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Chapter 9: Security by Design: Zero-Trust Architectures and Privacy-Preserving Computation in Finances

9.1. Introduction

The security properties of a digital financial system should be designed and verified from the ground up by systematically identifying the assets and potential threats, establishing trade-and-risk metrics, analyzing the existing security controls, and examining whether these controls provide adequate protection for the underlying assets against the underlying threats. This analysis typically shows that traditional security safeguards such as role-based access control, firewalls, and perimeter defenses are necessary but not sufficient. For digital financial systems based on privacy-preserving computation, some fundamental zero-trust principles must be adopted.

A zero-trust architecture assumes that every attempt to access a resource is a potential threat and therefore must be verified before being granted access. The core tenets of such an architecture include explicit verification, the principle of least privilege, the assumption of breach, end-to-end visibility, automation, and continuous risk assessment. Various architectural patterns can help implement these principles effectively in a financial environment, including micro-segmentation, identity-aware services, encrypted data in use, policy-based access control, and secure service meshes.

9.1.1. Overview of Security Considerations in Financial Systems

Security considerations in financial systems include the identification of primary assets, the specification of both logical and physical threats, the establishment of appropriate security controls, and the definition of a risk metric. Two specific components of security—zero-trust architectures and privacy-preserving computation—are highlighted. A zero-trust architecture mitigates the risk of a data breach by implementing extensive logging and monitoring, enforcing strict access policies based on the principle

of least privilege, applying strong encryption at all times, securing micro-segmentation of workloads, and introducing various forms of identity-aware access control. Privacy-preserving computation further enhances security by preventing the leakage of sensitive data during model training and application while aligning with regulatory requirements such as GDPR and its variants.

The threat landscape for financial institutions is extensive, with the risk of a data breach in the public domain ranking among the highest. Several changes affecting the risk landscape include greater pressure from regulators to reduce exposure to sensitive data, an increase in sophisticated supply-chain attacks that place internal apps at greater risk, and a significant uptick in insider risk and fraud attempts. Cyberattacks are becoming one of the top-three business risks facing companies globally, while ransomware attacks are expected to increase significantly. The integration of external service providers, many of which struggle to meet acceptable security operating standards, only adds to the overall risk profile.

Fig 9.1: Fortifying the Financial Perimeter: A Zero-Trust and Privacy-Preserving Framework for Mitigating Systemic Cyber-Risk and Supply-Chain Vulnerabilities

9.2. Foundations of Security by Design in Finance

As for any computing system, threats to financial systems can come from many directions. Data breaches for payment, investment, and other business information can

lead to identity theft, financial fraud, and reputational damage for customers and services. Internal risks associated with disgruntled employees or trusted vendors with access to sensitive data are difficult to eliminate completely. Attacks that exploit third-party supply chains, such as SolarWinds and the 2020 Ubiquiti Networks incident, can strike an institution indirectly. Additionally, financial regulatory requirements in areas like Know Your Customer (KYC) or Anti-Money Laundering (AML) efforts are increasingly strenuous and can lead to large penalties for non-compliance. As the number of interfaces and connected components continues to expand, additional pressure on network governance comes from modern digital transformations focused on adopting a microservices approach. These trends increasingly call for banking solutions to lead in development efforts, especially concerning data control and regulatory compliance, and to drive adoption into other sectors. Recent industry surveys confirm the trend toward a security-by-design approach as organizations adopt either a formal zero-trust security architecture or utilize its principles to inform security strategy and investment decisions.

The following Principles of Security by Design serve as a foundation: (i) The principle of least privilege defines minimal levels of access to systems, applications, and information required for an individual to undergo their assigned work duties. (ii) Continuous verification of identity, credentials, and configurations for users and assets, regardless of proximity, reduces risks of unauthorized access to sensitive data and production systems. (iii) A defence-in-depth strategy composes multiple layers of security in parallel to better withstand an attack and limit damage. (iv) Data minimization limits data collection and transfers to the least amount necessary, ensuring exposure is minimized. (v) Accountability assigns responsibility and liability for actions within a system to individuals and organizations. (vi) Verifiability affords independent confirmation of processes and controls for external parties and stakeholders.

9.2.1. Threat Landscape in Financial Systems

Financial systems face various security threats with potentially catastrophic consequences. These include the risk of data breaches, insider threats, attacks in the supply chain, manipulation or exploitation of third-party risk management processes, exploitation of third-party services, and regulatory pressures. The threat posed by hostile third-party services and serverless environments is aggravated by the location of sensitive data in third-party servers that may reside anywhere in the world. Support from different third-party services for money laundering without proper Know Your Customer or Anti-Money Laundering processes makes it easier for malicious users to wash and misuse their assets. The risk of insider threats, which constitute one of the top cybersecurity threats on an annual basis, is further exacerbated by the shortage of cybersecurity talent.

Data breaches in the financial industry represent only 1% of the total breaches in recent years; however, the impact of such breaches far exceeds that in other standard industries. Even the largest companies with a strong cybersecurity foundation fall victim to attacks, with the loss of important transaction details, payment information, and user credentials becoming a new trend. Damage from data breaches has become common, including mitigation costs, reputation loss, business disruption, regulation scrutiny, and financial losses stemming from theft and fraud. Continuous monitoring of insider risk has become a critical cybersecurity priority after a surge in insider incidents, which are approved and authenticated requests made with stolen administrator accounts. In addition to the financial costs, now various organizations and industry leaders are concerned about the reputational effects of data breaches.

9.2.2. Principles of Security by Design

The Principles of Security by Design answer specific threat considerations in financial systems. Private data is a valuable target for external attackers and disgruntled insiders; threats include external penetration, insider abuse, data compromise during service requests, malicious code injection into third-party services, and regulatory scandals such as money laundering. Data breaches are frequent across industries; the average cost of a breach in 2023 is USD 4.45 million, and the total cost to financial institutions exceeded USD 5 billion in 2022. Monetary loss, legal liability, reputational damage, and operational disruption motivate zero-trust controls for financial institutions. The Principles of Security by Design support zero-trust adoption—integrating least-privilege access, continuous verification, defense in depth, data minimization, and audit resources.

Security by Design introduces the Principles of Security by Design—fundamental building blocks for trusted systems. These principles guide decision-making in the face of conflicting requirements, reduce reliance on external actors, and provide verifiable assurances that security records and data usage are consistent. They include least privilege, continuous verification, defense in depth, data minimization, accountability, and verifiability. A system designed with these principles helps to mitigate failure 83%.

9.3. Zero-Trust Architectures in Financial Services

Adopting a zero-trust strategy for security improves the resilience of financial services against evolving threats. Zero-trust architectures are built on the following tenets: verification should be explicit rather than implicit; the principle of least privilege should be strictly applied; a breach should be assumed until proven otherwise; end-to-end visibility must be available; risk management processes should heavily rely on automation; and risk should be continuously assessed. Technical solutions that embody

these tenets support the security objectives of finance without introducing excessive performance overhead.

Core tenets of zero-trust architectures apply to all applications and services, and implementation is commonly addressed in systems-networks management policies. Six architectural patterns, however, are particularly relevant in finance: micro-segmentation, identity-aware services, encrypted data in use, policy-based access control, and secure service meshes. Micro-segmentation divides a network into smaller zones to limit lateral movement and facilitate detection of suspicious activity, especially from insiders or compromised accounts. Identity-aware services apply security and access policies to individual messages and requests based on various attributes, including the identity of the requester, integrity of the device, and security posture of the session. Encrypted data in use protects data exposed in system memory and during computation. Policy-based access control allows access to data and services only through defined methods and prevents information exfiltration by applying data handling policies to system calls. Secure service meshes create a dedicated application layer that enforces developer-defined policies to each microservice-to-microservice communication. Collectively, these patterns meet the security requirements of financial services and systems.

9.3.1. Core tenets of Zero-Trust

Zero-trust in finance draws on cross-domain experience and emphasizes ground-up identity observability and policy enforcement, thereby offering the most rigorous protection. Core tenets include verifying explicitly, following the principle of least privilege, assuming breach, maintaining end-to-end visibility, relying on automation, and using continuous risk assessment as a basis for data-driven security decisions.

Verify explicitly. Access requests must always be verified, regardless of source. Rather than assuming users within a network are secure, requests should be subject to authentication and authorization both before and during delivery. Security controls cannot be applied just once; they must be applied for every interaction and cover all users, devices, stations, and system components, including those that may not have been previously fully trusted. Under a zero-trust approach, even interaction within accounts does not guarantee security. Any user can be subject to temporary ban, suspension, or isolation.

Principle of least privilege. Access to sensitive assets must be limited to users who specifically need it and for the time they actually need it. The principle of least privilege is a well-known security design principle and is also a requirement of the PCI-DSS security standard. People should not have universal access to every aspect of a network or connected systems whenever they wish. In a zero-trust architecture, this requirement

can be fully enforced by making it obligatory for all users with general access to instantly seek special permission to use it. A request for sensitive access could trigger additional verification steps before being granted.

9.3.2. Architectural patterns for Zero-Trust in finance

Financial systems can apply zero-trust principles in several complementary architectural patterns: micro-segmentation, identity-aware services, encrypted data in use, policy-based access, and secure service meshes.

Micro-segmentation enables finer control and monitoring of data flow, reducing the attack surface in the event of a breach. It extends conventional network segmentation beyond traditional firewalls: north–south, east–west, and, more generally, intra-host traffic flows. Like-channels-of-interest connection patterns can be identified by monitoring the data flow in systems at runtime and instrumenting micro-segmentation accordingly.

Identity-aware services provide data flow control and auditing based on the identity of the parties involved in the communication. Permissioned ledgers constitute the archetype of such services. Their multiple-user, shared-state interoperability poses unique challenges that require specific solutions. Only some parties have the ability to append new blocks to the ledger; other parties validate the blocks; the policies that govern the introduction of records and assets govern the permissions to modify them. Traditional federation approaches—centralized, hierarchical authentication and authorization authorities (AA)—do not integrate naturally with permissioned ledgers.

Encrypted data in use enables control over more data flows. For example, cryptographic garbling of the code enables parties to create and evaluate their own private inputs over sensitive data. Such computations can happen over an encrypted circuit whose gates are secret sharded among the computing parties in such a way that all parties together can evaluate the circuit over their secret data, while any strict subset of them learn nothing. The most powerful enabling technology for computation on encrypted data is homomorphic encryption.

Policy-based access to services and data is used to ensure that requests to services and access to data are granted only to authorized systems and users, and that the right privileges are enforced at different levels of granularity. Automating control through logical policies written in policy definition languages diminishes the potential for human errors to escape testing. Policies are evaluated at different granularities, including traffic-level monitoring and filtering, service-level business continuity management, and support to security devices, response teams, and decision-makers.

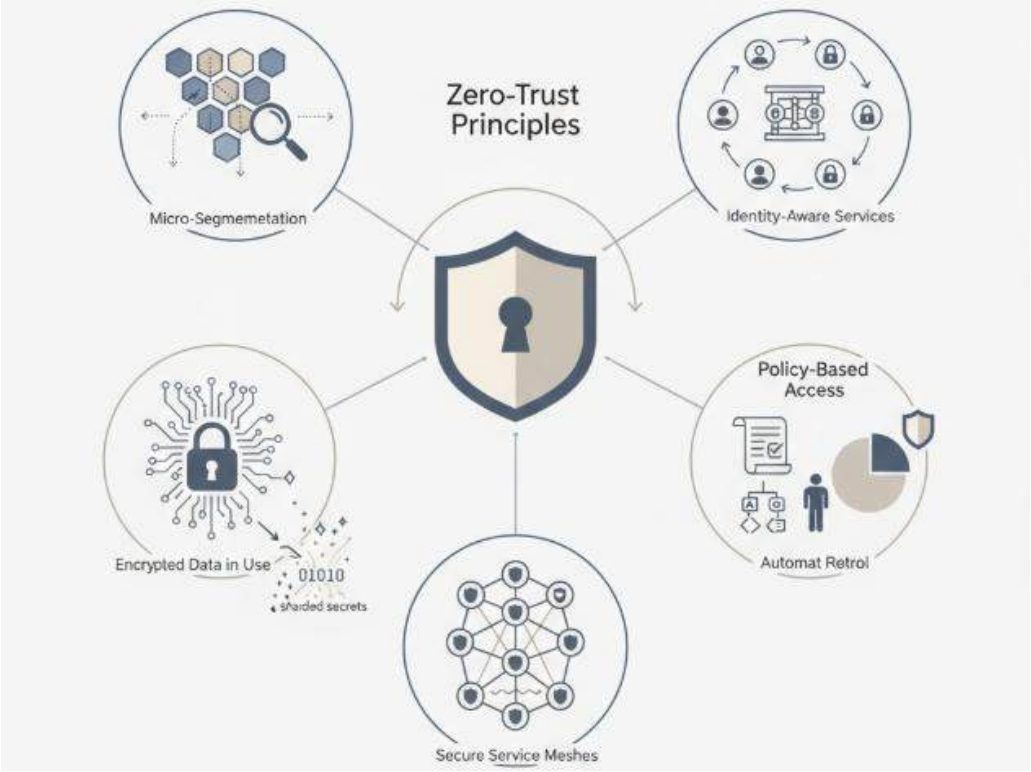

Fig 9.2: Zero-Trust Paradigms in Financial Infrastructures: A Unified Framework for Micro-Segmentation, Homomorphic Encryption, and Policy-Driven Access Control

9.4. Privacy-Preserving Computation Techniques

Adopting privacy-preserving computation techniques addresses the external and internal perils of data breaches while supporting compliance with regulatory requirements. Cryptographic protection can minimize the collection and storage of sensitive data. Threat agents can still exploit other approaches, such as model update, aggregation, and insider action, although further privacy guarantees can help. Financial institutions must balance the reduction of sensitive data exposure with regulatory requirements, which may compel data flows in other directions.

The necessary privacy-preserving cryptographic techniques can be divided into two groups: those that allow computations on encrypted data, such as homomorphic encryption, secure multi-party computation, and trusted execution environments—each of which may involve different stakeholders—and those that minimize the amount of sensitive information involved during model training, such as federated learning and differential privacy. Due to the inherent trade-off among performance, security, and privacy guarantees, any specific use case should carefully assess the applicability of

these solutions. Supporting the internal use of sensitive data by preventive and detective controls, especially data sharing among fraud detections in different institutions, can further counter insider threats and help improve the overall security level of the financial ecosystem.

9.4.1. Cryptographic foundations and secure computation

A central role in fortifying privacy-preserving computation is played by cryptography, along with hardware-based trusted execution environments. Both ideas are examined, alongside concepts pertaining to secret-sharing-based secure multiparty computation and differential privacy. Homomorphic encryption, efficiently supporting only addition or multiplication operations or both, generally entails prohibitive overheads, especially for data at end systems. Such operations are, however, amenable to execution in TEEs, which ensure that the software is devoid of backdoors and malicious code, thus maintaining end-to-end encryption through an isolated trusted environment.

Secret sharing, employed by secure multiparty computation, enables computation over a ciphertext decomposition of records spread across distinct servers. Information leakage that may otherwise occur during score generation or prediction is curtailed by differential privacy, achieved by cohorting user data and adding random noise to the results. For predictive analytics supporting anti-money-laundering or fraud-compliance operations, federated learning serves as a similar de-centralized mechanism that allows models to be trained without sharing the private data needed for credit scoring or identifying fraudulent behavior, but in such a way that the contribution of Banks toward model improvement is sufficiently privacy preserving by adhering to data localization and cross-border law-enforcement regulation.

9.4.2. Federated learning and data minimization

Federated learning allows multiple participants to collaboratively train a shared machine-learning model with their sensitive, local data without sharing it. Model updates are sent from individual data owners to a central aggregator, which averages the updates to create a single model update; this update is then shared with all participants. By sharing only model updates, federated learning addresses privacy concerns and alleviates issues with data localization and cross-border data transfer. Regulatory bodies such as the European Data Protection Board cite federated learning as a promising solution for compliance with strict data-protection regulations.

The aggregation typically preserves differential privacy, a strong mathematical notion of privacy guarantees. While differential-privacy mechanisms introduce noise and

therefore a trade-off with model accuracy, successful implementations demonstrate that the loss can be small relative to the model accuracy on the local data. However, federated learning requires careful design choices, including deciding the level of noise for each participating model owner; too much noise can compromise accuracy of the final model.

Federated learning aligns with the Principle of Data Minimization, a critical notion built into various regulations (such as the GDPR) and that is driving innovation towards banking without a bank. Yet participants also need to consider monetary aspects: federated learning usually involves extra infrastructure costs, and the communication of weight updates introduces latency and possibility of communication bottlenecks.

9.5. Integration of Zero-Trust and Privacy-Preserving Computation

Empowerment of zero-trust in financial systems consolidates and completes the two main security designs presented in Section 3 and Section 4—zero-trust architectures and privacy-preserving computation—while supporting their practical realization. As these designs support the protection of a financial institution's most critical assets, a careful analysis of the data flows, governance, and regulatory considerations under a zero-trust architecture design is thus included.

Data Flow. To accomplish the identity verification step, User Data are typically protected through encryption in transit, but are still replicated and stored unencrypted at various locations. A complete integration of zero-trust principles would therefore require segregation of the copy of User Data used for identity verification, making that copy available for use only during the verification step and eliminating any unencrypted copy. Verification of ownership of the payment means is achieved through encrypted data—clearly not locally or internally stored for speed purposes. For request handling, Response Data should only be protected through policy-based access control and enforced through a PEP. Payment processing should also be covered by Policy 1. It is important to remember that up to that point, Policy 1 states that the clearing agent can at any time have access to the data supporting the payments and can join those payment messages during execution.

As for encryption in transit and at rest, the Data are encrypted during use as long as the encryption keys are controlled by the party that is the owner of the Data. Moreover, at Data replication time, encryption keys can also be used to implement the principle of least privilege. Continuous monitoring of the Data access is under the control of the PEP that can inform the organization and allow the verification of actions.

9.5.1. Data flow design under Zero-Trust

Data flow design follows the seven pillars of zero-trust data protection. Identity must be established and continuously verified for all data participants across channels and systems (users, devices, apps, servers, networks, workloads, and endpoints). Policy-based access helps enforce least-privilege access to data based on risk, identity attributes, and security posture. Encryption protects data both in transit and at rest, while tamper-proof logging supports continuous monitoring and anomaly detection.

Data stored outside a controlled environment is encrypted in use, with all operations performed on ciphertext for strong protection during processing. Confidentiality and integrity are enforced on plaintext access and processing through whitelisting, role-based access, file integrity monitoring, and confidentiality agreements with third parties. Furthermore, a secure service mesh enables granular control over inter-service communication across boundaries, providing visibility, observability, and security automation at the application layer.

9.5.2. monetary, regulatory, and compliance considerations

Convergence of zero-trust and privacy-preserving computation in finance must also consider monetary, regulatory, and compliance aspects. Financial institutions are required to Know Your Customer (KYC) and perform Anti-Money Laundering (AML) operations, which involves collecting and storing critical personal information of customers, data localization policies demand that certain sensitive personally identifiable information cannot be transferred outside the borders of a country, and third-party service providers must share information with financial institutions to support services such as payment processing and credit scoring. Privacy-preserving approaches addressing these requirements are therefore paramount for providing privacy-preserving computation without running afoul of the financial regulations governing the industry. These requirements are key to making the data-sharing control and audit concepts integrate with the privacy-preserving approaches.

KYC requirements often depend on the jurisdiction of the transaction. A payment transfer between customers belonging to financial institutions in different countries typically involves increased risk of one of the parties engaging in illicit activities. As a result, the financial institution in the sender's country has the responsibility of monitoring that customer and potential flagging any suspicious transaction for further investigation. If the latter action is taken, the financial institution is required to submit a report to the local authorities with detailed information about the transaction, including personally identifiable information regarding both sender and receiver. For such KYC and AML processes, a computation where customers' personally identifiable information is not revealed, while still allowing suspicious transactions to be flagged and reported in a proper manner, can offer service providers significant competitive advantages.

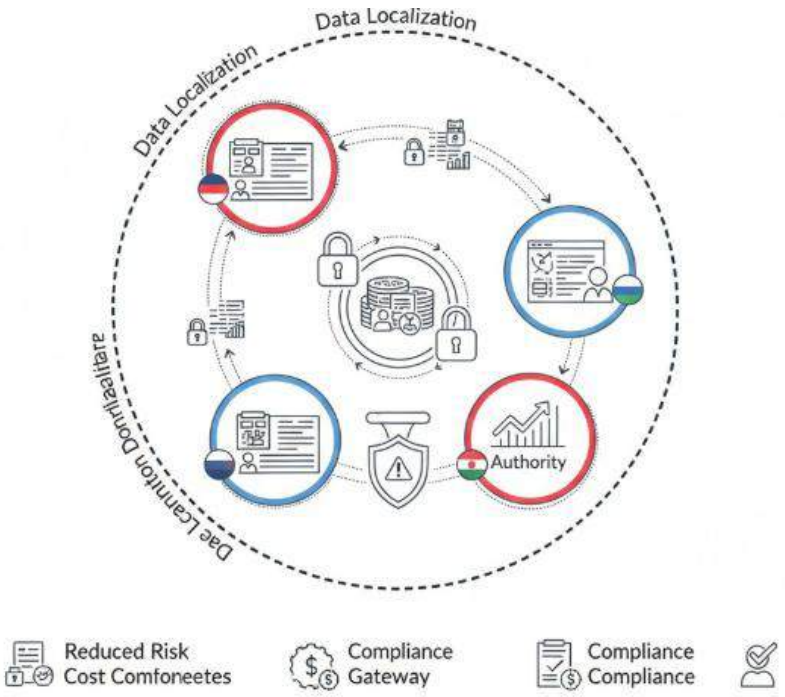

Fig 9.3: Regulated Confidentiality: Converging Zero-Trust Architectures and Privacy-Preserving Computation for Multi-Jurisdictional KYC/AML Compliance

9.6. Practical Architectures and Case Studies

Security-by-design principles guide the adoption of zero-trust principles and associated requirements through banking payment processing. The application of principles in practice illustrates the use and integration of zero-trust architectures with privacy-preserving computation through two case studies; a payment processing and settlement environment describes operational requirements before zero-trust data flows are annotated to indicate identity dimensions, orchestration, management, and policy-enforcement points. Monetisation, regulatory, and compliance requirements in anti-money laundering and fraud-detection solutions demonstrate financial-market considerations across application domains.

Financial firms offer and consume similar services in payments, markets, and investment, presenting opportunities in risk scoring that span disparate sources. When information-sharing obligations are fulfilled, model updates may be shared across organisations. Banks typically operate an enduring relationship of Know Your Customer (KYC) and Anti-Money Laundering (AML) with government regulators, enabling a form of controls network for transaction monitoring. Government authorities increasingly expect the inclusion of privacy-enhancing technologies within such

solutions; federated learning, privacy-preserving machine learning, or other similar solutions based on secure multi-party computation enable such requirements to be entertained.

9.6.1. Payment processing and settlement environments

Payments and settlement environments are critical to any financial institution, processing large monetary volumes to be completed within shorter time horizons. Such an environment is complex, involving assets managed by multiple actors, each of whom prefer to expose a limited degree of trust to the other sides.

Multiple operational phases are involved. In payment processing, interaction with clients is critical. Multilayered architectures, including switches and gateways, perform transactions for thousands of clients every day. Service delivery is supported through automatic 24 × 7 operations, which increase processing efficiency but also reduce reliability and security. Therefore, operational resilience requirements are essential. DPS have defined a Minimum Functionality for Payment Systems with Operational Risk Management. The principles are based on the dimensions of technology, complexity, interface with the user and three lines of defence. Life-cycle for new services should be managed rigorously, with strong dependence on testing.

In the settlement process, an increasing number of parties are digitally signing transactions. System encryption and digital signature management become critical issues. Data protection becomes the other necessary security infrastructure component. A trusted orchestration layer provides cryptographic protection as the transaction travels across the different secured digital façades of third parties, managing the interaction securely with all the necessary projections. The secrecy of the system data should also be guaranteed, preventing capture of exploitable information.

9.6.2. Anti-money laundering and fraud detection

Coloration, migration of capital, simulated payments or transfers, and transaction blurring are just a few of the methods criminals use to hide illicit money generated by drug and arms trafficking, human trafficking, etc. For all trades in the real world, there will be a payment, either a transfer or a confirmation. Banks are required to ensure that the identified parties comply with the “Know Your Customer” (KYC) principle. Nonetheless, through distributing a lot of data and blurring the information surface, criminals are capable of performing fraud and money laundering, thereby transferring the stains of transaction illegality to other financial institutions. Anti-money laundering (AML) is a requirement of every financial institution.

Usually, every bank develops their own set of rules for flagging a suspicious transaction, but financial intelligence units (FIU) analyze all institutions' data. An excessive amount of false positives make it difficult to find the real illicit activities; a solution is the sharing of non-readable information throughout institutions, exploiting the aggregation information without disclosing transaction details. Privacy-preserving techniques can be used by several banks for data analysis purpose while, at the same time, allowing them to generate and share a more precise risk score. By combining it with the validation of KYC–"Anti-money laundering" (KYC–AML) regulation, the analysis of all clients' banks and counting the indicators associated to them, an instant risk score can be produced. The FIU can utilize privacy-preserving techniques to elaborate the models and provide the institutions with a safer intelligence. Furthermore, the model could undergo a federated learning enabling all banks to share the risk without disclosing it.

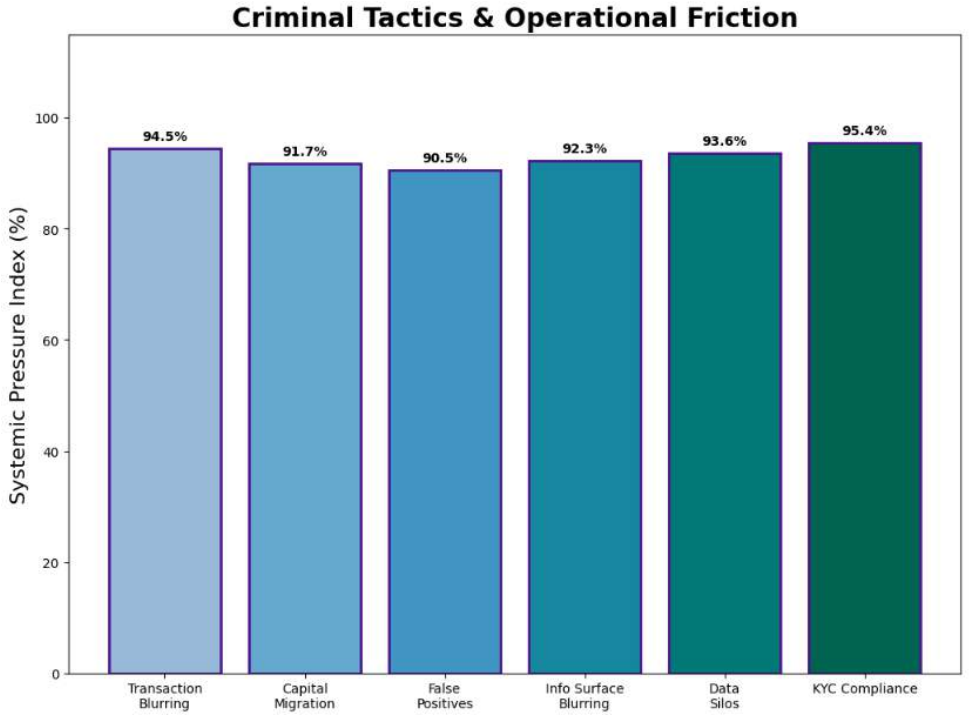

Fig 9.4: Criminal Tactics & Operational Friction

Fraud detection and anti-money laundering operations are classified as basic data sharing in which each classification or scoring model is exploited with privacy-preserving computation so that encrypted data are externally shared and the risk of each party is analyzed as a function of other parties' behaviour. The results of this process can be shared towards a final entity that can use privacy-preserving techniques to manage the global detection and share only the information needed to elaborate the risk score with

the proper legal aspect; at the end all institutions are able to evaluate the risk of the transaction without disclosing the data whose relation is checked.

9.7. Conclusion

The previous sections integrate zero-trust architectures with privacy-preserving computation in financial systems, where Security by Design addresses both data security and exposure concerns. Adopting automate-verifiable-zero-trust patterns for data flows and governance strengthens resilience against security incidents and breaches, aligns with customers' demands for privacy, and supports regulatory compliance. Strongly authoritative and completely encrypted Payment Processing and Settlement Architectures, and AML-related data-mining for Fraud Prevention and Detection, illustrate practical-zero-trust deployments.

Although Trust No One is well known within security communities, diffusion and realization of its requirements is still immature, particularly in finance. Indeed, both designs and implementations of Security by Design remain rare, as acknowledged in Cyber Threat Progress Report 2022. Future work should further integrate automatic verification with Zero-Trust principles. The Bank of England's publication requires financial-regulatory-focus on automation, Privacy by Design, and data protection. Recommendations developed propose accomplishing Design and Control for its Security, at minimal-cost and over a reasonable time period.

9.7.1. Key Takeaways and Future Directions in Financial Security

Integration of zero-trust principles with privacy-preserving computation provides a compelling approach to secure sensitive actions and data in the finance sector. Data flows and governance model for complex monetary, regulatory, and compliance considerations—such as know-your-customer and anti-money-laundering requirements in payment services—demonstrate the concrete, practical implications of Security by Design. Despite the attractiveness of the approach, obstacles remain. Financial services are often hosted on multi-tenancy public clouds, and sensitive data typically cross borders without technical controls that satisfy regional regulations. Recognizing that no system is infallible or otherworldly, Security by Design emphasizes Security: a Culture of Professional Focus and Attentional Investment that motivates vigilance and performance in managing security risk. Hence, Security by Design cultivate genuine Righteousness that inspires appropriate scrutiny and challenge of everything relating to security, identity, privacy, and fraud. Just as software became software engineering and cybersecurity transformed into security engineering, the responsibility to be righteous

through Security and Privacy reminds every finance employee to be Security and Privacy Professional at work.

Practical architectures supporting common actions in payments, settlements, and anti-money laundering provide specifics in achieving Security by Design. Future Security-by-Design investigations demand the same instinctively inclusive urge that not only naturally motivates openness, transparency, and the sharing of information but also recognises Security and Privacy as skilful capabilities requiring the appropriate supervision, investment, and training. Security and Privacy are Special-purpose Operations. Security and Privacy must be Special-purpose Functions: Functions Essential to incorporate Design for Security and Design for Privacy into every professional act by Special-purpose People, Well-trained, Self-disciplined, and Professional—and not assign Security and Privacy as a Special-purpose Task to be where "No One Knows and No One Cares." In pursuing these Security and Design goals, and in balancing the next Security and Privacy investments across Managing-righteousness Culture and Righteousness-Professional Skill, the latest demands on the Security and Privacy S-and-P respectively will shape future Financial Services Security and Privacy Engineering directions.

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