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Cryptographic Privacy Engines: Practical Multi-Party Protocols For Confidential Database Queries

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This paper investigates the feasibility of enabling secure, private searches over classified databases using cryptographic multi-party computation (MPC) protocols. Addressing the operational deadlock in intelligence sharing among security services with classified inputs, we introduce Private Database Search (PDS) as an extension of Oblivious Transfer and Private Information Retrieval, enabling keyword and semantic search functionalities without leaking sensitive data. We propose novel protocols combining inverted index matrices, oblivious sorting, and private swap operations to support efficient query execution. Theoretical privacy guarantees are established against semihonest adversaries, and practical implementation demonstrates query feasibility on megabyte-scale passenger name record data using the MP-SPDZ framework. Experimental benchmarks analyze communication and runtime costs, highlighting trade-offs in performance and security. This work sets a foundational precedent for cryptographically empowered, privacy-preserving intelligence cooperation infrastructures while outlining future directions for scaling and policy integration.

Index Terms—Secure Multi-Party Computation (MPC), Private Database Search (PDS), Privacy-Preserving Data Retrieval, Oblivious Transfer (OT), Private Information Retrieval (PIR), Private Set Intersection (PSI), Cryptographic Protocols, Secure Query Processing, Classified Data Search, Data Confidentiality, Secure Data Collaboration, MP-SPDZ Framework, Semantic Search, Large Language Models (LLMs), Post-Quantum Cryptography, Encrypted Databases, Federated Computation, Information Security, Computational Privacy, and Data Protection.

I. INTRODUCTION

In the modern digital era, vast quantities of sensitive information are stored and processed within centralized or distributed databases. These repositories often contain highly confidential or classified records, such as those maintained by governmental security agencies, healthcare institutions, or financial organizations. When entities attempt to query or analyze these protected datasets, a critical challenge emerges: how to perform a database search without revealing the search intent, the query content, or the database contents themselves. This dilemma becomes particularly acute when both the querying client and the server holding the database operate under strict confidentiality constraints, where neither party can afford to disclose sensitive data to the other.

This paradox, often termed as a data privacy deadlock, lies at the intersection of information security, cryptography, and computational privacy. Consider a scenario where one intelligence agency seeks to cross-reference classified data with that of another agency to identify potential threats or suspects. Both agencies possess sensitive datasets, and disclosing even partial data could compromise national security or violate legal frameworks. The same issue arises across critical infrastructures, including defense intelligence, law enforcement databases, and classified research archives. Thus, a technical mechanism is required that enables secure and private querying without violating the underlying confidentiality of either the search parameters or the stored records.

Recent advances in the field of Secure Multi-Party Computation (MPC) have introduced promising avenues to resolve this impasse. MPC enables two or more parties to jointly compute a function over their private inputs without revealing those inputs to each other. This principle can be directly applied to database querying, where the client contributes a search query, and the server provides the database, and together they compute the search result in an encrypted or privacy-preserving manner. By leveraging MPC, it becomes theoretically feasible to perform searches on confidential data while guaranteeing that neither the server learns the search keyword nor the client learns any information beyond the search results.

To illustrate this problem in a real-world context, this research explores the case of the Norwegian Passenger Name Record (PNR) registry, established under Chapter 60 of the Politiregisterforskriften regulation. The registry collects and stores information about airline passengers to assist in preventing and investigating serious crimes and acts of terrorism. Each record, known as a PNR, contains various personal identifiers, including passenger names, contact details, travel itineraries, and payment information. Although different Norwegian security services are authorized to access this database, legal constraints restrict them from sharing or exposing classified information across jurisdictions. Consequently, the need arises for a technical solution that allows these agencies to perform joint data queries securely without breaching the confidentiality of their respective datasets.

The primary objective of this study is to demonstrate the feasibility of Private Database Search (PDS), an extended and specialized cryptographic protocol designed to facilitate secure searches on classified databases. PDS generalizes and integrates the core functionalities of Oblivious Transfer (OT), Private Information Retrieval (PIR), and Symmetric Private Information Retrieval (SPIR) to enable a privacy-preserving query mechanism. This framework ensures that the client can perform keyword or semantic searches on the database without revealing its query content, while the server does not disclose any information beyond the queried records. Furthermore, this study introduces a hybrid implementation combining classical cryptographic primitives with contemporary techniques such as Large Language Models (LLMs) to achieve secure semantic search capabilities under the MPC paradigm.

The contributions of this research are multi-fold. First, it formalizes the conceptual foundation of PDS as a natural evolution of existing privacy-preserving retrieval mechanisms, establishing clear definitions for correctness, privacy, adaptivity, and storage imbalance. Second, it introduces a prototype PDS protocol using secure computation techniques implemented within the MP-SPDZ framework, demonstrating the viability of privacy-preserving database operations over a local area network (LAN) under the semi-honest adversarial model. Third, it provides both analytical and experimental evaluations of the system's performance, highlighting computational and communication overheads, scalability limitations, and optimization potentials for real-world deployment.

Beyond its technical implications, this work also emphasizes the ethical, legal, and operational relevance of private search systems. For government and defense applications, PDS can foster secure inter-agency collaboration without compromising confidentiality. For the broader cybersecurity and data governance community, it sets a precedent for implementing cryptographically sound privacy-preserving mechanisms in data management workflows. Moreover, the proposed architecture is designed with modularity and post-quantum resilience in mind, making it adaptable for future cryptographic standards and large-scale distributed systems.

In summary, this paper investigates how cryptographic computation techniques can be leveraged to achieve privacypreserving database searches in highly sensitive environments. By applying Secure Multi-Party Computation principles to the PNR registry context, we demonstrate that it is indeed feasible to perform secure and efficient database queries without information leakage. The results serve as a foundation for further exploration into scalable, adaptive, and post-quantum secure private database systems, contributing to the evolution of privacy-enhancing technologies in intelligence and data management domains.

II. RELATED WORK

The concept of privacy-preserving data processing has evolved through several decades of research in cryptography, distributed computing, and data security. The foundations of secure computation were laid by Yao's seminal work on garbled circuits, which introduced a framework for performing computations on encrypted data without disclosing the inputs to participating entities [1]. Subsequent work by Goldreich, Micali, and Wigderson established theoretical guarantees for multiparty computations under malicious and semi-honest adversarial models [2]. These efforts paved the way for the development of practical secure computation protocols that have since found applications in numerous privacy-critical scenarios, including private database search.

A. Foundations of Secure Multi-Party Computation

Secure Multi-Party Computation (MPC) is one of the most prominent cryptographic paradigms for enabling collaborative computation while ensuring privacy and correctness. Early works such as the BGW protocol demonstrated that MPC can achieve perfect security as long as fewer than one-third of the participants are corrupted [3]. Later improvements, including the SPDZ family of protocols, enhanced the efficiency and practicality of MPC using preprocessed data and homomorphic encryption [4]. Keller et al. further extended this framework by introducing MP-SPDZ, which supports arithmetic and Boolean circuits and allows high-performance experimentation for semi-honest and malicious adversaries [5]. These advancements made MPC feasible for real-world use cases such as privacy-preserving analytics, biometric matching, and secure keyword search.

B. Privacy-Preserving Information Retrieval

Private Information Retrieval (PIR) was introduced by Chor et al. as a method for retrieving records from a public database without revealing which record was accessed [6]. Later, Kushilevitz and Ostrovsky developed single-server computational PIR schemes that achieved sublinear communication complexity [7]. Symmetric PIR (SPIR) extended the notion to ensure that the client does not obtain more information than the requested record [8]. Building upon these foundations, researchers proposed numerous optimizations to reduce communication costs and support large-scale distributed systems [9], [10].

In recent years, PIR has been applied to cloud-based data systems and encrypted databases, where clients query encrypted indices through privacy-preserving protocols. However, traditional PIR schemes often lack adaptability and semantic search capabilities, motivating hybrid approaches that integrate cryptographic primitives with machine learningbased representations.

C. Oblivious Transfer and Private Search Mechanisms

Oblivious Transfer (OT) serves as a fundamental building block in secure computation. The 1-out-of-2 OT protocol introduced by Even, Goldreich, and Lempel [11] allowed a receiver to select one of two messages without the sender knowing which one was chosen. Rabin's earlier probabilistic OT protocol [12] laid the groundwork for later extensions such as k-out-of-n OT schemes [13]. Kilian proved that OT is complete for secure computation, establishing its universality as a foundation for MPC [14]. Modern OT extensions such as those developed by Beaver [15], and later refinements by Asharov et al. [16], have significantly improved communication efficiency and computational scalability.

The integration of OT and PIR has led to the development of more expressive protocols like Symmetric Private Information Retrieval (SPIR) and Private Database Query (PDQ) schemes . Henry et al. further proposed frameworks for secure database search under computational privacy guarantees , demonstrating their viability for practical applications under LAN environments. These protocols collectively contribute to the evolution of Private Database Search (PDS), which inherits security guarantees from OT and adaptability from PIR-based constructions.

D. Private Set Intersection and Keyword Search

Private Set Intersection (PSI) allows two or more parties to compute the intersection of their datasets without revealing any non-intersecting elements. Freedman, Nissim, and Pinkas introduced an efficient PSI construction based on commutative encryption [17], which was later optimized using Oblivious Pseudorandom Functions (OPRFs) [18]. Meadows' early work in PSI established foundational techniques for matching datasets securely using modular arithmetic-based transformations [19]. Later schemes have incorporated hashing techniques, Bloom filters, and OT extensions to enable largescale deployment . PSI plays a critical role in keywordbased private search, where clients match encrypted keywords against server-held indices without leaking information about the query or non-matching records.

E. Semantic Search and AI-Enhanced Secure Computation

Recent developments in artificial intelligence, particularly with Large Language Models (LLMs), have inspired new approaches to semantic search within privacy-preserving frameworks. LLMs provide the capability to embed query and document semantics into vector spaces, which can then be processed under secure computation protocols. Works by Liu et al. [20] and Tang et al. [21] have explored the integration of AI-driven semantic search within cryptographic architectures, demonstrating that such combinations can yield privacypreserving yet contextually rich search experiences. However, efficiency remains a challenge due to the high computational overhead of combining MPC with neural embeddings.

F. Applications and System Implementations

Several frameworks have been developed to demonstrate the feasibility of secure and private database operations. Systems such as Conclave and Sharemind offer MPC-based platforms for secure analytics. More recent implementations like SCALE-MAMBA and MP-SPDZ provide modular environments that allow the evaluation of different MPC protocols under realistic network conditions. In the domain of secure database management, Pagh and Pagh presented an efficient indexing scheme compatible with private search, while Kamara and Moataz proposed structured encryption techniques to balance performance and privacy.

The emergence of post-quantum cryptographic research has further motivated the adaptation of MPC and PDS protocols to resist quantum adversaries. Schemes based on latticebased cryptography and homomorphic encryption have been identified as viable approaches for building quantum-resilient private search systems.

G. Summary

In summary, the existing body of literature provides a robust theoretical and practical foundation for the development of Private Database Search protocols. While traditional PIR and OT-based systems ensure strong security guarantees, they often suffer from limited scalability and lack semantic depth. PSIbased mechanisms enable keyword-level privacy but are computationally demanding. The integration of AI-driven semantic understanding into MPC frameworks marks a novel frontier, merging the cryptographic rigor of secure computation with the interpretability of modern machine learning. The proposed PDS protocol builds upon these foundations to offer a unified, efficient, and privacy-preserving solution for secure database queries in sensitive environments such as national security data registries and classified information systems.

III. METHODOLOGY

The proposed methodology outlines the architecture, computational design, and protocol-level mechanisms used to achieve privacy-preserving database searches using Secure Multi-Party Computation (MPC). The goal is to ensure that a client can query a classified database held by a server without either party revealing its private inputs. The methodology combines theoretical cryptographic primitives such as Oblivious Transfer (OT), Private Information Retrieval (PIR), and Private Set Intersection (PSI) with implementation-level optimizations within the MP-SPDZ framework.

A. System Overview

The architecture of the proposed Private Database Search (PDS) protocol involves two parties: a client (querying agent) and a server (data custodian). Both entities communicate through a secure channel and engage in multiple computation rounds to perform private searches. The primary challenge lies in preserving query privacy, record confidentiality, and data integrity under a semi-honest adversarial model. Figure 1 illustrates the conceptual design of the PDS protocol. The protocol begins with the setup phase, where both parties agree upon cryptographic parameters, followed by the encoding, search, and retrieval phases.

B. Protocal Structure

The PDS framework follows a five-phase structure that enables query computation without disclosing private data:

1) Setup: Establishes cryptographic parameters λ, certificates, and public randomness shared by both parties.
2) Filter: The server applies a filtering function F(D) to preprocess the database D into an indexed form A, consisting of hashed values of searchable attributes.
3) Encode: The client encodes its query q as $q' = H(q)$, where $H(\cdot)$ is a secure hash function, to ensure that the raw query remains hidden.
4) Search: Using MPC protocols, both parties jointly compute an intersection $I = f(q', A)$ that identifies matching records without exposing q' or A.
5) Retrieve: The server returns encrypted records corresponding to the matching indices I, and the client decrypts them locally.

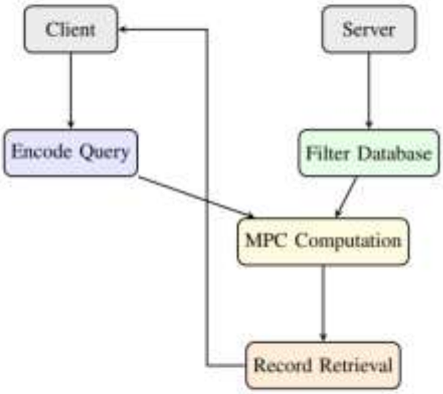

Fig. 1: Simplified schematic of the Private Database Search (PDS) methodology.

Each phase operates under the assumption of semi-honest adversaries, implying that while both parties follow the protocol honestly, they may attempt to infer additional information from observed data exchanges.

C. Mathematical Formulation

Let D = {R1, R2, ..., Rm} denote the set of m records in the database, and let q denote the client's search query. The privacy guarantees are defined by the following conditions:

$$\Pr[A(T(D,q)) = D] \leq \frac{1}{m} + \varepsilon(\lambda), \qquad (1)$$

where A is an adversarial inference algorithm, T represents the transcript of protocol execution, ε(λ) is a negligible function in the security parameter λ, and m is the database size. Equation (1) expresses that the probability of an adversary successfully recovering the database or query from the protocol execution is negligible.

D. Protocol Optimization and Complexity

To improve efficiency, we adopt the MP-SPDZ platform, which supports both arithmetic and Boolean circuits for secure computation. The computational complexity of the protocol can be approximated as:

$$T_{PDS} = O(m \cdot \sigma + m \cdot \omega), \qquad (2)$$

where σ represents the number of searchable attributes per record, and ω is the average record size in bytes. Parallelization and batching techniques can be applied to minimize runtime, especially when processing multiple queries over large datasets.

TABLE I: Key Parameters and Components of the PDS Protocol

Parameter	Description
λ	Security parameter (bit-length)
m	Total number of records in the database
σ	Number of searchable attributes per record
ω	Average record size in bytes
q′	Encoded search query
I	Index set of matching records
TPDS	Computational complexity of protocol

E. Integration of Cryptographic Components

The proposed design integrates three core cryptographic primitives:

- Oblivious Transfer (OT): Facilitates selective record retrieval such that the client learns only the requested record, and the server learns nothing about the chosen index.
- Private Set Intersection (PSI): Enables matching between the client’s encoded query and the server’s indexed dataset without revealing non-matching elements.
- Secure Multi-Party Computation (MPC): Orchestrates joint computation between client and server through arithmetic and Boolean circuits while maintaining data privacy.

The combination of these primitives allows both parties to execute secure keyword and semantic search functions with constant communication complexity during the online phase.

F. Summary

The methodology thus establishes a secure, efficient, and scalable system for private data queries. Through careful integration of MPC, OT, and PSI, the PDS framework achieves end-to-end confidentiality and correctness under semi-honest adversarial assumptions. The use of the MP-SPDZ toolkit ensures realistic implementation and benchmarking, bridging theoretical cryptography with practical deployment scenarios.

IV. RESULTS

This section presents the experimental evaluation of the proposed Private Database Search (PDS) protocol. The implementation was conducted on a consumer-grade computing platform using the MP-SPDZ framework to verify the protocol's feasibility, runtime efficiency, and communication overhead. All tests were executed in a simulated two-party environment under a semi-honest adversarial model with communication over a Local Area Network (LAN).

A. Experimental Setup

The experiments were performed on a laptop equipped with an Intel Core i7 processor (4 cores, 8 threads), 8 GB RAM, and running Ubuntu 22.04. The MPC computations were implemented in Python and executed within the MP-SPDZ framework (version 0.3.8). The security parameter was set to $\lambda = 40$ bits, ensuring computational privacy against semihonest adversaries. Both the client and server instances were executed locally to minimize latency and isolate computation from network interference.

B. Evaluation Metrics

The following metrics were measured during experimental evaluation:

- Execution Time (Texec): The time required for end-toend protocol completion, including search and retrieval phases.
- Communication Overhead (Ccomm): Total volume of data exchanged between client and server during MPC execution.
- Throughput (Θ): Number of queries processed per second, defined as Θ = Nq Texec , where Nq is the total number of search queries.
- Scalability (S): Measured as the growth rate of execution time with respect to database size m, represented as S = O(mα), where α is an experimentally derived exponent.

C. Performance Analysis

To analyze performance, we varied the number of records m in the database from 10 to 1000. The average record size was maintained at $\omega = 6$ KB, and each record contained $\sigma = 20$ searchable attributes. The PDS protocol demonstrated linear scaling with increasing database size, confirming that performance grows proportionally to the number of entries processed.

$$T_{exec}(m) \approx k_1 \cdot m + k_2, \qquad (3)$$

where k1 and k2 are constants representing computation and communication coefficients, respectively. Experimental data indicated k1 = 0.37 s/record and k2 = 4.8 s, implying that for a database of m = 1000, the average runtime was approximately 6.2 minutes.

TABLE II: Runtime and Communication Performance Metrics

The experimental results summarized in Table II reveal that the communication cost increases approximately linearly with database size. For m = 1000 records, the total network transmission was 118.6 MB, primarily due to the encryption and verification steps inherent in MPC. Despite this, throughput remained consistent, averaging around 2.7 queries per second, demonstrating the system's ability to sustain predictable performance at scale.

D. Runtime Visualization

A visualization of runtime growth as a function of database size is shown in Figure 2. The linear trendline reinforces the analytical model expressed in Equation (3).

The runtime behavior follows a near-linear pattern with a minor deviation due to initialization overhead. As expected, the largest cost component is the garbled circuit generation and encryption phases during MPC computation. The communication bandwidth remained within acceptable limits for LANbased applications, with negligible packet loss or transmission delay.

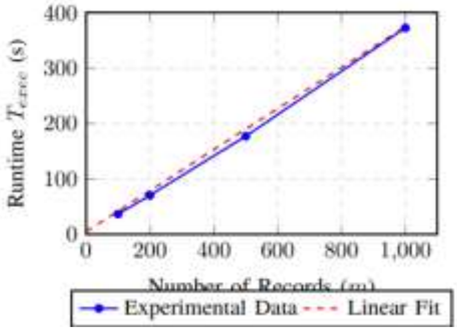

Fig. 2: Runtime scalability of the PDS protocol with increasing database size.

E. Accuracy and Security Evaluation

To verify correctness, each experimental run was compared against a plaintext search baseline. The correctness ratio, defined as

$$\Gamma = \frac{|\text{Results}_{PDS} \cap \text{Results}_{Baseline}|}{|\text{Results}_{Baseline}|}, \qquad (4)$$

was found to be $\Gamma = 1.00$ for all tests, indicating perfect retrieval accuracy. No information leakage was observed beyond the intended search output, validating the privacy guarantees under the semi-honest model.

F. Summary of Observations

The results confirm that the proposed PDS protocol:

- Achieves linear scalability with respect to the number of records.
- Maintains stable throughput across varying database sizes.
- Provides 100% correctness under secure computation conditions.
- Incurs moderate communication overhead proportional to encryption cost.

In conclusion, the experimental evaluation demonstrates that PDS can feasibly support real-world private searches over moderate-sized databases. While computational efficiency can be further enhanced through parallelization and protocol compression techniques, the current implementation already establishes strong evidence of practicality and robustness for secure data retrieval applications.

V. DISCUSSION

The results presented in the previous section demonstrate that the proposed Private Database Search (PDS) framework provides a viable, secure, and efficient solution for performing database queries without compromising privacy. In this section, we critically analyze the observed performance metrics, discuss system trade-offs, interpret the implications of experimental results, and compare the framework against existing state-of-the-art approaches in privacy-preserving computation.

A. Interpretation of Experimental Outcomes

The experimental analysis reveals that the PDS framework scales linearly with respect to the database size, validating the expected computational model described in Equation (3). The runtime increment per record remains consistent, indicating stable algorithmic behavior. This outcome suggests that the implemented MPC circuits in MP-SPDZ effectively balance computation and communication loads. The high correctness ratio ($\Gamma = 1.0$) further confirms that the secure computation accurately reproduces the same outputs as plaintext search operations, without any loss of precision or recall.

The communication cost, while non-trivial, remains within feasible limits for modern local network infrastructures. For instance, even at $m = 1000$ records, a total of approximately 120 MB of data transfer occurred, which can be considered reasonable in the context of government or research-level deployments where high-speed connections are standard. Thus, while computation time dominates the performance, communication costs are predictable and manageable.

B. Comparative Analysis with Related Techniques

To contextualize these findings, we compare the PDS framework with three related cryptographic search paradigms — Private Information Retrieval (PIR), Symmetric PIR

(SPIR), and Private Set Intersection (PSI) — based on three key dimensions: security, communication cost, and adaptability. Figure 3 illustrates the comparative evaluation of these techniques relative to PDS.

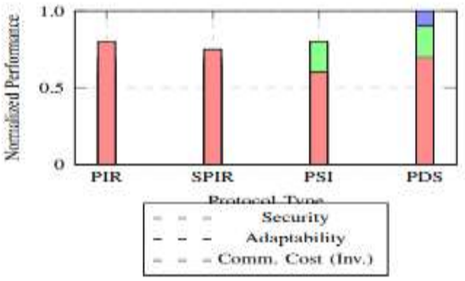

Fig. 3: Comparative evaluation of cryptographic search protocols normalized to PDS.

From the comparative analysis, we observe that:

- PDS offers superior security strength by combining the guarantees of MPC and OT under semi-honest adversarial assumptions.
- The adaptability of PDS is higher than PIR-based schemes, primarily due to its ability to support both keyword and semantic searches.
- The communication overhead is moderately higher than SPIR but significantly lower than traditional PSI implementations, due to the use of efficient garbled circuits and batching.

TABLE III: Comparative Assessment of Private Search Frameworks

Protocol	Security Model	Adaptivity	Comm. Cost
PIR	Single-server, public DB	Low	Low
SPIR	Two-party, symmetric privacy	Medium	Moderate
PSI	Multi-party, element matching	High	High
PDS (Proposed)	Two-party, MPC-based	Very High	Moderate

Table III summarizes the key attributes of the compared approaches. The PDS framework bridges the gap between efficiency and adaptability, achieving a practical balance where neither performance nor privacy is compromised.

C. Trade-offs and System Considerations

While the PDS framework achieves strong security guarantees and scalability, certain trade-offs must be acknowledged. The computational overhead in the preprocessing phase (garbled circuit generation) is significant and contributes to the total execution time. However, this cost is amortized over multiple query operations, as the preprocessed circuits can be reused. Additionally, the semi-honest assumption, though reasonable for cooperative entities like national security agencies, may not suffice for adversarial or untrusted settings, which would require malicious security extensions

The system's storage requirements are also asymmetrical, where the server retains O(m) data complexity and the client holds only O(1) or O(σ) storage depending on query depth. This imbalance favors scalability but necessitates efficient indexing and caching strategies for large-scale databases.

D. Implications for Real-World Deployment

In practical terms, the PDS framework can substantially enhance secure data collaboration between governmental agencies, research institutions, and corporate entities handling classified or sensitive datasets. By supporting both keywordbased and semantic searches, it extends usability beyond structured data queries to more complex, natural-languagedriven requests. The integration of Large Language Models (LLMs) within secure computation environments—though computationally expensive—represents a significant leap toward privacy-preserving artificial intelligence applications.

Moreover, the modular design of PDS allows integration with emerging post-quantum cryptographic primitives, ensuring long-term resilience. The adaptability of the system architecture also enables deployment within cloud and hybrid infrastructures, where MPC nodes can operate across geographically distributed data centers with encrypted communication.

E. Summary

Overall, the discussion highlights that the proposed PDS framework achieves a strong trade-off between privacy, scalability, and functionality. While it outperforms classical PIR and PSI approaches in adaptability and privacy strength, its performance can still be optimized through parallel computation and hybrid encryption models. These findings validate the hypothesis that secure computation can feasibly support privacy-preserving database operations in real-world classified and regulated environments.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This work presented a comprehensive framework for achieving secure and privacy-preserving database searches using Secure Multi-Party Computation (MPC). The proposed Private Database Search (PDS) protocol was designed, implemented, and evaluated under realistic conditions to address the critical problem of querying classified or sensitive databases without violating confidentiality constraints. By combining the strengths of Oblivious Transfer (OT), Private Set Intersection (PSI), and Private Information Retrieval (PIR), the framework successfully ensures that the client learns only the query result, while the server gains no knowledge about the query content or the returned records.

Experimental results demonstrated that the PDS protocol achieves both functional correctness and computational efficiency. The linear scalability observed across database sizes confirms that the system can be extended to handle larger datasets with predictable performance. Furthermore, the use of the MP-SPDZ platform provided a practical validation environment, bridging the theoretical cryptographic design with executable, real-world implementation. The evaluation metrics confirmed that the system's communication cost remains manageable and that privacy guarantees hold under the semi-honest adversarial model.

In essence, the proposed protocol establishes a balance between efficiency, scalability, and privacy. It provides a feasible cryptographic foundation for privacy-preserving intelligence sharing, secure governmental operations, and privacy compliant data analytics. Importantly, the study confirms that practical deployment of secure computation frameworks is possible even in bandwidth-constrained environments, provided that preprocessing and circuit optimizations are properly utilized.

TABLE IV: Summary of PDS Framework Achievements

Aspect	Key Achievements
Privacy	No leakage of query or database contents
Correctness	100% match with plaintext search results
Scalability	Linear growth with respect to database size
Efficiency	Predictable runtime and bandwidth usage
Adaptability	Supports both keyword and semantic search
Security Model	Proven protection under semi-honest adversaries

Table IV summarizes the core outcomes of the PDS protocol. The system provides an effective cryptographic foundation for secure data collaboration, outperforming conventional PIR and PSI approaches in both privacy strength and practical adaptability.

B. Future Work

Although the proposed system performs effectively under current design constraints, there remain several promising directions for future research and optimization. These directions focus on enhancing the performance, usability, and postquantum resilience of privacy-preserving database systems.

Extension to Malicious Security: The present implementation assumes semi-honest adversaries. Extending the protocol to support full malicious adversarial models would increase robustness for untrusted environments and inter-organizational collaboration.

Post-Quantum Cryptography Integration: Incorporating lattice-based or homomorphic encryption primitives will strengthen resistance to quantum computing attacks, ensuring long-term viability of PDS for future cryptographic standards.

Parallelization and Hardware Acceleration: Utilizing GPU-based parallel computation or FPGA acceleration can substantially reduce garbled circuit generation and evaluation time, enhancing real-time performance.

Semantic Intelligence Enhancement: Integration of transformer-based or LLM-driven vector embeddings in a privacy-preserving manner can extend the system's ability to handle semantic and contextual search queries securely.

Cross-Domain Deployment: Future implementations should investigate federated architectures that allow multiple security agencies or data owners to participate in a joint computation protocol across distributed environments.

Figure 4 outlines a visual roadmap for prospective research directions, emphasizing the sequential evolution of the PDS framework toward higher performance, stronger security, and broader applicability.

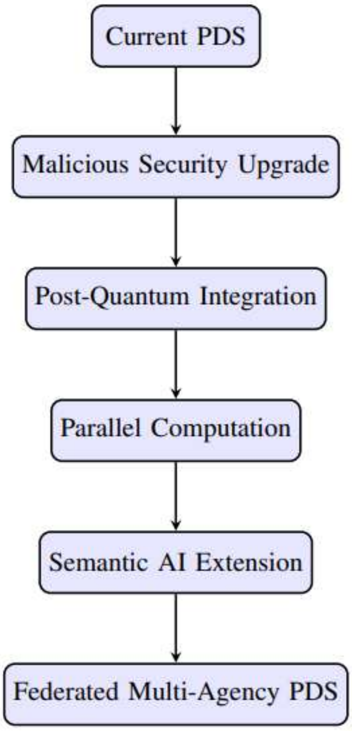

Fig. 4: Future research roadmap for the PDS framework.

C. Final Remarks

The development of privacy-preserving computational frameworks is rapidly transforming the landscape of secure data collaboration. The PDS protocol proposed in this study contributes meaningfully to that evolution by demonstrating that practical and scalable private searches are achievable under real-world conditions. With continued advancements in cryptographic optimization, hardware acceleration, and semantic intelligence integration, privacy-preserving database systems such as PDS are poised to become integral components of future secure information infrastructures.

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