



Privacy-Preserving Federated AI for Customer Intelligence

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Abstract

Cross-enterprise customer intelligence analytics seek to discover valuable insights from secure collaboration between multiple enterprises, although sensitive business data and competing interests often restrict data sharing. Federated AI enables distributed machine learning without sharing models and supporting inferencing or prediction tasks involving the aggregated intelligence of isolated, possibly heterogeneously governed datasets. The applications are crucial for risk control analytics or enriching data-driven decision systems, while cooperation can be organized in a formal consortium or on an ad-hoc basis.

Federated AI offers several potential benefits: it minimizes the issues associated with cross-enterprise data sharing and overcomes the limitations of local analysis. Nevertheless, it also introduces new privacy, security and system-level threats, such as data leakage via model sharing or model inversion and membership inference attacks against sensitive model information. Exploring the federated AI paradigm for cross-enterprise customer intelligence analytics is essential for determining its applicability, identifying missing privacy-preserving mechanisms and addressing latent security risks. These aspects can thus be analysed and adapted into a privacy-preserving security-enhanced federated AI platform proposed through design science research. Realizing and endorsing the potential advantages in a production environment, however, requires further exploration.

Keywords: Federated AI for Customer Intelligence, Cross-Enterprise Data Collaboration, Privacy-Preserving Machine Learning, Federated Learning Architectures, Distributed Customer Analytics Platforms, Secure Multi-Organization Data Analytics, Privacy-Enhanced AI Systems, Data Governance in Federated AI, Cross-Enterprise Risk Analytics, Collaborative AI Decision Systems, Model Inversion Attack Mitigation, Membership Inference Attack Protection, Secure Model Sharing Frameworks, Federated Data Intelligence Platforms, Confidential AI Collaboration Environments.

1. Introduction

Data-driven customer intelligence shapes business strategy by generating actionable information from diverse data sources. However, data silos limit analytics capabilities and data '

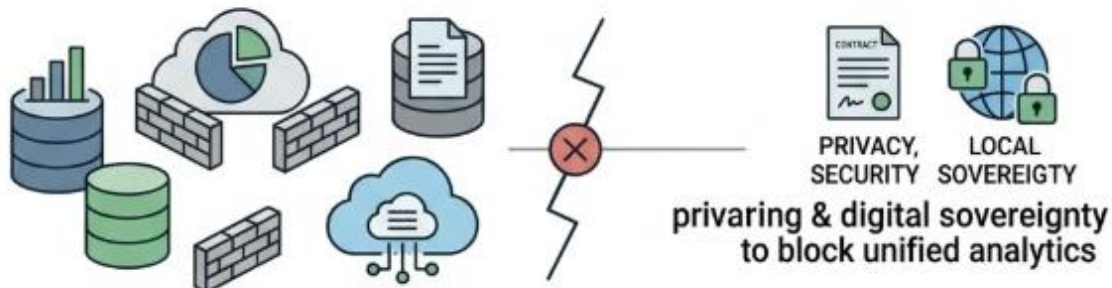


Digital sovereignty requirements further complicate collaboration attempts. Federated techniques address these challenges by performing analytics across data sources while respecting local governance policies, thus alleviating privacy and contractual concerns. A federated approach offers security advantages when using publicly available data to augment sensitive customer stores. Nevertheless, federated techniques introduce new threats and require security-aware architectural design.

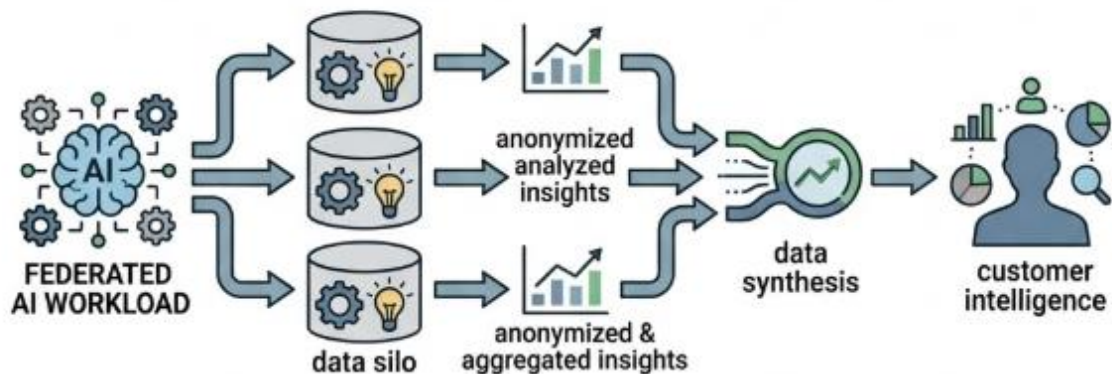
A risk–benefit analysis examines the suitability of federated techniques for cross-enterprise customer intelligence and identifies an architectural foundation for federated AI workloads. Cross-enterprise customer intelligence, privacy, and security requirements provide the scope, and the analysis draws on lessons learned from a federated data-science platform for customer experience analytics within the retail sector. The research questions are as follows: (1) Do federated techniques alleviate the challenges of cross-enterprise customer intelligence? and (2) What architectural features are necessary for secure federated customer-intelligence analytics?



THE CHALLENGE: DATA SILOS & SOVEREIGNTY



THE FEDERATED APPROACH: SECURE AGGREGATION



SYSTEM IMPACT & GOVERNANCE

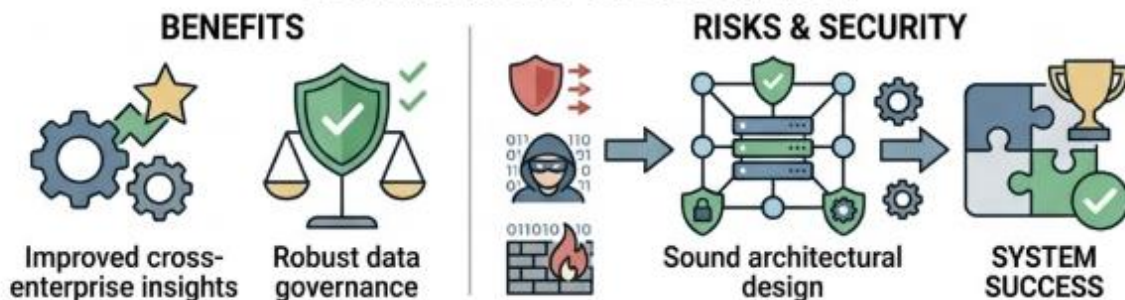


Fig 1: Orchestrating Customer Intelligence: A Risk–Benefit Analysis and Architectural Framework for Secure, Cross-Enterprise Federated AI



2. The Rationale for Federated Approaches in Customer Intelligence

Customer data is an asset of significant value for any enterprise since it directly affects customer experience, retention, and long-term growth. Nevertheless, data silos in proprietary information systems limit further analytics, such as cross-enterprise market basket analysis, customer product affinity, or risk-scoring for organisations in banking, financial services and insurance (BFSI) that face stiff data-mining competition. Sensitive and confidential customer information, such as health-related products, also cannot be exchanged due to privacy policies and regulations. Although organisations frequently pursue customer intelligence analytics (customer experience management, CRM, customer lifecycle management, etc.) with coarse data granularity, there is still an opportunity for a deeper understanding of their customer base, their affinities with products offered by other enterprises, and the experiences shared by customer clusters.

Instead of trying to combine siloed datasets into a common system with a single point of failure and breach, a federated approach is advocated, where data remain in their respective silos, and distributed data fusion models address privacy and confidentiality concerns with several model pseudo-code implementations. A federated strategy offers a well-defined trust and risk-management framework to encourage collaboration in customer experience management. Analysing the privacy budget offers an additional sensitivity-zone requirement to determine when two models may share a calculation, especially in the context of banking, financial services and insurance (BFSI) institutions. The actual value-added begins when analytics privacy is traded-off against accuracy.

3. Methodology

A business-oriented approach is adopted to establish the technical foundations of federated AI platforms serving cross-enterprise customer intelligence analytics. Interactions with domain experts from the banking and retail sectors highlight current limitations, next-generation aspirations, and medium-term priorities, providing motivation as well as use-case breadth. These insights inform the design of a preprototype evaluation framework, employing a mix of quantitative measures and qualitative evaluations using pilot implementations with sample datasets. The focus is on the fundamental capabilities required for predictive analytics serving collaborative use cases, framing the discussion around customer intelligence and governed customer experience as meaningful representative use cases.



The evaluation framework is then applied to assess the applicability and expected success of federated approaches for generic customer intelligence analytics in banking and financial services, and in improving customer service and experience in retail environments. A mapping and scoping of the banking and financial services use case is also presented, concentrating on data governance and risk treatment aspects. Additional supporting dimensions such as regulatory compliance, ethical considerations, and alignment with overarching business and technology strategies are synthesized at a higher level.

Equations 1) Actually present or implied in the article

1. Differential Privacy privacy budget relation

- privacy budget: ϵ
- smaller $\epsilon \Rightarrow$ stronger privacy, but lower utility/accuracy
- reported points:
 - $\epsilon = 0.7 \Rightarrow$ accuracy $\approx 70\%$
 - $\epsilon = 0.3 \Rightarrow$ accuracy $\approx 53\%$
 - $\epsilon = 0.1 \Rightarrow$ accuracy $\approx 39\%$

2. MPC adversary threshold

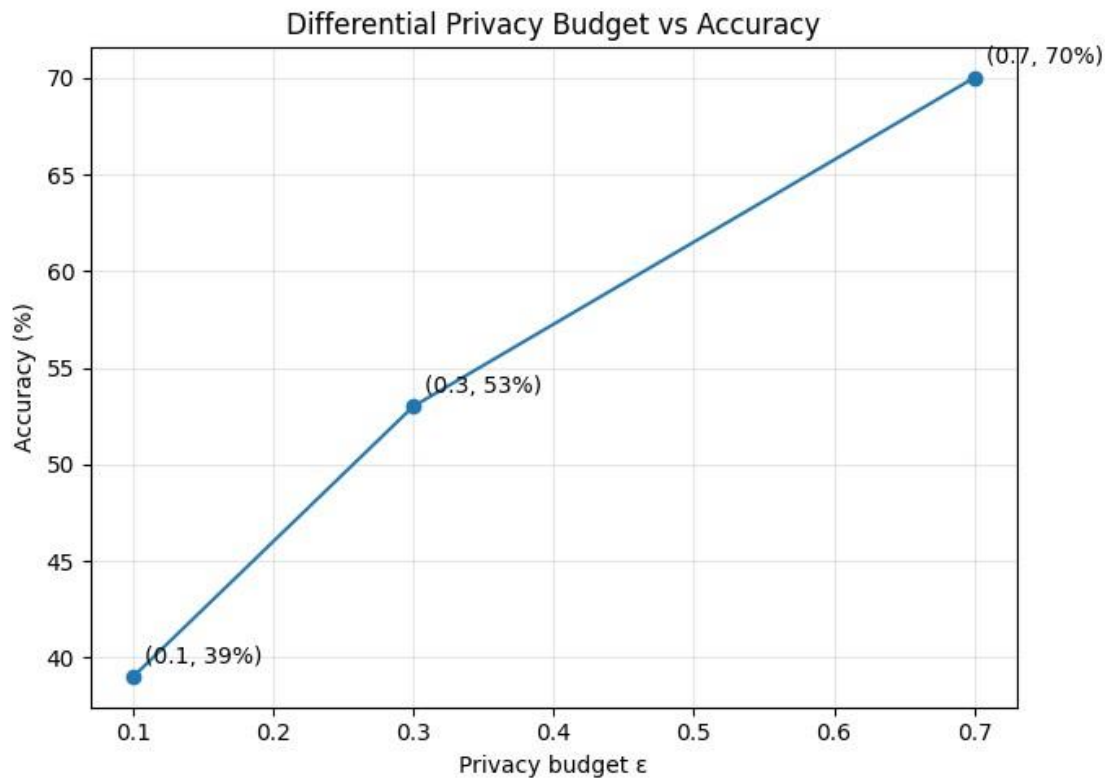
- for at least four parties, security holds when passive adversary subset size is

$$|A| < \left\lceil \frac{k}{2} \right\rceil$$

where k is the number of parties.

3. MPC communication/computation statement

- for two parties: one communication round and one computation round
- cost includes two shares per variable and multiplication overhead.



4. Objective of the Study

To establish the foundations for cross-enterprise customer intelligence analytics on federated AI platforms, fulfilling data locality and privacy-preserving computation objectives, and subsequently addressing trust, security, performance, and regulatory requirements. Modern customer intelligence analytics enables organizations to find hidden patterns and gain insights into the needs and preferences of customers. Enterprises possess rich datasets on customer behaviours, but often in silos with limited acquisition scope. Organizations are therefore exploring cross-enterprise customer intelligence analytics as collaborative partnerships and alliances emerge. Consolidation into single centralized servers is, however, impractical due to privacy, data residency, governance, and business model requirements, leading to interest in federated AI technologies.



Federated AI technology applies machine learning and artificial intelligence algorithms directly to local data with results shared to achieve global models. Federated AI platforms enable training and deployment of models across data sources without direct access to the underlying data, supporting customer intelligence applications while respecting data locality and privacy. A federated approach is advantageous since it can achieve customer intelligence without disrupting data locality and sovereignty policies by maintaining sensitive datasets within their organizational boundaries, addressing regulations that limit the cross-border transfer of personal information by ensuring that customer data remains within the same jurisdiction and further complying with external audits and data governance requirements.

5. Research Summary

Research summary findings, key contributions, and practical implications are recapped, and results are linked to research questions and enterprise use cases. Despite stringent privacy, intellectual property, and regulatory constraints, reliable customer intelligence analytics for cross-enterprise banking, financial services, retail, and customer experience use cases are indeed feasible.

The study validated and operationalized prior research on federated AI platforms and their utility for secure, cross-enterprise customer intelligence analytics involving data sharing across enterprise borders, with three concrete use cases. The analysis not only demonstrated that privacy-preserving computation can be sufficiently efficient to meet the needs of cross-enterprise analytics but also defined the foundations, frameworks, enabling technologies, design considerations, and risk management aspects essential for real-world deployments of federated AI platforms. As a result, use cases involving privacy-preserving sharing of trained models or insights derived from data—the outputs being less sensitive than the original training data—present even fewer obstacles to implementation.

6. Architectural Foundations of Federated AI Platforms

Federated AI platforms rely on computing capabilities and data storage being distributed across many networked organizations, thus addressing concerns related to privacy, governance, and data location. Many clients may want to contribute to a customer intelligence analytics project without sharing their sensitive datasets. To satisfy these security objectives, specific architectural principles are proposed. These are data locality and privacy-preserving computation, which seek to provide the ability to keep sensitive data not yet ready for sharing stored locally and to enable privacy-sensitive computations without sharing local data.



Interoperability and standardization deal with the integration of distinct systems across corporate or geographical boundaries. Federated principles put the primary burden of ensuring cross-platform cooperation on the clients rather than the service provider. Automated procedures, such as in enforcement of contracts or maintenance of security postures, are still advisable for all stakeholders.

The locality principle states that data should be stored in its natural environment, creating a data-locality-based security model according to which only connectors to each analysis participant need to be secured. Sensitive data should be shared only when business value justifies exposure for reasons related to company business models, policies, or relevant governmental regulations. When data locality is preserved and sensitive data are stored where they can be controlled, privacy preservation can be achieved by computation on the data without explicit sharing and according to specific policies or regulations.

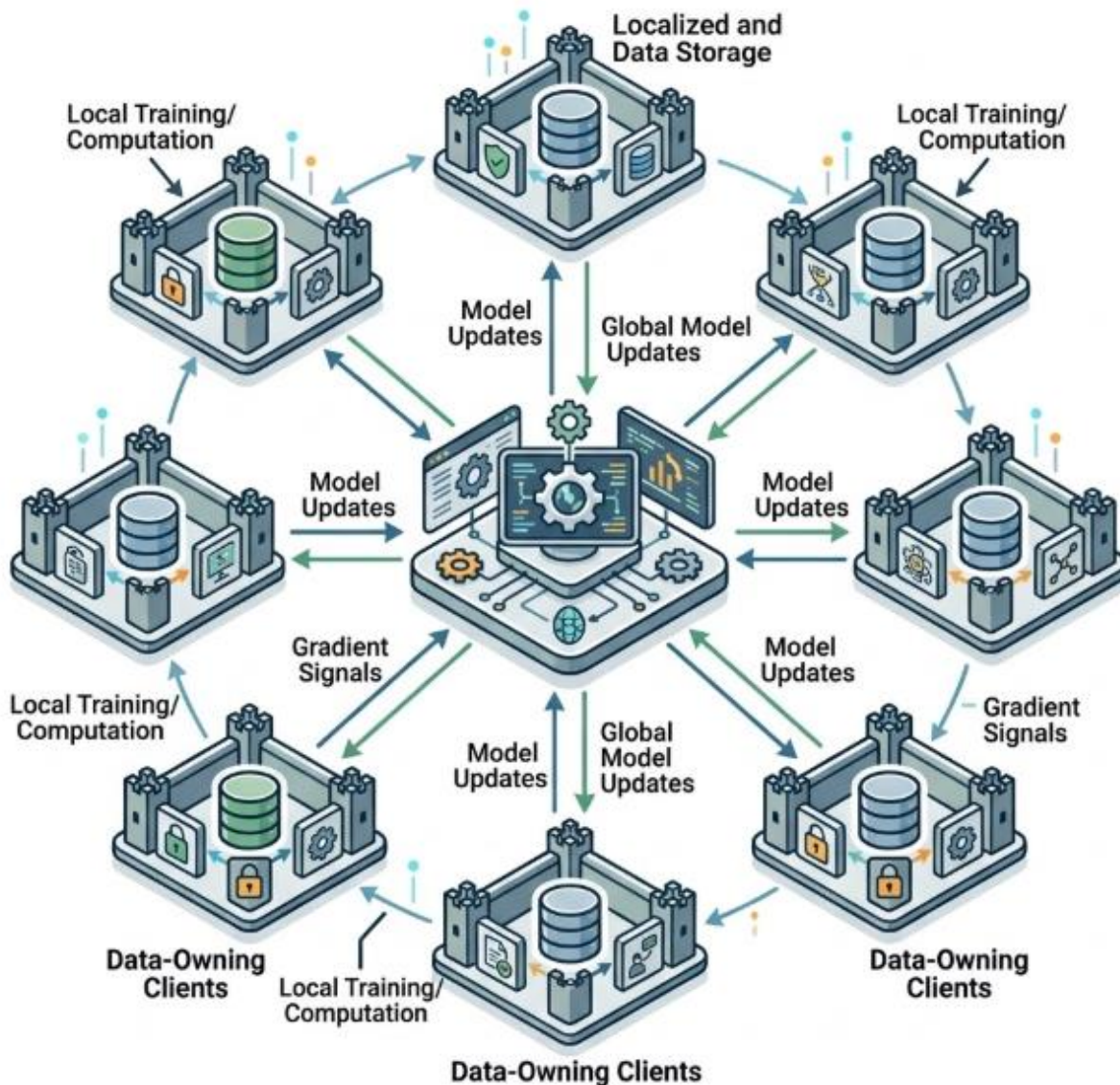


Fig 2: Data Locality and Privacy-Preserving Computation: Architectural Principles for Trustworthy Federated AI Ecosystems

6.1. Data Locality and Privacy-Preserving Computation



The principle of locality stipulates that data remain under the governance of the enterprise that originated it; thus, computation over these data must be executed by the enterprise that holds a specific data set in its own environment. Data locality naturally addresses concerns about privacy and confidentiality, reducing the risk of exposing sensitive data to third-party services. Complementing the principle of locality, privacy models—such as differential privacy and secure multi-party computation—permit the analytical exploitation of confidential data without disclosing information about the individual customers represented in the federated analytical results. Differential privacy guarantees that the output of a query—e.g., a machine-learning model or an aggregated analytics result—does not permit inferring whether an individual customer’s record is contained in the queried database. Secure multiparty computation breaks the computation of a function over private data into a set of subcomputation among trusted parties that reveal no information beyond the output by exchanging encrypted messages created under specific cryptographic assumptions.

Applying the proposed federated AI platform to cross-enterprise customer-intelligence analytics enables collaborative data-driven exploration and exploitation of business opportunities. Advanced technologies are required to fulfil the demands of the proposed federated AI customer-intelligence analytics platform, supported by the principle of locality and privacy-preserving computation on the customer-intelligence data sets stored in participants’ premises. The specific types of technology are: (1) Privacy-preserving computation on audited data: Applying privacy models, including differential privacy and secure multi-party computation, allows customer-intelligence analytics to be computed on the participants’ data without violating the data-governance and confidentiality-policy agreements validated by the governance layer; and (2) Standardization–Interoperability technology: Automating, governing, and controlling the transformation of customer-intelligence data into a standard shape is crucial for connecting heterogeneous systems of participants and enabling cross-analytical computations while preserving the data-governance policies in each use case.

Standardization in cross-enterprise cooperation encompasses three different types: application standardization—enabling expressiveness, extensibility, and description of the purpose and function of the overall federation; data-schema standardization—enabling the specification of a generic schema accommodating all participating enterprises’ customer-intelligence data; and ontologies and standards—governing the correct mapping of application data to the standardized data schema. The governance of these standards is crucial to maintain the evolution and upgrade of the ecosystem components over time, enabling cooperation among different sectors and industries.



Equation 2) Differential Privacy equation derivation

2.1 Core DP definition

$$\Pr[M(D) \in S] \leq e^\epsilon \Pr[M(D') \in S]$$

Meaning of symbols

- M : randomized mechanism or algorithm
- D, D' : neighboring datasets differing in one individual record
- S : any possible output event
- ϵ : privacy budget

Step-by-step interpretation

4. Take two nearly identical datasets D and D' , differing by one customer record.
5. Run the same mechanism M on both.
6. Compare probability of any output set S .
7. If the ratio is bounded by e^ϵ , then one person's presence/absence does not change the output much.
8. Therefore:
 - small ϵ means tighter bound
 - tighter bound means stronger privacy
 - stronger privacy usually needs more noise
 - more noise reduces model accuracy



2.2 Noise scale derivation

For Laplace DP noise, the standard mechanism is:

$$\tilde{f}(D) = f(D) + \eta$$

where

$$\eta \sim \text{Laplace}\left(0, \frac{\Delta f}{\varepsilon}\right)$$

and

$$b = \frac{\Delta f}{\varepsilon}$$

is the Laplace scale.

Step-by-step derivation

9. Let $f(D)$ be the exact query/model statistic.

10. Let Δf be the sensitivity:

$$\Delta f = \max_{D, D'} |f(D) - f(D')|$$

over neighboring datasets.

11. To guarantee ε -DP, add Laplace noise with scale:

$$b = \frac{\Delta f}{\varepsilon}$$

12. Therefore:

- if $\varepsilon \downarrow$, then $b \uparrow$
- if $b \uparrow$, added noise magnitude grows
- if noise grows, predictive utility typically falls



6.2. Interoperability and Standardization

Security and governance are paramount in federated Customer Intelligence. Participating organisations must trust each other, know who accesses shared models, and enforce usage policies. They require formal mechanisms for sharing models, addressing copyright and ownership, and reconciling incompatible schema versions. Trust models underpinning federated learning are diverse, offering concepts such as credential recovery, policy enforcement, and auditing.

Cross-environment federated learning protocols demand access control during model training and inference. Common solutions use proxy servers to mediate access, although they may not support multi-destination requests. Protocols for transferring trained models between different federated learning servers are more flexible. Essential aspects include model version management—guarding against data poisoning from buggy versions—and compatibility resolution for conflicting properties that arise in parallel development. A federated AI platform for secure customer intelligence also hinges on model interoperability. Standardised data schemas and ontologies enable model sharing in banking, telecommunications, and retail. Datasets on customer demographics and transactions conform to JSON Schema without sensitive attributes, while ontologies for data extraction and advance-charging support compliance with regulations like GDPR and CCPA. Formal-validation specifications are under development for ontology-compliance controls.

Secure Cross-Enterprise Customer Intelligence Analytics Systems need Trust and Access Control Frameworks. Federated asset sharing, spanning clouds from multiple owners, organisations, and environments, needs sophisticated access-control mechanisms. Approaches rely on secure audit trails, using tamper-proof digital-signature techniques for accountability, and distinct policies for authorisation, auditing, and enforcement.

7. Cross-Enterprise Collaboration Mechanisms

Cross-enterprise customer intelligence applications require various collaboration frameworks. Facilitating data sharing and consolidation across enterprise boundaries entails the establishment of trust between the collaborating parties, the delineation of sensitive information, and the implementation of access controls to mitigate exposure risks. Additionally, sense-making of customer intelligence data on behalf of the stakeholders involved relies on shared data science and appropriate models. Several frameworks can assist with these requirements, including (i) trust frameworks encompassing authentication, authorization, policy enforcement, and audit; and



(ii) secure model federation with dedicated collaboration protocols for model sharing and version reconciliation across different organizations.

Most organizations prioritize protecting customer data from unauthorized access by malefactors and providing their customers with transparent risk exposure policies. Customer intelligence purposed for use cases involving multiple organizations creates additional risk categories. Trust frameworks specify the dimensions of the risk landscape by aiding the identification of the parties that must be trusted within a given use case scenario, as well as the aspects of these parties that require validation and verification. Given that customer intelligence is often considered sensitive, distracting customers or affecting their experience must be avoided when modeling or analyzing it by preparing the pertinent data science and analysis models diligently.

7.1. Trust Frameworks and Access Control

Federated AI Platforms for Secure Cross-Enterprise Customer Intelligence Analytics

Trust Models and Cross-Enterprise Access Control

Trust is foundational to the success of federated cross-enterprise analytics. Trust frameworks define the partners' relationships and assign responsibilities, with layers ranging from low- to high-level trust. At the lowest layer, trust is based on authenticating partners' identities and establishing secure communications. The second layer addresses “who can do what,” specifying authentication and authorization of users accessing resources in any partner's site. The third layer concerns “who sees what,” defining the information shared between trusted partners within a federation and assuring that consents are respected. The fourth layer requires auditing capabilities to enable proof of proper access and usage of sensitive information. The highest trust layer deals with formally specifying business rules governing information disclosure across enterprises.

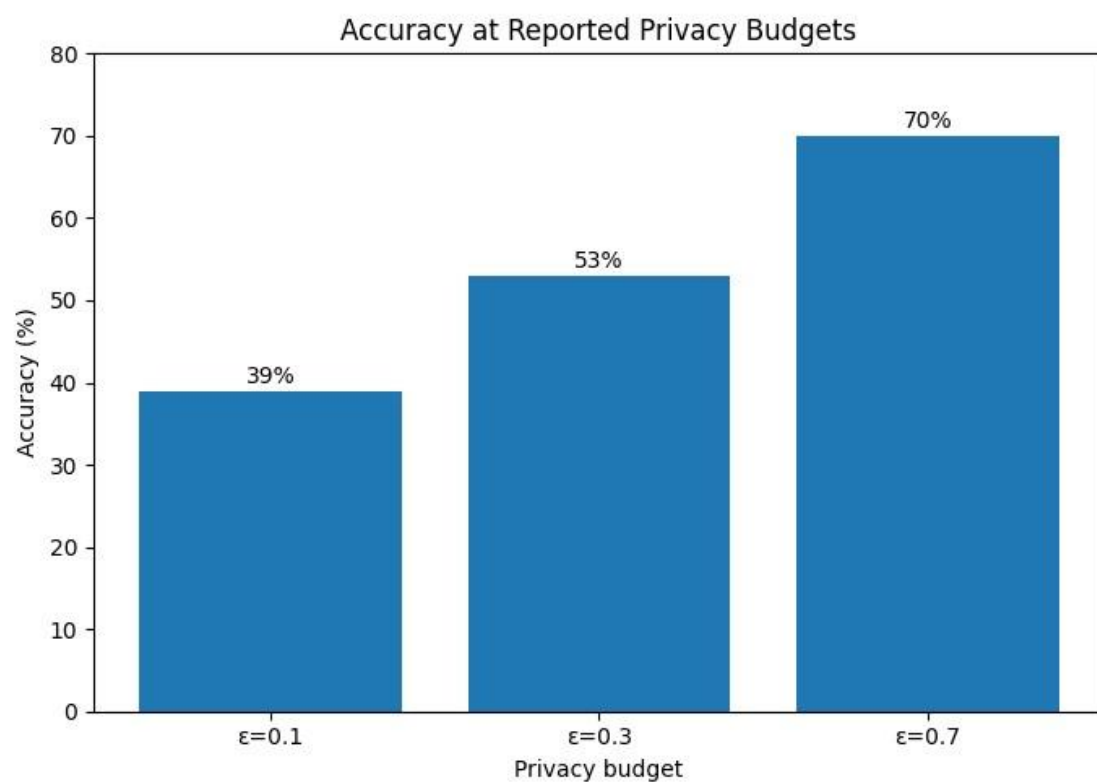
The access control mechanism supported by federated frameworks is crucial for enterprise comfort and appeal. While cross-enterprise collaboration introduces the risk of data loss, controlled information sharing allows companies to benefit without losing knowledge capital. Trust management approaches specify access control policies and integrate the process with authentication and authorization services.

7.2. Secure Model Federation and Collaboration Protocols



Specification and Implementation Guidelines. Secure Model Federation enables cross-institutional knowledge sharing using predictive models while limiting privacy risks. Using Bank A and Bank B as examples, predictive models trained on each bank's data can be made available to the other bank through three stages: (1) Bank A encapsulates its model with a preconfigured security level, (2) the encapsulated model is passed as an input to a Model Sharing helper, and (3) the Model Sharing helper sends the output to Bank B. During the process, a trusted third party ensures that Bank B obtains the prediction from Bank A's model as a black box, without compromising the confidentiality of Bank A's model and dataset. Including an additional prediction service among the support functions enables a decentralized architecture, which eliminates the trusted third party but requires establishing trust between the two banks.

Model Versioning and Reconciliation. Predictive approaches are parametric but the parameter settings differ depending on the prediction task and data characteristics. To provide accurate predictions at all times, banks should store multiple versions of a model and compare performance periodically. Discrepancies in accuracy usually arise due to data changes at model owners or in the environment. When the difference is significant, a process should be triggered for model retraining, testing, and migration. To enable automated reconciliation, versions should be stored in a reconciliator, which oversees reconciling different model versions and selecting the best version for each type of prediction task.



Equation 3) MPC threshold derivation

3.1 Main inequality

$$|A| < \left\lceil \frac{k}{2} \right\rceil$$

Where:

- k : number of parties
- A : adversarial subset
- $|A|$: number of corrupted/passively observed parties



3.2 Largest allowed adversary subset

Because $|A|$ must be a whole number and must be strictly less than $\lceil k/2 \rceil$,

$$|A|_{\max} = \left\lceil \frac{k}{2} \right\rceil - 1$$

3.3 Step-by-step examples

For $k = 4$

$$\left\lceil \frac{4}{2} \right\rceil = \lceil 2 \rceil = 2$$

Need:

$$|A| < 2$$

Largest valid value:

$$|A|_{\max} = 1$$

For $k = 5$

$$\left\lceil \frac{5}{2} \right\rceil = \lceil 2.5 \rceil = 3$$

Need:

$$|A| < 3$$

Largest valid value:

$$|A|_{\max} = 2$$

For $k = 6$

$$\left\lceil \frac{6}{2} \right\rceil = 3$$



Need:

$$|A| < 3$$

Largest valid value:

$$|A|_{\max} = 2$$

For $k = 7$

$$\left\lceil \frac{7}{2} \right\rceil = \lceil 3.5 \rceil = 4$$

Need:

$$|A| < 4$$

Largest valid value:

$$|A|_{\max} = 3$$

8. Privacy-Preserving Techniques in Practice

In analytics and machine learning, two of the most studied approaches for privacy-preserving computation are Differential Privacy and Secure Multi-Party Computation.

The privacy guarantee of Differential Privacy (DP) is linked to a Privacy Budget term ϵ . The smaller this budget, the greater the privacy provided, but the more inaccurate the analytic results become. Privacy is enforced by injecting noise to the outputs of the analytics. Adding DP to the federated bank-customer use-case with historical transaction data for three banks gives an accuracy of around 70% with a budget of 0.7, around 53% with a budget of 0.3, and around 39% with a budget of 0.1.

Secure Multi-Party Computation (MPC) enables collaborative data processing without that any party is able to learn anything about other parties' private data. When only two parties cooperate (which is not a realistic scenario in production), the protocol needs just one communication and one computation round. The price, though, is high: two shares per variable and a multiplication is introduced (plus any multiplication to be multiplied). With three or more parties, the protocol generalizes from binary to true representations, so any number in $\{1, \dots, k\}$



can be reconstructed by a third party. With at least four parties, if a passive adversary is in control of a subset of size less than $\lceil k/2 \rceil$, the whole protocol is secure in the semihonest model, providing privacy and correctness Properties.

8.1. Differential Privacy and Noise Addition

Privacy budgets govern information flow during analytics involving sensitive data. Formal privacy guarantees help establish the amount of sensitive information that is hidden from other parties when they observe the results of statistical analyses, while noise mechanisms are applied during results publishing to achieve desired levels of differential privacy. However, the usability of available differential privacy literature is limited; sound fundamentals are buried under abstract definitions, and there is little advice on practical application. For example, results may be misleading if noise is added for a group of aggregated queries that represents only a small fraction of the total number of queries issued to the protected database, since such noise provides relatively little protection against other queries. When there are auxiliary databases—linked in the minds of the analysts or even physically, at least for some of the parties involved in the analysis—sufficient privacy guarantees must be provided for all the involved databases jointly, not just for the privacy-sensitive databases.

Parties designing differential privacy protection therefore need to be aware of all the queries that will be issued to the database, including external and side-channel queries. Protection for a federation of independent databases, where neither the shares of the same sensitive attribute nor an auxiliary linked attribute are available to any of the parties, offers a better approximation for separate databases, even in the presence of correlation among something that makes the attack stronger, than the protection typically present in a local or centralized database setting. Yet, in practical customer intelligence scenarios, meaningful conclusions are typically based on quite simple black-box data mining methods that cannot easily be expressed in the form of a series of aggregations over defined sets.

Equation 4) Two-party MPC cost relation

- one communication round
- one computation round
- two shares per variable



- multiplication overhead introduced.

This can be written in direct symbolic form as:

4.1 Share count

If the number of variables is n , and each variable is split into two shares:

$$S = 2n$$

where S is total share count.

4.2 Multiplication overhead

If the original computation contains m multiplications, then the secure protocol introduces at least proportional multiplication-related secure operations. A minimal abstract relation is:

$$C_{\text{mult}} \propto m$$

This is the strongest faithful equation possible from the text because the paper does **not** provide an exact constant, asymptotic bound, or benchmark formula.

4.3 Total two-party round cost

From the article:

$$R_{\text{comm}} = 1, \quad R_{\text{comp}} = 1$$

8.2. Secure Multi-Party Computation

Secure multi-party computation enables the accurate analysis of distributed customer intelligence data without centralization or data leakage risks. With these protocols, participants can learn the outcome of joint computations by communicating only a small amount of information with one another. The solution applies Shamir's secret-sharing scheme for linear evaluation functions and Yao's garbage evaluation for nonlinear functions. With this hybrid approach, the computation is divided into an ordered sequence of communication rounds among the collaborating parties and a small number of rounds of secure point-to-point communication.



Security is proven in the semi-honest model, where malicious participants are guaranteed to learn nothing about the inputs other than what can be deduced from the output. Though the communication cost of the protocol is proportional to the size of the functions being evaluated, extensive benchmarking demonstrates that even with limited scale-up of the collaboration the complete training of deep neural networks can be performed in a time comparable to just training on locally available data. The protocol is suitable for use as a secure backend in any general-purpose multi-party computation system; indeed, it is the first example of a very general class of such backends.

While a single run of the hybrid approach may incur many communication rounds, this overhead can be largely masked through asynchronous scheduling. Explicit consideration of communication timing also leads to an efficient multilateral version of Yao’s three-party solution for firm functions.

Type	Purpose
Application standardization	federation purpose/function description
Data-schema standardization	common data shape across enterprises
Ontologies and standards	correct mapping to shared schema

9. Security Threats and Risk Mitigation

A prominent research avenue in privacy-preserving AI focuses on enabling collaboration among independent stakeholders while limiting information sharing to what is strictly necessary. Even without the transmission of input data, the model sharing and provisioning processes still entail significant risks. For instance, as a consequence of overfitting, machine-learning models may reveal information present in the training dataset, thus enabling adversaries to partially reconstruct the data or ascertain the presence of specific records. Security assessments have pointed out possible leakage channels and corresponding threat vectors. Mitigations have been proposed, as well as specialized detection schemes. The methods outlined in Section 8.1 can help tackle these challenges: strictly enforcing differential-privacy guarantees during the model-training phase ensures resilience against data underfitting attacks, for instance, and adaptive-noise mechanisms specifically designed to address model-inversion risks can maintain analytics accuracy while also reducing the risk of information leakage.

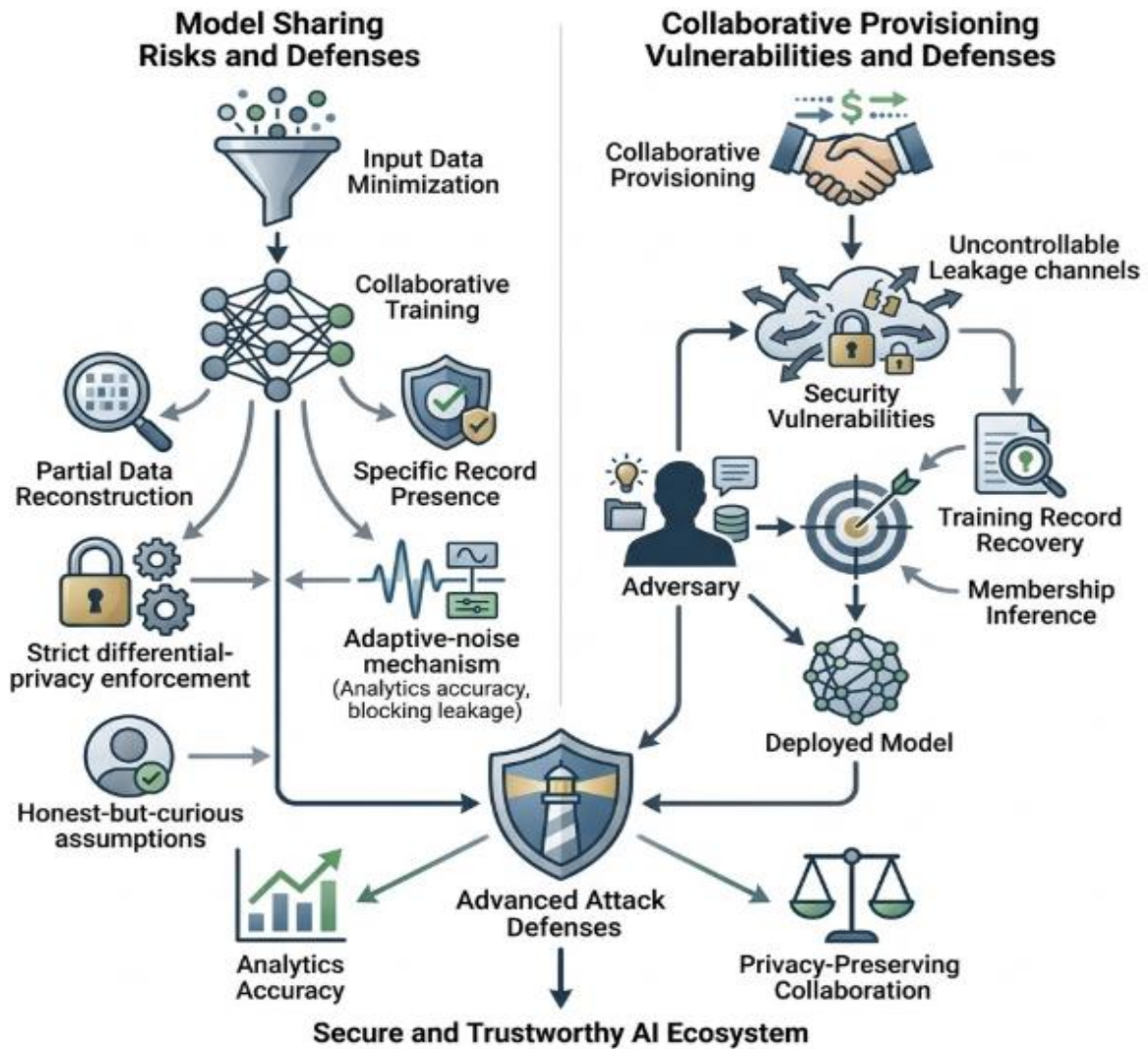


Fig 3: Differential Privacy as a Defensive Mechanism Against Model-Inversion and Membership-Inference Attacks in Collaborative, Privacy-Preserving AI

Conversely, even with strict model-sharing controls in place, security vulnerabilities remain an unavoidable by-product of the collaborative-provisioning process. In this scenario, leakage channels are largely uncontrollable, and the chance of successful recovery of a training



record or at least of an inference about its membership largely hinges on the amount of training data and the knowledge—and possibly the data—held by the adversary. Recent studies have identified valid architectures for the model-provisioning process, described main attack strategies oriented toward membership inference, and proposed selective mitigation techniques. The previous differential-privacy-based methods, in addition to honest-but-curious assumptions, can also support defenses against these advanced attacks.

9.1. Data Leakage Scenarios and Mitigations

Success or failure in federated operations hinges on trust between parties. In shared, cross-organizational scenarios involving an external entity, risk cannot be eliminated; it can merely be minimized within acceptable limits. Trust frameworks help define and govern relationships among parties in a collaborative AI platform. Risk treatment entails not only avoiding data leaks during a specific activity but ensuring that information cannot be disclosed through repeated engagement. Three key aspects determine the extent and consistency of data leaks during the collaboration: how much redundancy is available, whether leakage detection is in place, and how any extracted information is controlled.

Analysis of the security threats associated with leaks from a federated customer intelligence platform similar to those depicted in Figures 10 and 11 has pinpointed several channels through which sensitive information could be disclosed. For example, Company A and Company B may collaborate with a third party to enhance customer intelligence through federated model lifecycle management and sharing, but these implementations expose both organizations to leakage risks when using federated models for decision-making. When A leverages B's federated models, it may disclose secrets through combination of its own information with B's model. These vulnerabilities can be controlled in multiple ways, primarily by adding sufficient redundancy, deploying a leakage–impact detection mechanism, establishing a risk management mechanism, and applying a common trust framework across participating organizations.

9.2. Model Inversion and Membership Inference Risks

The vectors for model inversion and membership inference risks attack previously unobserved datasets outside of the model training phase and are based on the privacy leakage caused by membership information in the training dataset. For model inversion attacks, the objective is to reconstruct the input data from a prediction. This kind of attack can be performed in two ways based on the properties of the prediction: the first is a classification attack



constructed using the class distribution probabilities and the second is a regression model inversion attack under continuous value prediction. Both types of model inversion attacks use template images or noises as the input image, or even random points located in the same feature space as the training set.

A membership inference attack aims to determine whether a specific instance is included in the local training datasets. This is believed to be a binary task with a set of positive and negative samples. The model can be learned via supervised learning by feeding the output probabilities released from the local model into a new model. To the best of the knowledge, model inversion attacks utilize known target label information, whereas membership inference attacks do not assume any knowledge about the target label. However, membership inference attacks can be strengthened when the target test image set is given. Models are inevitably exposed to this potential risk during external utilization, and therefore an auditing mechanism should be adopted for risk assessment.

Privacy budget ϵ	Accuracy A	Accuracy loss from 70%	Relative loss
0.7	70%	0	0%
0.3	53%	17 points	24.29%
0.1	39%	31 points	44.29%

10. Performance, Scalability, and Latency Considerations

10.1. Benchmarking Federated Workloads. Workload performance represents a crucial technical aspect of federated AI platforms. Design choices in federated frameworks introduce datacenter orchestration overheads, impacting execution latencies. Several benchmarks incidentally encompass communication overheads entailed by federated methods (e.g. TensorFlow Federated), while others focus specifically on communication overheads associated with federated SGD (e.g. HFL). End-to-end benchmarking of federated workloads—incorporating all architectural layers from resource allocation to payload delivery—is scarce and emerging.

Benchmarking studies reveal that integrated cost-performance indicators are heavily influenced by workload characteristics, and that straightforward autoscaling configurations are sufficient to ensure elasticity. While communication overheads can be substantial, adequate system usage diminishes per-operation overheads to negligible proportions. For workloads with



low resource consumption, greater allocation granularity facilitates responsive scaling and reduces execution latencies.

10.2. Resource Allocation and Elasticity. Key factors influencing the overall scalability of federated AI platforms include scheduling, autoscaling of compute resources, and performance-wise allocation of data under varying resource loads. The federated learning workload is characterized by aggregation of gradient updates communicated from edge devices to the central server (typically the cloud), which usually receives periodic updates of user-specific model parameters. The modelling framework separate batch sizes are defined for the outer aggregation phase and inner communication phases, since inference is performed on target nodes hosting the data owners. Aiming to reduce latent costs in edge device usage (e.g. battery consumption), limited memory in mobile phones, and ISP network caps, the suggestion mandates high expresó. The overall system performance is decreased, resulting in increased operation wait and execution times as a function of global spark execution mode initially—spanning across the internal communication task latency.

10.1. Benchmarking Federated Workloads

Federated workloads must be benchmarked to draw conclusions about their performance and, especially, their scalability and latency. Benchmarks are devised that emulate several classes of federated computations from real-world use cases. Each class encapsulates a distinct federated workload characteristic. These classes combine to form a benchmark suite that encompasses many samples from federated workloads for a range of applications. The individual benchmark execution times indicate whether any of these workload patterns are performance bottlenecks in federated computations. They also help to identify performance members of various workload classes, so that value-added compute resource capacity can be purchased selectively. The logical base exposed by the individual workload profiles provides guidance for cost-performance optimization strategies as federated AI platforms scale elastically to meet demand.

Federated workloads are expected to experience rapid growth in organizations across industry sectors and regions. Early entrants will have their platforms evaluated: performance under expected peak conditions, projected costs, and economic viability. Platform-as-a-Service (PaaS) actors, especially in cloud computing, will aim to monetize the burgeoning federated workload opportunities. Key attributes of such offerings are also emerging: autoscaling capability, pricing model, and identification of platform performance limits. These attributes help



PaaS providers monitor, schedule, and tune operation of their federated services and shared resources accordingly.

Interval	Slope m	Intercept c	Equation
$0.1 \leq \varepsilon \leq 0.3$	70	32	$A(\varepsilon) = 70\varepsilon + 32$
$0.3 \leq \varepsilon \leq 0.7$	42.5	40.25	$A(\varepsilon) = 42.5\varepsilon + 40.25$

10.2. Resource Allocation and Elasticity

Provisioning capacity in a federated system can begin with simple static allocation based on expected workloads—expected use cases are evaluated with baseline profiles for various federated workloads to define best-fit configurations for the federated system nodes. As production use increases, auto-scaling based on real-time demand becomes more desirable, enabling cost-optimization through ad-hoc scaling of the federated system. For use patterns with periodic peaks, elasticity can be provided through a burst-buffer approach: a resource-pool set up to support temporary bursts in workload and shared among multiple federated system nodes—enabling provisioning of additional capacity when needed, and releasing resources back when load subsides. Static provisioning, elasticity, and real-time scaling combine in a data-management-driven solution that employs a data-locality algorithm when moving data across facilities, such that, when coupled with ready availability of data, the federated workloads can be executed as close to the data sources as possible—minimizing performance impact while capitalising on the local resources at low-to-normal cost.

Under real-time scaling, control logic can monitor resource use and automatically add or remove instances based on the level of utilisation. Such dynamic control is also essential when operating in a cloud environment, where instance availability depends on the overall demand across all tenants. Overall monitoring tools can also employ alerts based on application-monitoring tools, or thresholds exposed by the management layer. A combination of real-time scaling with periodic burst capabilities optimises operating costs while supporting shifting demand.

11. Case Studies and Illustrative Scenarios

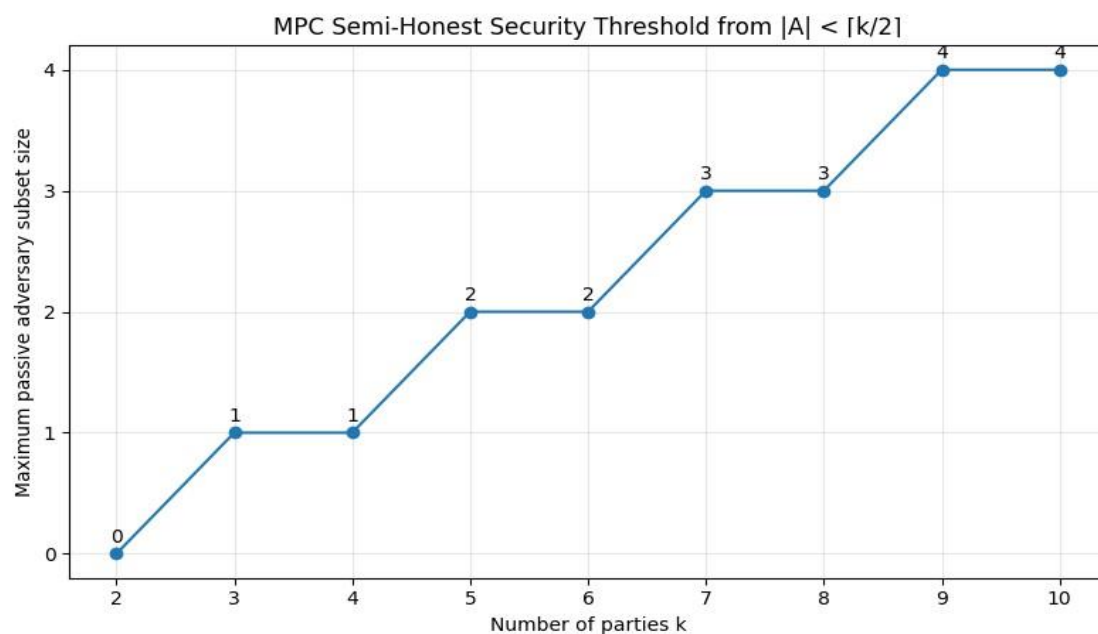
Two case studies highlight cross-enterprise customer intelligence projects: a banking and financial services collaboration analysing transaction data, and a retail partnership that integrates



customer experience data across service providers. Both illustrate the rationale, governance, and operational protocols for federated AI in sensitive domains.

The banking and financial services use case brings together multiple financial institutions to enable customer-intelligent analytics across transaction data. Data from granular transactions, integrated with payment behaviour across institutions, supports a multitude of applications such as market basket analysis, anomaly detection, and differential privacy. The regulatory environment makes it mandatory to maintain data privacy while enabling richer data through collaboration for a better customer experience. The integrated solution tightly binds the federated environment with comprehensive controls for each step of the query federation process to protect sensitive customer information from leakage.

The retail and customer experience analytics use case focuses on customer experience data spread over multiple service providers in the retail ecosystem that are not commonly shared with other partners. Customer experience feedback forms the backbone for improvement solutions for various parts of the service journey. The federated analytics engine integrates customer experience data across providers, improving accuracy in providing suggestions to stakeholders for enhancing customer experience. Internal custodial feedback with customer information is protected through differential privacy, while SAS's Private Connectivity enables a seamless data-sharing experience within the collaboration network.



Equation 5) Federated averaging equation implied by the article

$$w^{(t+1)} = \sum_{i=1}^N \frac{n_i}{\sum_{j=1}^N n_j} w_i^{(t+1)}$$

Where:

- N : number of participating enterprises
- n_i : local sample count at enterprise i
- $w_i^{(t+1)}$: locally updated model
- $w^{(t+1)}$: global aggregated model

Step-by-step derivation

13. Each enterprise trains locally and gets model $w_i^{(t+1)}$.

14. Enterprises with more data should contribute more weight.

15. Total data:

$$n = \sum_{j=1}^N n_j$$

16. Weight of party i :

$$\alpha_i = \frac{n_i}{n}$$

17. Since:

$$\sum_{i=1}^N \alpha_i = 1$$

the global model becomes the weighted average:

$$w^{(t+1)} = \sum_{i=1}^N \alpha_i w_i^{(t+1)}$$

11.1. Banking and Financial Services Collaboration

In a yet unimplemented cross-enterprise scenario for banking and financial services, risk management and forecasting models require data-sharing capability for improved performance and better financial forecasts. The proposed, extended solution architecture enables customer balance rate prediction for the participating enterprises, considering the privacy of sensitive customer data on credit cards, assets, and transactions. Privacy is primarily ensured by data integration and operation within the federated learning framework. Data integration across these enterprises in a compliant way can also be an enabler of additional services that require complete customer transaction histories (e.g., preventing overdrafts and providing better credit risks). This use case outlines these aspects, presents its architecture, and discusses security and privacy.

A second scenario, yet unimplemented, involves collaboration of enterprises from the same industry for enhancing customer experience. Retail business intelligence analytics often benefit from sharing customer transaction data from multiple stores of the same retailer or customer experience analytics for a specific retail category from multiple retailers. The proposed architecture extends the solution to support data integration between systems of trustable partners in a compliance-preserving way, aiming to achieve regulatory compliance (e.g., trading supervision) and the desired outcome (e.g., customer journey analytics) in a secure and usable



manner. Privacy is primarily by noise addition, made applicable in cross-store or cross-retailer use cases thanks to data integration within the federated analytics framework.

11.2. Retail and Customer Experience Analytics

Adoption of AI for Customer Experience Intelligence (CXI) offers opportunities to advance customer retention, growth, acquisition, loyalty, recommender systems, journey and service experience improvement. CXI operates on sensitive data such as customer interactions, customer feedback and sentiment, customer history, and customer preferences. The infrastructure for CXI includes data lakes, cloud storage, AI and analytics platforms that typically rely upon Customer Data Platforms to enrich Analytics and/or AI engines. It can provide better accuracy and cover more concepts with larger training data.

A federated AI platform integrates sensitive data enabling secure CXI. Privacy safeguards such as data masking, differential privacy, and secure multi-party computation can minimize data disclosure. An illustrative use case demonstrates federated CXI across three fictitious retailers under a single privacy policy. The cloud service provider (CSP) implements the integration and cross-inference operations. Enriching the learning dataset by sharing sensitive data across the retailers improves analytics accuracy while meeting data-protection regulations. The implementation uses masks to safeguard privacy and secure multi-party computation for sharing sensitive data.

12. Regulatory and Ethical Dimensions

Data protection regulations are crucial for the sustainable development of federated AI. Indeed, the sharing of models trained on sensitive personal data, such as those associated with customer intelligence analytics, must comply with requests from legal authorities, especially when trained for the banking and financial services sector. Enterprises must also ensure that federated AI platforms do not inadvertently breach rules associated with cross-border data flows, as, for instance, the GDPR requires that personal data must not be transferred to a third country or an



requests may require that shared data can also be rendered irrecoverable. Commission Implementing Decision (EU) 2021/914 of June 4, 2021, provides a framework for cross-border data transfers from the European Economic Area (EEA) to third countries that do not guarantee the same protection as the GDPR. Organizing cross-enterprise services, such as those for AI model federations, involves different jurisdictions; it is impossible to ensure universal compliance solely through legislative or regulatory means.

Governance involves establishing trust, human resources development, and operating policy agreements. Organizations such as the Data Trust Alliance and the Trusted Data Ecosystem Consortium explore mechanisms for attaining such trust needed for cross-border data flows. The core idea is to inspect organizations for compliance with provisions equivalent to those of the GDPR. Consequently, it may be possible to aggregate customer intelligence across organizations in different jurisdictions, even those lacking a formal agreement on mutual recognition. Regulators can define standard sets of data-sharing rules (e.g., rules determining whether a data-sharing enterprise has been hacked that then travel in combination with the data). The work reports the results and guidelines from a collaboration project involving European data protection authorities.

12.2. Fairness, Accountability, and Transparency

Federated AI technologies amplify model training potential while circumventing cross-enterprise data sharing hurdles. However, multiple contentious fairness, accountability, and transparency elements remain unaddressed. “Customer intelligence is an important use case for cross-enterprise collaboration; federation lowers the risk of data leakage yet introduces new attack vectors; privacy budgets can negatively impact accuracy. Moreover, compliance with regulatory frameworks such as GDPR is paramount.” Guaranteeing fairness and auditability of federated models, alongside transparent processes, is pivotal for enterprises aspiring to a market-leading position in cross-enterprise collaboration. Therefore, fairness attributes—unbiased results for all population groups; auditability; and transparent operations—are fundamental aspects that underpin customer intelligence use cases.

Algorithmic decision-making can inadvertently lead to adverse bias against population subgroups; proposals now mandate equal treatment for all groups, predictability of outcomes, and equitable compensation for decision recipients. Federated Model Training (FMT) requires consideration of data distribution across systems—global representation, even distribution across training parties, and reliable contribution to accuracy of model parameters become essential—and answers to those questions should be sought. Bias detected in the output of models shared by



Cloud A and Cloud B must be examined to satisfy the fairness principle; inspection at the individual institution level informs the assessment, and further mitigating actions can be undertaken prior to deployment. These activities, supported by a formalized governance plan, must be documented to ensure auditability of the collaborative approach.

13. Roadmap for 2024 and Beyond

Emerging Standards and Ecosystem Mockups

Ensuring cross-solution interoperability among federated AI, decentralized federated learning, secure multi-party computation, and differential privacy analytics requires coherent harmonization among solution vendors. Towards this goal, stakeholders in the broader secure federated AI ecosystems already have a preliminary roadmap for federated AI solutions with operationalizing federated AI at its core. Emerging standards and community input are also expected to support the realization of ecosystem mockups that reflect these objectives and ambitions.

Ecosystem mockups that present a vision for the industry at large in preparations for a federated AI ecosystem with first-mover advantages are expected to emerge rapidly. Standardization efforts further bolster these inspiring operational opportunities. Applications covering cross-border federated AI-powered traffic analytics in smart cities, federated AI-enabled Financial Service Watch Group Analytics, financial crime prevention, as well as federated AI in retail customer experience management are under exploration to inspire and shape replica and operation within constrained boundaries.

13.1. Emerging Standards and Ecosystem Mockets

Expected standards progress is an essential precondition for the collaborative ecosystem. Interoperability milestones should emerge from collaborative implementation among supporting partners and public institutions, covering these facets:

1. Bidirectional federation and sharing of intelligence assets and models among banks. The Artificial Intelligence In Banking Working Group of the Bank for International Settlements (BIS) Innovation Hub Bangkok Centre has initiated a proof of concept for federated learning that enables banks to train a model together without the need to share sensitive customer data.



2. Bidirectional coordination of customer data location and of risk and accounting data and models among banks and agents for real estate, loans, investments, and credit cards (covering risk management, sensitive AML, and possibly also accounting) that would establish an operational underground economy for the Asian Digital Monetary Economy Network, enabling de-risking and elimination of the cost for the trillions of USD in cross-border money transfers today.

3. Bi-directional federation and sharing of analytics models for customer experience among travel agencies, airlines, hotels, education and training institutions, banks, telecommunication operators, and other data owners to enable sharing of general models and covering the latent risk of each touchpoint.

13.2. Strategic Implications for Enterprises

The development of federated AI platform capabilities is expected to shape business ecosystem strategies and deployment priorities through 2024 and beyond. As with previous technology cycles, awareness of the value of external data sources will catalyse adoption of federated development methodologies. Having the potential to provide insights as part of a regulatory-compliant, ethical approach to data intelligence, unified models supporting fairness, accountability, and transparency will ultimately become a defence against external scrutiny, and federated AI platforms supporting such models will be prioritised through ecosystem collaboration over standards creation, moving the technology towards widespread use. In turn, federated AI platforms will naturally facilitate deployment and execution of traditional enterprise resource workloads across partner systems underpinned by flexible, short-lived data management, access control, and risk management mechanisms.

Early adopters of federated AI platforms, including their deployment for particular use cases across selected partners, will subsequently be positioned to pursue wider partner networks more aggressively. Vendor and advanced enterprise pockets including commercial Offerings will also accelerate the following steps in adoption roadmaps by reconciling natural development and operations silos within synergy-oriented business ecosystems operating cloud-native collaboration architectures. For enterprise operators, risk assessment and management will ultimately constitute the most significant aspect of federated development and operational strategy.

14. Conclusion



Federated AI Platforms for Secure Cross-Enterprise Customer Intelligence Analytics provides an objective, evidence-based analysis in a formal structure, emphasizing clarity and scholarly rigor. Cross-enterprise exchanges between multiple organizations represent a powerful means to enhance analytics capabilities, combining customer and market intelligence for hard-to-derive outcomes. However, barriers related to data sharing and privacy—such as federated cross-enterprise data silos, lack of privacy-preserving multitenancy, conflicting data governance policies, siloed collaboration points between companies, and the need for coordinated, platform-based third-party access—have yet to be addressed in a fully secure manner, even in common federated AI applications. Contributing to a growing corpus of research on federated approaches in enterprise AI, this effort focuses on security aspects. The analytical framework provides clear definitions and objectives for federated AI systems, using these categories to identify the underlying security concerns and the required mitigation mechanisms.

As a laboratory for new and emerging research topics in enterprise AI, customer intelligence analytics presents a rich vein for study. Hence, a range of use cases are evaluated. Two have been explored through detailed experimentation rather than theoretical formulation: cross-enterprise voice-of-customer analytics through an extended-yet-standardized three-party federated analytics workflow, and federated cross-enterprise data sharing for personalized and contextualized customer experience management. Other use cases—including financial-services data sharing for fraud detection and KYC/AML compliance—illustrate how the overarching federated-architecture classification scheme can facilitate other aspects of the federated approach. A focus on security, achieved through the use of standard privacy-preserving techniques, demonstrates that federated platforms can meet demanding security and risk-management requirements. The established set of principles and contributions forms a roadmap for deploying privacy-preserving cross-enterprise federated AI workloads in practice.

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