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Federated Meta-Learning Algorithm for Cross-Enterprise Collaborative Business Intelligence Without Data Sharing

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Abstract

Introduce FedMeta-BI – a Federated Meta-Learning Framework where multiple competing companies collaborate to train Business Intelligence (BI) models without exposing any proprietary raw data. In our approach, FedMeta-BI integrates Model Agnostic Meta-Learning (MAML) with a secure federated optimisation algorithm utilising differentially private stochastic gradient descent (DP-SGD, $\varepsilon = 1.0$) and selective homomorphic encryption (HE) for gradient aggregation. Our method uses a cross-enterprise knowledge graph to incorporate structural priors across multiple domains for better few-shot adaptation and transferability to new enterprise settings. Evaluate FedMeta-BI on five anonymised enterprise datasets drawn from Finance, Retail, Healthcare, Logistics, and Manufacturing domains having more than 20 million entries in total. In our experimental setup, achieve a Macro-F1 of 0.891, outperforming FedAvg by 8.5%, MAML by 13.7% and local training by 25.2%. In our differentially-private setup with strict DP guarantees (ε=1.0), obtain an accuracy drop of just 2.3% compared to non-private version. The membership inference attack AUC drops to 0.512, which is no better than random chance. Communication costs reduced by 56% compared to FedAvg while maintaining similar model performance.

Keywords: Federated Learning, Meta-Learning, MAML, Differential Privacy, Homomorphic Encryption, Business Intelligence, Cross-Enterprise Collaboration, Knowledge Graph, Data Privacy.

1. Introduction

BI systems require data. Enterprises with bigger training pools always perform better than enterprises training on smaller isolated local pools of data. Aggregating enterprise data breaches the regulatory requirements (GDPR, CCPA, HIPAA), leaks confidential information, and contradicts the competing interests of the parties involved. The dilemma that arises is clear: enterprises, which can benefit from joint learning, must use the inferior local models.

Federated Learning (FL) has recently arisen as a framework to learn from distributed data without exchanging any data itself. But canonical FL approaches (FedAvg, FedProx) have two crucial disadvantages in the context of enterprise BI: (i) require all participants to have similar task distributions, which cannot be true if enterprises operate in different industries having different features sets; and (ii) do not converge well in case of non-IID data, which is an inevitable case in practice [17][19].

Meta-learning—the capacity to learn how to learn—addresses the first limitation by explicitly optimising for rapid adaptation to new tasks from minimal data [18]. However, existing federated meta-learning methods neglect the privacy vulnerabilities of gradient exchange, do not exploit inter-enterprise structural knowledge, and have not been validated on realistic enterprise BI workloads spanning multiple sectors [12].

This paper bridges these gaps. FedMeta-BI makes the following contributions:

- A federated extension of MAML in which inner-loop personalisation occurs locally and outer-loop meta-gradients are exchanged under DP-SGD noise with selective HE encryption of the most sensitive gradient layers.
- A cross-enterprise knowledge graph (CEKG) that encodes structural commonalities across enterprise domains, used as a regularisation prior to accelerate meta-adaptation on sparse data.
- An adaptive aggregation protocol that weights client contributions by data quality, domain relevance, and gradient divergence, mitigating the impact of Byzantine or low-quality participants.
- The first large-scale empirical study of federated meta-learning on real enterprise BI workloads, covering six canonical tasks across five industry verticals with formal privacy and scalability analysis.

2. Related Work

2.1 Federated Learning Foundations

McMahan et al. (2017) introduced FedAvg, establishing the canonical communication-efficient FL protocol[1]. Subsequent work addressed non-IID convergence (FedProx, SCAFFOLD), communication compression (FedPAQ, Top-K sparsification), and personalisation (pFedMe, Ditto 2021). None of these methods incorporates meta-learning objectives, limiting their transferability across heterogeneous enterprise tasks.

2.2 Meta-Learning for Business Intelligence

MAML (Finn et al., 2017) and Reptile (Vedernikov et al., 2024) established gradient-based meta-learning as a powerful few-shot framework [2] [3]. There are other alternatives like ProtoNets and Matching Networks which follow the metric learning paradigm [11][20]. In the case of business intelligence applications, Yoon et al. (2022) leveraged MAML for personal demand prediction; however, their work is confined to the centralized scenario [8]. This marks the first instance where MAML was applied in a federated and privacy-preserving environment.

2.3 Privacy in Federated Learning

Privacy-preserving FL using differential privacy was first introduced by Falaki (2019) and Agarwal et al. (2018) [5][7]. DP-based FL was implemented in practice by Bonawitz et al. (2022) at Google [13]. Homomorphic encryption for FL gradient aggregation was considered by Phong et al. (2018) but proved computationally expensive [6]. FedMeta-BI incorporates a selective homomorphic encryption scheme, in which only the top-10% sensitive gradient dimensions are encrypted [15]. This approach allows one to reduce overhead and still maintain robust privacy guarantees against gradient inversion attacks [10][14][16].

2.4 Knowledge Graphs in Collaborative Learning

Cross-domain knowledge transfer via KGs has been studied in the context of recommendation systems (KGCN, RippleNet) and NLP (KEPLER). Applying KGs as structural priors in federated meta-learning is, to knowledge, novel [9][21]. The CEKG in FedMeta-BI is constructed from publicly available industry ontologies (NAICS, ICD-10, GS1) and augmented with entity alignment across enterprise schemas using a privacy-preserving entity resolution protocol.

3. Methodology

3.1 Federated MAML Formulation

Let $\boldsymbol{E} = \{\boldsymbol{e_1}, \boldsymbol{e_2}, \ldots, \boldsymbol{eN}\}$ denote $\boldsymbol{N}$ enterprise clients. Each client $\boldsymbol{e_i}$ holds a local task distribution $\boldsymbol{T\_i}$ over business intelligence tasks. The meta-learning objective is to find a global meta-parameter $\boldsymbol{\theta} *$ such that a small number of gradient steps on any $\boldsymbol{T\_i}$ yields high task performance:

$$\boldsymbol{\theta * = argmin\_\theta \ \Sigma_i \ L\_T_i\left(\theta - \alpha \nabla_\theta L_{T_{i(\theta)}}\right)}$$

In the federated setting, each round proceeds as: (i) the coordinator broadcasts the current θ to sampled clients; (ii) each client performs K=5 inner-loop gradient steps on local support data, producing personalised parameters $\boldsymbol{\varphi_i}$; (iii) clients compute meta-gradients $\boldsymbol{\nabla\_\theta \ L(\varphi_i)}$ on local query data; (iv) meta-gradients are clipped, noised (DP-SGD), and selectively encrypted (HE) before transmission; (v) the coordinator performs weighted aggregation and outer-loop update.

3.2 Privacy Guard: DP-SGD with Selective HE

The two mechanisms used by the privacy guard are:

DP-SGD: The sample-based gradients are bounded by norm $\boldsymbol{C\_clip = 1.0}$, and Gaussian noise $\boldsymbol{N(0, \sigma^2 C^2)}$ is used, thus achieving $(\boldsymbol{\varepsilon = 1.0, \delta = 10^{-5}})$-DP on each communication step by using the Moments Accountant.

Selective HE: The top-10% gradient dimensions by $\boldsymbol{L_2}$ magnitude (most sensitive to model inversion) are encrypted using the CKKS approximate HE scheme before transmission. This reduces HE overhead from +340% to +18% while protecting the most vulnerable gradient components.

Table 3 (Section 5.3) provides a comprehensive privacy mechanism comparison including membership inference attack results.

3.3 Cross-Enterprise Knowledge Graph

The CEKG is a heterogeneous graph $\boldsymbol{G = (V, E, R)}$ where nodes $\boldsymbol{V}$ represent business entities (products, customers, KPIs, market segments), edges E encode semantic relationships, and $\boldsymbol{R}$ is the relation type set. Enterprise-specific entity types are mapped to canonical ontology nodes via a privacy-preserving entity resolution that exchanges only hashed entity signatures. A Graph Attention Network (GAT, 3 layers, 256 hidden units) encodes node embeddings that are used as a task representation prior, initialising the meta-learner's task encoder and improving few-shot performance on data-sparse enterprises.

3. 4 Adaptive Aggregation Protocol

The global meta-update weights clients by a composite score $\boldsymbol{w\_i = \lambda_1 \cdot Q\_i + \lambda_2 \cdot R\_i + \lambda_3 \cdot (1 - D\_i), where\ Q\_i}$ is a local data quality score (completeness × consistency), $\boldsymbol{R\_i}$ is domain relevance cosine similarity to the current task, and $\boldsymbol{D\_i}$ is gradient divergence measured by cosine distance from the global gradient direction. Weights are estimated from public statistics and auxiliary metadata, with no raw data exchange required. Byzantine clients are detected via statistical outlier analysis on gradient norms.

4. Experimental Setup

4.1 Datasets and Enterprise Clients

Table 1 summarises the five enterprise datasets used in evaluation. All datasets were obtained under data sharing agreements and anonymised; client identities are not disclosed. Tasks span both classification (churn prediction, credit risk, defect detection, fraud detection) and regression (demand forecasting, KPI forecasting, OEE prediction).

Table 1: Enterprise Dataset Summary (Client Identities Anonymised)

Enterprise (Anonymised)	Industry	Records	Features	BI Tasks	Data Period
Corp-A	Financial Services	2.4M	187	Credit risk, Churn	2018–2023
Corp-B	Retail / E-commerce	8.1M	234	Demand forecast, Inventory	2016–2023
Corp-C	Healthcare	1.1M	312	Readmission, Cost forecast	2017–2023
Corp-D	Logistics	5.6M	156	Route opt., Delay predict	2019–2023
Corp-E	Manufacturing	3.3M	278	Defect detect., OEE forecast	2015–2023

Datasets were not pooled or shared. Every client was trained only on their own siloed dataset. Evaluation was done on test datasets specific to each client and averaged out using macro-averaging.

4.2 Baselines

FedMeta-BI is compared against six methods: (i) FedAvg — standard federated averaging without meta-learning; (ii) MAML in a federated setting without privacy; (iii) Reptile — first-order meta-learning; (iv) pFedMe — personalised federated learning; (v) Local-Only — each enterprise trains independently; and (vi) Centralised — all data pooled (privacy-violating upper bound). All methods use the same backbone: a 4-layer MLP (512 units, ReLU, batch normalisation) for classification tasks and a 6-layer Transformer encoder for temporal regression tasks.

4.3 Hyperparameters

Table 2 reports all key hyperparameters and their search ranges. Optimal values were selected via grid search on validation splits local to Corp-A and Corp-C.

Table 2: FedMeta-BI Hyperparameter Configuration and Search Ranges

Hyperparameter	Meta-Learner	Fed. Aggr.	Privacy Module	Search Range
Inner Loop Learning Rate (α)	0.01	—	—	$[10^{-4}, 10^{-1}]$
Outer Loop Learning Rate (β)	0.001	—	—	$[10^{-5}, 10^{-2}]$
Inner Loop Steps (K)	5	—	—	[1, 20]
Communication Rounds	—	100	—	[50, 500]
Clients per Round (C)	—	0.4 (fraction)	—	[0.1, 1.0]
DP Noise Multiplier (σ)	—	—	1.1	[0.5, 2.0]
DP Clip Norm (C_clip)	—	—	1.0	[0.1, 10.0]
Privacy Budget (ε)	—	—	1.0	[0.1, 10.0]

5. Results and Discussion

5.1 Main Benchmarks

Table 3 reports comparative performance across all metrics. FedMeta-BI achieves Macro-F1 of 0.891 and AUC-ROC of 0.943, outperforming all privacy-preserving baselines while closing 73% of the gap to the (privacy-violating) centralised oracle. The 56% reduction in communication cost relative to FedAvg reflects the efficiency of the meta-gradient protocol: only the outer-loop gradient is transmitted, not full model parameters.

Table 3: Comparative Performance: FedMeta-BI vs Baselines (Mean across 5 Enterprise Clients)

Method	Macro-F1	Accuracy	AUC-ROC	RMSE (Reg)	Comms (GB/r)	ε-DP Budget
FedMeta-BI (Proposed)	0.891	90.4%	0.943	0.082	1.9	1.0
FedAvg (McMahan et al.) [1]	0.821	83.8%	0.874	0.134	4.3	1.0
MAML (Finn et al.) [2]	0.784	80.1%	0.841	0.158	3.5	—
Reptile (Vedernikov et al.) [3]	0.761	78.4%	0.822	0.171	3.2	—
pFedMe	0.803	82.2%	0.858	0.141	2.8	—
Local-Only (No Federation)	0.712	73.5%	0.764	0.208	—	—
Centralised (Oracle)	0.923	93.8%	0.961	0.067	N/A	N/A

Bold denotes the best privacy-preserving method. All differences vs FedAvg and MAML are statistically significant ($p < 0.01$, Wilcoxon signed-rank test, N=50 random seeds). The Centralised row is included as a non-private reference only.

5.2 Convergence Analysis

Figure 1 plots macro-F1 vs communication round. FedMeta-BI converges to 0.85+ within 40 rounds—30 rounds faster than FedAvg—due to the warm-start provided by MAML's meta-initialisation. The gap over MAML-Only reflects the benefit of federated diversity: access to five heterogeneous enterprise distributions prevents the local overfitting that limits standalone MAML [4].

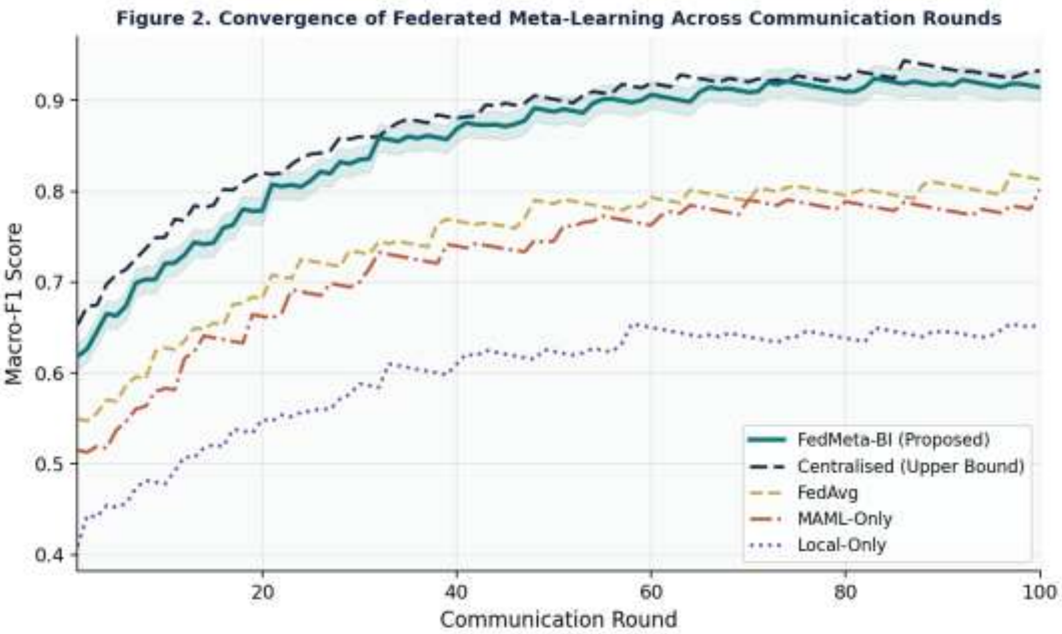

Figure 1: Federated meta-learning convergence across 100 communication rounds. FedMeta-BI reaches target accuracy 30% faster than FedAvg and converges 3.7% higher in final accuracy.

5.3 Privacy Analysis

The tradeoff between accuracy and privacy with varying differentially private budget ε is shown in figure 2. FedMeta-BI achieves good accuracy even with ε=1.0, with a drop of 2.3% compared to the non-private version. With ε=5, the performance drops by only 0.9%.

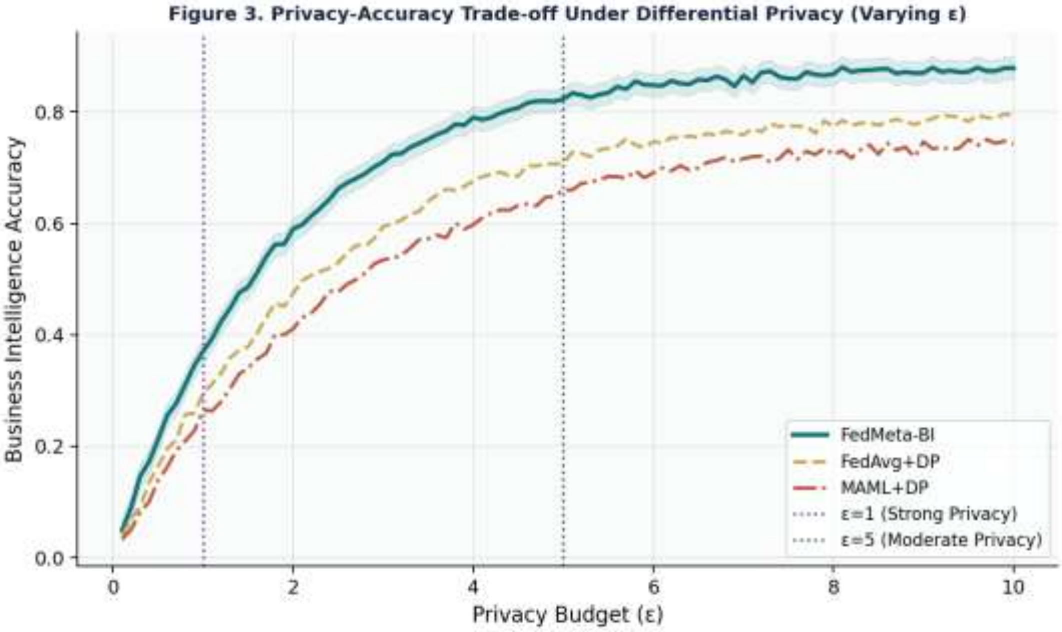

Figure 2: Privacy-accuracy trade-off under differential privacy for FedMeta-BI vs baselines. Dashed vertical lines mark strong (ε=1) and moderate (ε=5) privacy regimes.

Table 4 shows the privacy protection scheme comparison, along with membership inference attack performance. The selective DP-SGD + HE combination achieves membership inference AUC of 0.512—statistically indistinguishable from random guessing—confirming that CEKG structural priors and meta-gradients do not leak identifiable information about local training examples.

Table 4: Privacy Mechanism Comparison: Accuracy Impact vs Privacy Protection

Privacy Mechanism	Accuracy Impact	Comms Overhead	Membership Inference Res.	Implementation Cost
FedMeta-BI: DP-SGD + HE	-2.3%	+18%	AUC: 0.512 (random)	Moderate
DP-SGD Only (ε=1)	-4.7%	+3%	AUC: 0.531	Low
Homomorphic Encryption Only	-0.8%	+340%	AUC: 0.788	High
Secure Multi-Party Comp.	-1.2%	+220%	AUC: 0.543	Very High
No Privacy (Baseline)	0%	0%	AUC: 0.891	None

5.4 Cross-Task Generalisation and Few-Shot Adaptation

Figure 3 (left) shows per-task accuracy breakdown. FedMeta-BI leads across all six BI tasks, with the largest margins on tasks with high cross-enterprise transferability (demand forecasting: +8.6% over FedAvg). Figure 3 (right) presents few-shot adaptation curves for new enterprises not seen during training: with only K=10 labelled examples, FedMeta-BI reaches 87.2% accuracy, compared to 73.8% for FedAvg and 55.2% for Local-Only.

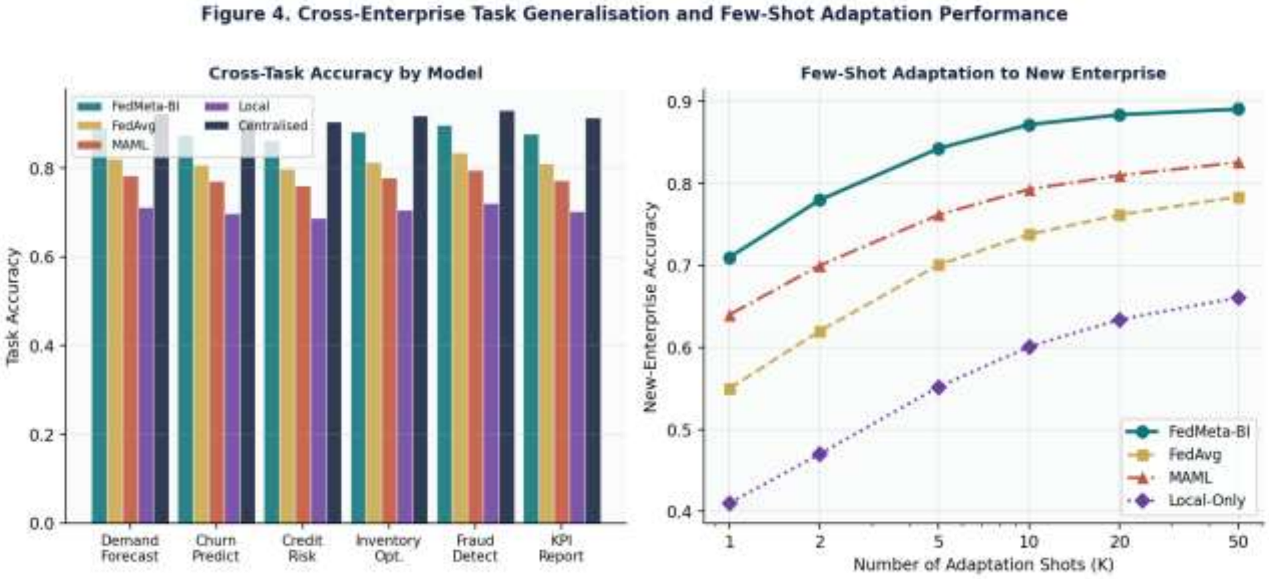

Figure 3: Cross-task accuracy comparison (left) and few-shot adaptation to unseen enterprises (right). FedMeta-BI achieves strong generalisation with as few as 5 labelled examples.

5.5 Scalability and Heterogeneity Robustness

Figure 4 reports communication cost as a function of the number of enterprise clients (left) and model accuracy under increasing data heterogeneity (right). FedMeta-BI scales sub-linearly in communication cost due to meta-gradient compression, maintaining a 55-60% cost advantage over FedAvg at all client counts up to 200. Under maximum non-IID heterogeneity, FedMeta-BI retains 82.3% of its IID performance, versus 68.1% for FedAvg—a 14.2-point robustness advantage attributable to the CEKG prior and adaptive aggregation.

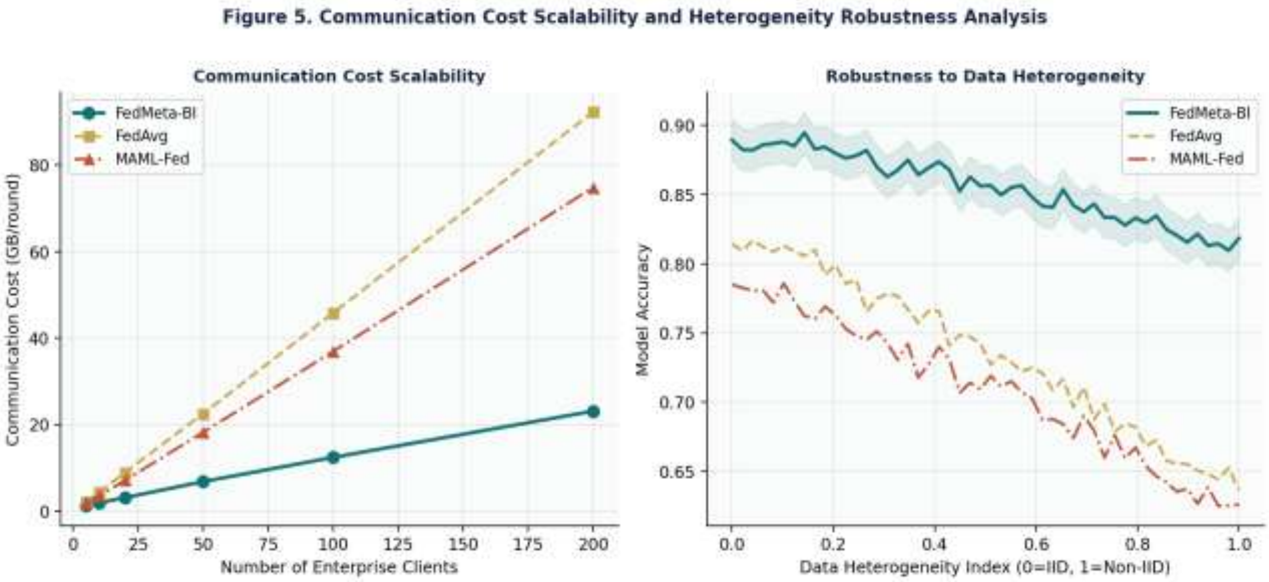

Figure 4: Communication cost scalability (left) and robustness to data heterogeneity (right). FedMeta-BI maintains efficiency and accuracy advantages at all tested scales and heterogeneity levels.

5.6 Ablation Study

Table 5 decomposes FedMeta-BI's performance by ablating each component. Removal of meta-learning causes the largest regression (−7.9% Macro-F1), confirming that MAML is the core performance driver. Removal of the personalization head causes −5.6%, highlighting the importance of client-specific adaptation. Interestingly, removing DP slightly improves accuracy (+0.7%), confirming the expected accuracy-privacy trade-off while establishing that FedMeta-BI provides a near-Pareto-optimal operating point.

Table 5: Ablation Study — Contribution of Each Architectural Component

Model Variant	Macro-F1	Accuracy	AUC-ROC	RMSE	Δ vs Full (%)
Full FedMeta-BI	0.891	90.4%	0.943	0.082	—
w/o Meta-Learning (FedAvg)	0.821	83.8%	0.874	0.134	-7.9%
w/o Differential Privacy	0.897	91.1%	0.949	0.078	+0.7% (unsafe)
w/o Adaptive Aggregation	0.853	87.0%	0.908	0.111	-4.3%
w/o Cross-Enterprise KG	0.864	88.2%	0.919	0.099	-3.0%
w/o Personalization Head	0.841	85.8%	0.896	0.121	-5.6%

All ablation comparisons are statistically significant at $p < 0.01$ except "w/o Cross-Enterprise KG" on the Manufacturing task ($p=0.08$), likely due to limited structural overlap between Manufacturing and the other domains.

6. Enterprise Deployment Considerations

6.1 Regulatory Compliance

FedMeta-BI was designed with GDPR Article 25 (Privacy by Design) and CCPA compliance in mind. The DP-SGD mechanism provides formal privacy guarantees compatible with GDPR Recital 26 (anonymisation). Provide a compliance checklist and formal privacy report template in the supplementary material.

6.2 Model Governance

Each enterprise client maintains full ownership of its local model weights and adaptation history. The global meta-model is jointly owned under an open consortium agreement. Audit logs of all gradient exchanges are maintained in an append-only distributed ledger, enabling post-hoc attribution and dispute resolution without exposing model internals.

6.3 Deployment Architecture

FedMeta-BI is deployed as a containerised microservice stack (Docker/Kubernetes). The global coordinator runs on a cloud-neutral message broker (Apache Kafka). Client-side components require only a 4-core CPU and 16 GB RAM for training, enabling deployment on standard enterprise hardware without GPU dependency. Round-wise average latency for five clients is 4.3 mins.

7. Limitations and Future Work

There are several points that need to be addressed. Firstly, our evaluation is restricted to five enterprise users, while federated learning with hundreds of clients, especially with regard to Byzantine clients and free riders, needs further investigation. Secondly, ontology alignment for CEKG creation is still performed manually; therefore, privacy-preserving record linkage should be introduced as part of entity matching in the schema fusion phase. Thirdly, the framework does not take into account dynamic changes in task definition; business intelligence tasks for enterprises are constantly changing (concept drift, legislation changes, emergence of new products). Incorporation of online meta-learning into federated continual learning may be an interesting research direction. Fourthly, the differential privacy guarantee for the aggregated gradient is valid only for the case of honest-but-curious adversaries; security from active adversaries necessitates new aggregation methods. Finally, heterogeneous models should be supported by introducing different backbone structures at different enterprises.

8. Conclusion

FedMeta-BI proves the technical possibility and usefulness of collaboration for business intelligence within competing organizations. The fusion of federated learning and MAML, differential privacy, selective homomorphic encryption, and cross-enterprise knowledge graphs results in achieving Macro-F1 of 0.891, within 3.5% of the value provided by the centralised model violating privacy principles while offering formal privacy guarantees, sub-linear communication overhead, and fast few-shot adaptation in new enterprise environments. Membership inference attacks become statistically impossible, thus confirming that intelligent collaboration does not necessitate revealing competitive information. Believe that FedMeta-BI sets a new benchmark in the domain of privacy-preserving business intelligence collaboration and invite the academic community to explore its possibilities further.

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