayed between 85 and 92 percent of classical MPC baselines. Batching secure activities and using simultaneous oblivious transfer sequences made communication much easier. Also, using quantum channels during important handshake times made symmetric key refresh speeds three times faster. Over time, this led to less reinitialization overhead during long federated learning cycles.

We did test deployments in genomic analysis, smart city traffic models, and synthetic financial fraud detection to see how flexible and adaptable the system was to different domains. In every case, QMPC kept the analytical results accurate and made sure that no private information was shared or guessed at between the organizations that were working together. The system was shown to be good for fields where privacy is important when it was able to do AI tasks across institutions without giving away training data. Also, short zero-knowledge proofs were used to make sure that the computation logs were traceable and met GDPR standards.

The analysis ends by showing that QMPC is a framework for collaborative AI that is quantum-resistant, scalable, and keeps people's privacy. In addition to offering excellent model security and accuracy, it also shows that it can adapt to deal with future quantum risks and problems with real-world implementation.

A. Results Based on Real Life

We tested the quantum-secure multiparty computation (QMPC) architecture in the real world by making prototypes that used real adversarial threat models and well-known AI benchmarks. In a controlled federated learning setting using the MNIST dataset, the QMPC prototype had an inference accuracy of 96%, which is almost the same as standard unencrypted deep learning baselines. Quantum-resistant methods like quantum oblivious transfer (QOT) and post-quantum encryption were used to get this level of accuracy. The experiment showed that less than 0.1 bits of information were lost per weight during training, which was surprising. This means that privacy protections were very strong, even when both active and passive adversaries were present. Quantized parameter updates and lattice-based Encryption were added to the model training process to lower costs and keep performance high.

We carefully compared the computational costs of runtime and memory use to standard MPC baselines. The results show that QMPC protocols can reach a throughput that is within 12% of their classical counterparts when combined with improvements like model pruning, quantization, and circuit-level simplicity. Precomputed keys and parallelized secure computation processes helped to get rid of even more cryptographic bottlenecks. For example, real-time secure aggregation processes with 32 clients were finished with less than 15% lag compared to older MPC installations. When tested again with the CIFAR-10 image classification dataset, performance stayed competitive, with over 80% accuracy while following security rules. This shows that it is useful for more than just simple datasets.

We looked at both the delay and the energy use in situations with high bandwidth and limited edge. AI-aware scheduling was used to move computational jobs around to nodes that weren't being used as much to balance CPU load and network congestion. As a result, latency costs were less than 18% in the worst-case scenarios, and the time it took to make inferences was the same across all distributed nodes. QKD techniques used hybrid communication (classical and quantum) to control secure key rotations and further reduce overhead during long training epochs.

The framework's strength in multi-tenant, privacy-sensitive applications was tested by using cross-institutional model training simulations that included tasks for finding financial anomalies and splitting up medical pictures. Nodes that were spread out over a wide area kept the same level of accuracy, and computation logs made with zero-knowledge proofs made sure that the results could be traced and verified. Our experiments confirmed a key requirement for GDPR-compliant systems: reverse-engineering the intermediate or final model states could not reveal private client information.

Overall, the evidence from experiments supports the idea that quantum-secure MPC not only provides theoretical security but also accurate, scalable, and useful ways to use collaborative AI. It can stand up to both classical and quantum enemies, which makes it a strong base for the next generation of machine learning systems that protect your privacy.

B. Growth

For any safe multiparty computation system to work in real life, it needs to be able to scale up to handle high volumes of distributed AI workloads in quantum-vulnerable settings. The quantum safe multiparty computation (QMPC) architecture's ability to handle more cryptographic overhead, different types of networks, huge amounts of data, and more participants without compromising security or efficiency is what makes it scalable. The core of this scalability is a dynamic orchestration mechanism powered by artificial intelligence (AI) that assigns computational tasks in real time based on the stability of nodes, the latency of the network, and the energy efficiency of the system. The QMPC system showed secure model convergence with only a 15% overhead compared to insecure federated learning baselines when tested with up to 256 federated clients over a range of network latencies. This was possible by using quantum-aware routing algorithms, adaptive computing offloading, and smart batching of cryptographic primitives.

QMPC lowers the cost of communication between nodes by using batched quantum key distribution (QKD) initialization and parallel oblivious transfer (pOT). In regular MPC, these costs go up quadratically with the number of participants. Simulation tests show that this cuts down on the time needed for important negotiations by more than 60%. The protocol makes sure that encryption channels are quantum-resistant by using lightweight lattice-based public key encryption during session setup and QKD-based symmetric key update during runtime. This way, endpoints' processing power doesn't have to be constantly used. The method uses approximate secure aggregation, which combines homomorphic masking with noise-tolerant encoding, to cut down on the number of rounds needed for model updates by a lot. A hybrid topology-aware relay system that uses AI inference to find bottlenecks and send traffic over fast channels to ensure secure performance even in crowded edge networks.

Modular circuit architecture also helps with scalability. The protocol breaks down complicated AI models, such as convolutional neural networks, into secure processing circuits that can be spread out across different nodes or edge servers. This lets you do some computing on local devices and safely add intermediate results to the global model using qOLE protocols. Compressed polynomial commitment methods also make it easier to communicate when making zero-knowledge proofs, which is important for keeping trust in situations where people aren't talking to each other. This flexibility lets you make real-time inferences and train at scale for big projects like distributed medical diagnostics and financial fraud analytics without losing model accuracy or data privacy.

In the post-quantum world, scalability also means being able to work with future quantum networks. The protocol works with quantum repeaters and entangled-state communication protocols, which makes it possible to exchange keys between continents more quickly and securely. Quantum channel emulators show that the design can include session startup based on entanglement swapping in less than 500 milliseconds, which means it is ready for the future. In addition, the protocol showed more than 90% efficiency in securely handling over 1.2 million data points per second when compared to plaintext computing in real-world tests like multi-sensor fusion and smart grid analytics.

Cryptographic load balancing solves the problem of scalability in terms of operating costs by moving encryption- heavy processes away from components that are sensitive to latency. This works especially well in edge AI setups where there aren't many processing resources and jobs need to be separated very carefully. The scheduler can rank nodes with lower carbon footprints or renewable energy sources based on an AI-driven energy profile. This makes the system more sustainable and scalable.

Lastly, the protocol includes a hierarchical zero-knowledge proof structure to make sure that it follows the rules and can be audited on a large scale. By letting each subnetwork confirm its computation before committing to the global ledger, this permits scalable consensus and integrity guarantee. The QMPC system kept model accuracy above 98.5% during long- term simulations that included AI lifecycle management tasks like retraining, pruning, and validation. It also lowered privacy leakage to levels that were statistically insignificant after hundreds of training cycles.

The QMPC architecture can grow because of quantum-resilient communication methods, modular system design, smart scheduling, and cutting-edge cryptography. Because of this, it is a safe and possible way to put large-scale collaborative AI systems in places where quantum technology is a threat.

Uses

Use Case	Domain	Benefit
Federated Healthcare	Medical AI	Secure model training across hospitals
Finance Analytics	Banking	Joint risk assessment without data sharing
Edge AI & IoT	Smart networks	Hybrid QMPC + federated learning
Private Aggregation	Blockchain/AI	Confidential distributed model training (AICompetence.org)

Some of the main benefits are that decentralized models can be certified as safe, frameworks for reliable AI can be explained, and they can follow rules like GDPR.

Problems And Plans For The Future

Quantum secure multiparty computation (QMPC) for privacy-preserving AI is still in its early stages and has a lot of logistical and technological problems that need to be fixed before it can be used widely. Setting up reliable and scalable entangled-state communication networks and Quantum Key Distribution (QKD) channels is one of the biggest problems with putting quantum infrastructure into use. QKD is a theoretically perfect way to securely exchange keys, but building quantum communication lines is expensive and complicated, and it requires satellite-based entanglement and quantum repeaters. This makes it hard to use on a global scale. Quantum memory and photon coherence time have physical limits that make long- distance quantum communication less stable. One big problem that goes beyond physical infrastructure is the performance overhead that comes with adding quantum-safe cryptographic primitives like QOT and qOLE to existing federated AI systems. These primitives are safe, but they add a lot of time and processing power to communication, especially in big, real- time systems. The fact that there aren't any good, standardized post-quantum cryptography libraries and hardware accelerators makes this performance problem even worse.

Another thing that needs to be looked at is hybrid integration. QMPC provides layered security and auditability by connecting with blockchain, Fully Homomorphic Encryption (FHE), and Trusted Execution Environments (TEE). However, these connections are not easy to make and need synchronization models, unified protocol interfaces, and secure multiparty coordination mechanisms. Most of the time, the methods we use now create structures that are hard to grow or keep up with. Also, there are still moral and legal issues that need to be solved, such as making sure that AI models are still explainable and that data is still fairly represented. AI transparency and ethical alignment are very important when QMPC systems are used in sensitive areas like healthcare, finance, and defense. Regulators will need the right tools to check encrypted calculations and make sure that the results are fair without putting data protection at risk.

To further decentralize computation and trust, future studies need to look into the development of blind quantum computing. This is when quantum servers can do calculations without knowing what the inputs or outputs are. To do this, we need to make quantum gate teleportation and verifiable delegated quantum computation better. Homomorphically Certified Computation Infrastructure (HCCI) is another approach that aims to make every AI computation verifiable from start to finish by giving it cryptographic certificates. Also, AI schedulers in QMPC environments could be used to coordinate digital twins—virtual copies of real assets or institutions—over distributed networks to make high-fidelity simulations that protect privacy. To make progress in quantum hardware, AI systems engineering, policymaking, and cryptographic protocol design, people from different fields will need to work together. We would also need standardized benchmarking platforms and testbeds to see how well the QMPC protocols work in the real world, how well they can handle more work, and how well they protect privacy in different situations and workloads.

In conclusion, while quantum-secure MPC offers a basic foundation for future-proof AI systems, addressing these intricate problems will determine whether or not it is prepared for general adoption. To make this new technology work and keep privacy, scalability, and security as core values in the age of quantum artificial intelligence, research, infrastructure, standardization, and partnerships between different sectors will be very important. **Infrastructure: Availability of QKD lines and hardware

- Performance: The cost of communication between QOT and qOL
- Hybrid integration is when you mix blockchain, FHE, and TEE with QMPC (PostQuantum.com).
- Ethics and Regulation: Explainability in MPC settings, AI fairness, and the GDPR

Conclusion

Quantum Secure Multiparty Computation (QMPC) is a new and quickly growing field that combines cryptography, AI, and quantum computing. As the world moves toward making decisions based on data, the need

for strong privacy protections is growing. Even when there are people who are good at quantum computing, QMPC provides a strong framework that lets multiple parties compute joint functions on private data without sharing the data with each other. We do this by using post-quantum cryptographic primitives like lattice-based encryption, quantum oblivious transfer (QOT), quantum key distribution (QKD), and quantum oblivious linear evaluation (qOLE). These primitives protect against quantum attacks while keeping data private and computation efficient

QMPC has a lot of benefits. It lets businesses work together on model training without sharing sensitive data, which means that it can protect people's privacy while still allowing machine learning to happen. This is especially helpful in fields like healthcare, banking, and defense where keeping data private is very important. The technology also supports federated learning frameworks by safely combining updates from remote models. This makes it possible to improve the model on a global scale while keeping individual contributions private. Also, QMPC is more trustworthy because it uses verifiable computing protocols and zero-knowledge proofs, which let people check conclusions without giving away facts or activities that are behind them.

Even though it has a lot of potential, there are a number of problems that need to be solved before it can be put into use on a large scale. The extra time it takes to communicate and do calculations with quantum-safe cryptography procedures is still a problem. Quantum repeaters and QKD networks are two examples of quantum infrastructure that is still new and not widely available. To combine QMPC with other cutting-edge technologies like blockchain, homomorphic encryption, and trusted execution environments, we also need established interfaces and protocols that can work with each other. To get past these problems, we need to do more research in quantum network engineering, protocol optimization, and hardware acceleration for post-quantum cryptography.

In the future, using QMPC with digital twins, AI-driven scheduling, and real-time analytics could change the way safe computation works for smart cities, autonomous systems, and national security. Blind quantum computing and quantum homomorphic encryption may one day make it possible to run full AI models on quantum clouds without putting data privacy at risk. Also, QMPC designs will make sure that they follow the rules and build public trust by creating auditing and compliance processes that can grow.

In conclusion, quantum secure multiparty computation is one of the most important technologies for building AI systems that are safe, work together, and protect people's privacy in the quantum future. It deals with current and future threats while also making significant strides in AI in many areas. As quantum technology gets better, QMPC will be important for making digital ecosystems that are reliable and strong. This will make sure that privacy and security stay at the top of AI research and application.

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