Federated Learning for Traffic Flow Prediction

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Introduction

Motivation and Need for Research of Traffic Flow Prediction (TFP)

Urban planning and traffic control

Impacts on land use

Crucial for traffic management

Sustainable urban development

Critical function of Intelligent Transport Systems

Problem with Traditional Methods

Centralized Machine Learning Techniques

Significant data privacy and security risks

Stricter data privacy regulations

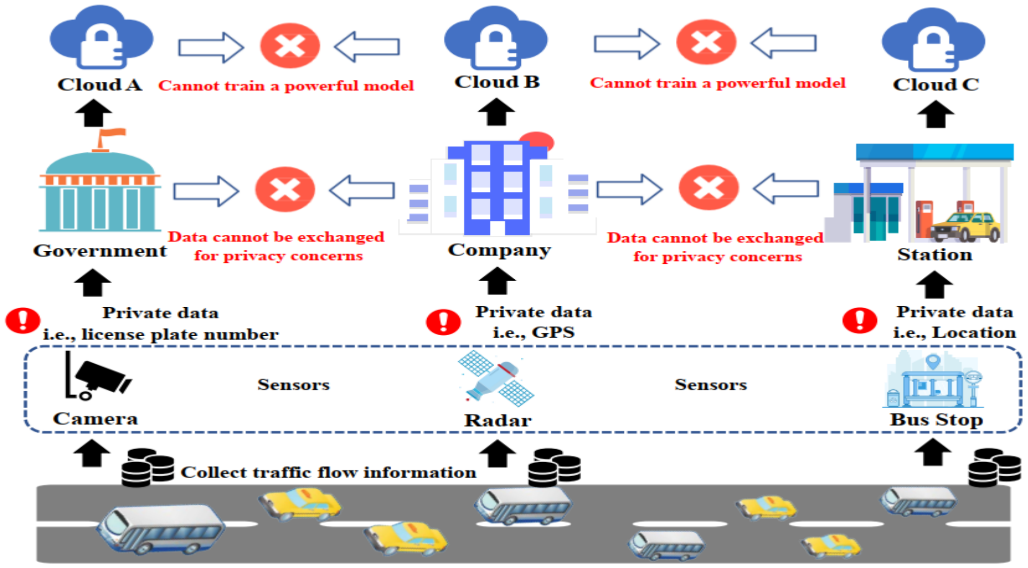


Fig. 1. Privacy and security problems in traffic flow prediction[1]

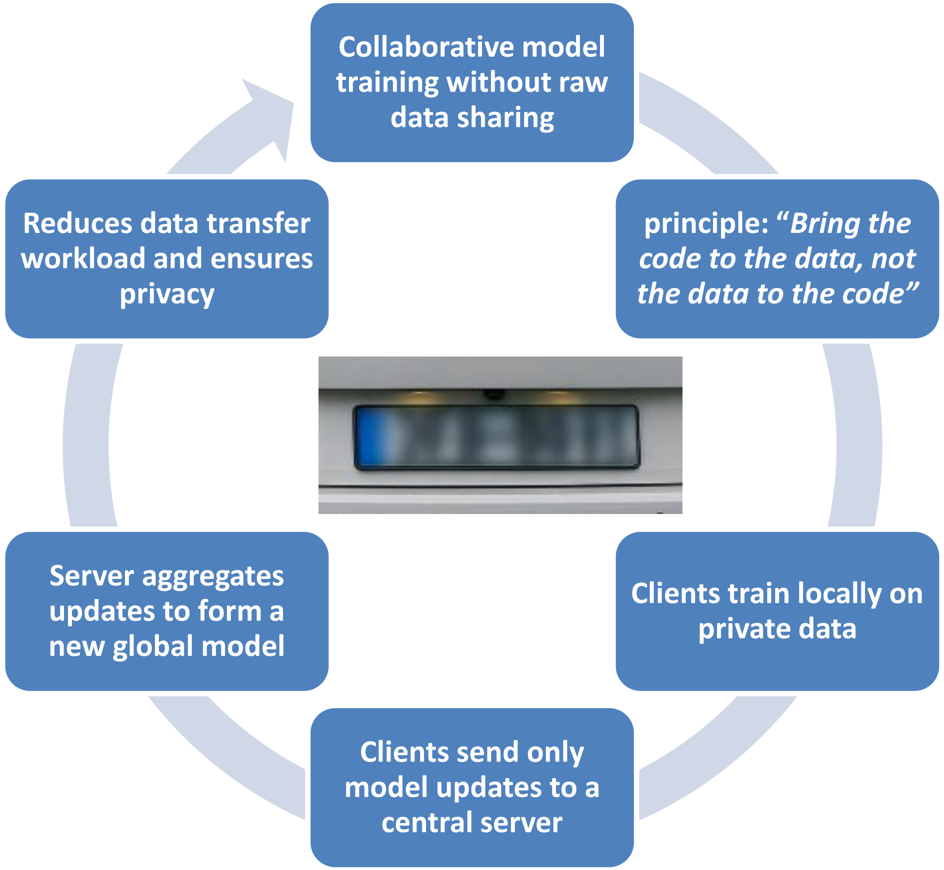
[1] Y. Liu, J. Yu, J. Kang, D. Niyato, and S. Zhang, "Privacy-Preserving Traffic Flow Prediction: A Federated Learning Approach," *IEEE Internet of Things Journal*, 2020

Introduction

Federated Learning (FL)

Privacy preserving machine learning model developed by Google in 2016.

Advantages of FL over Centralised Machine Learning Techniques in TLP



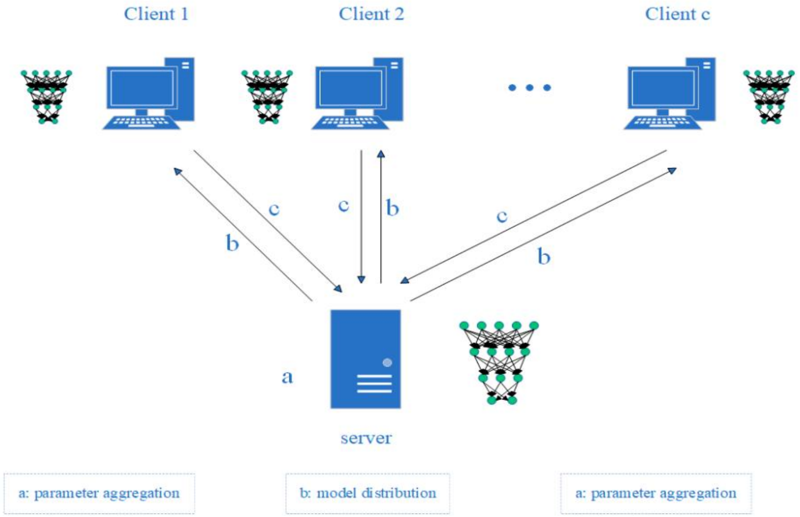


Fig. 2. Collaborative training process of federated learning[7]

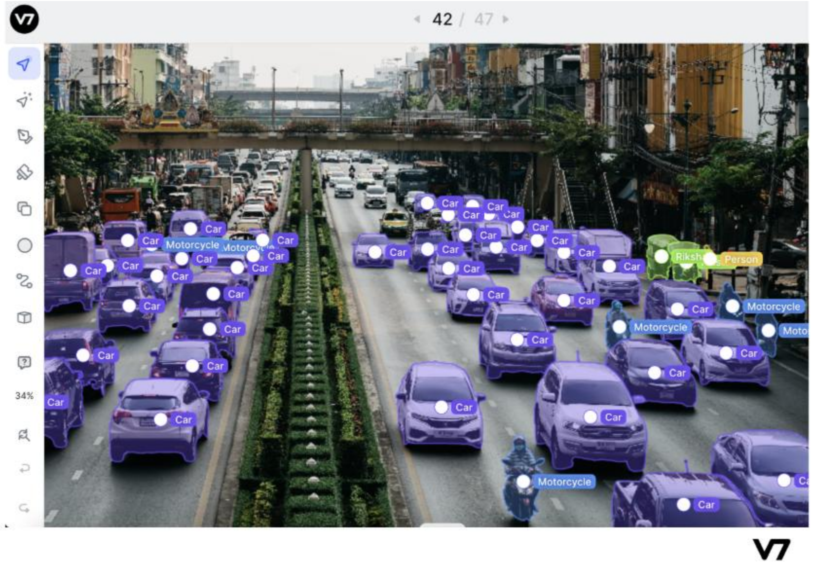


Fig. 3. Road object detection for traffic flow analysis in V7
Credit : https://www.v7labs.com/blog/federated-learning-guide

[7] G. Bo and J. Tang, “A Short-Term Traffic Flow Prediction Method Based on Personalized Lightweight Federated Learning,” *Italian Nat. Conf. on Sensors*, 2025.

Methodology: FL Architectures for Traffic Flow Prediction

FLSTAGCN Model

- Combines FL with Spatial-Temporal Attention GCN (STAGCN)
- **Shi et al. (2024)** demonstrated FLSTAGCN using real-world traffic datasets (e.g., **PeMSD7**, **METR-LA**) to predict short-term traffic speed and flow.

Results showed **competitive accuracy** when compared with centralized models like DCRNN and STGCN.

Pros	Cons
Privacy-Preserving	Computationally Intensive
Spatio-Temporal Modeling	Communication Overhead
Attention Mechanism	Non-IID Sensitivity
Scalable Across Clients	Difficult to deploy in low resource env
Improved Aggregation	

- **Real world Application Potential** - Smart Cities Traffic Systems, Regional Traffic Authorities Collaboration, Connected Vehicles / Edge Devices, Event Management and Urban Planning, Autonomous Vehicle Infrastructure.

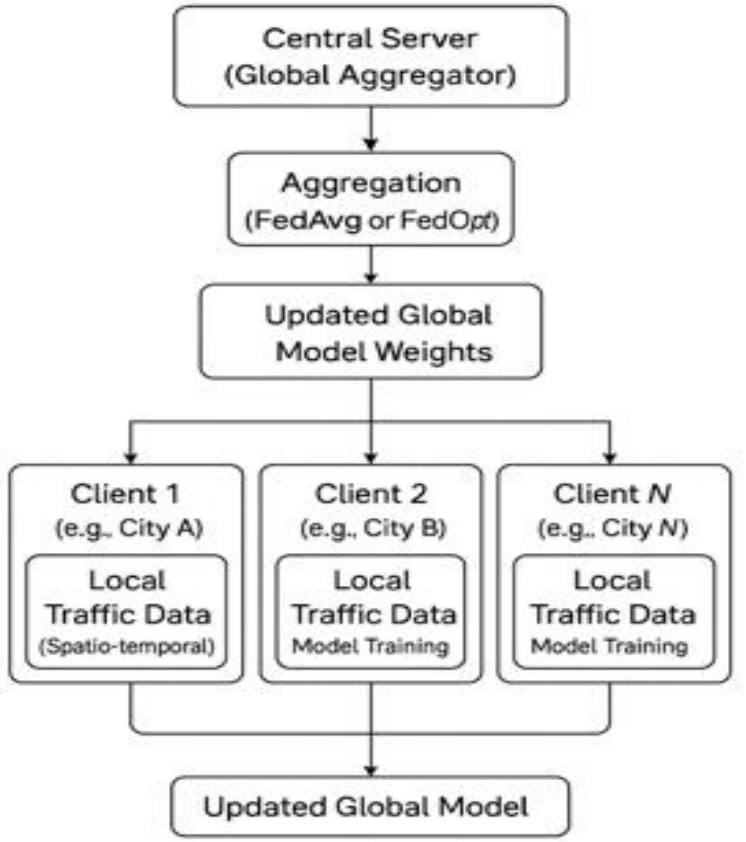


Fig. 4. System architecture of FLSTAGCN model

[5] L. Shi et al., “FLSTAGCN: Traffic Flow Prediction Based on Federated Learning and Attention Graph Convolutional Network,” *Proc. IEEE Int. Conf. Systems, Man and Cybernetics*, 2024.

PLFL Model

- Dynamic model pruning + weighted client personalization.
- Cities with region-specific traffic patterns .
- Used in highway management systems where rural, urban, and high-density areas have different traffic behaviors.
- PLFL personalizes predictions for each region without data sharing.

Pros	Cons
Personalization	Training Complexity
Communication Efficiency	Aggregation Challenges
Resource Optimization	Hyperparameter Tuning
Improved Accuracy on non IID	Model Drift Risk
Scalability	

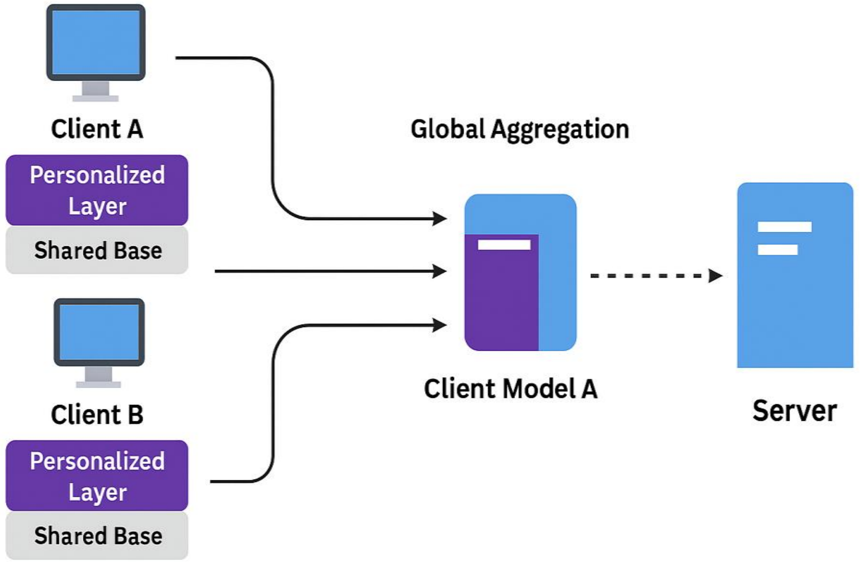


Fig. 5. Personalized Federated Learning Visual Workflow

- **Other Applications -** Healthcare, Finance and E Commerce

[8] J. Guo, X. Feng, and H. Zheng, “Personalized Federated Learning with Neighbor Aggregation for Traffic Flow Prediction,” *Int. Conf. Innovative Computing and Cloud Computing*, 2023.
[18] H. Lai, J. Guo, X. Feng, and H. Zheng, “Communication-Efficient Personalized Federated Learning for Traffic Flow Prediction,” *Int. Conf. Innovative Computing and Cloud Computing*, 2024
[7] G. Bo and J. Tang, “A Short-Term Traffic Flow Prediction Method Based on Personalized Lightweight Federated Learning,” *Italian Nat. Conf. on Sensors*, 2025.

BFRT Model

- Blockchained Federated Real-Time Traffic Prediction
- Real-Time/Online FL Models for TFP.
- Authors used real-world traffic datasets (like METR-LA or PeMS) and simulated RSU deployment scenarios to validate real-time prediction.
- BFRT achieved lower real-time predictive error compared to standalone FL or centralized methods.

Pros	Cons
Real-Time Prediction	Computational Overhead
Blockchain Integration	Resource Usage
Edge Deployment	Complex Implementation
Privacy-Preserving	
Scalability & Trust	

- **Real-World Applications -** Urban Traffic Control Centers, Autonomous Vehicle Infrastructure, Smart Highways / Tollways, City Wide Fleet Management

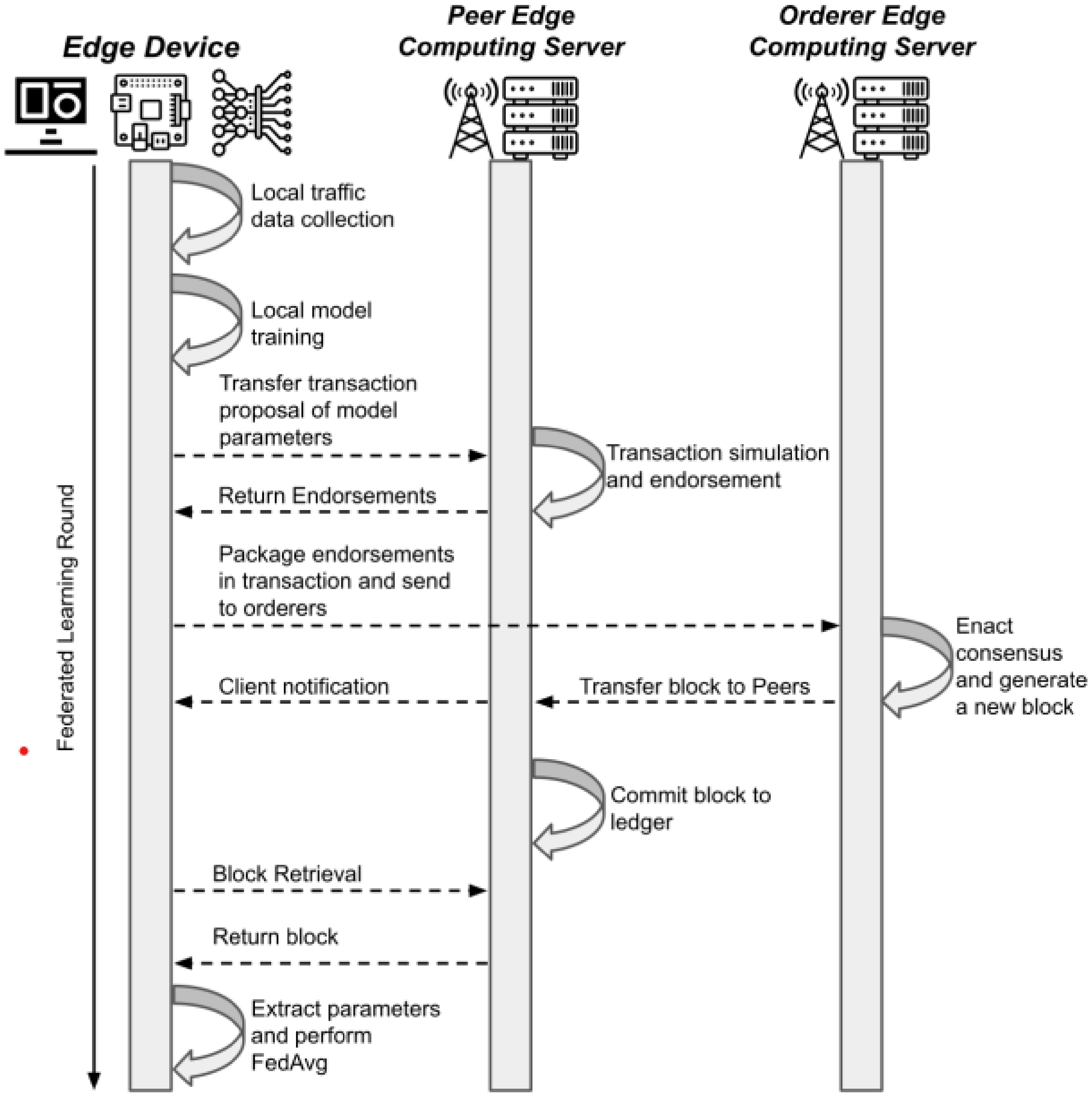


Fig. 6. Workflow of the BFRT system [10]

[10] C. Meese, H. Chen, S. Asif, W. Li, C. Shen, and M. Nejad, “BFRT: Blockchained Federated Learning for Real-time Traffic Flow Pre diction,” *Proc. IEEE/ACM Int. Symp. Cluster, Cloud and Internet Computing*, 2022.

FedTPS Model

- Regions with limited sensor coverage (e.g., rural or newly developed areas) benefit from synthetic data to simulate missing traffic patterns.

- **Other Applications -** Healthcare, Finance and Retail.

Pros	Cons
Addresses Non-IID & Data Scarcity	Dependency on Synthetic Data Quality
Improved Generalization	Needs Tuning
Modular Architecture -2 phases	Training Overhead
Better than Centralized & FL Baselines	

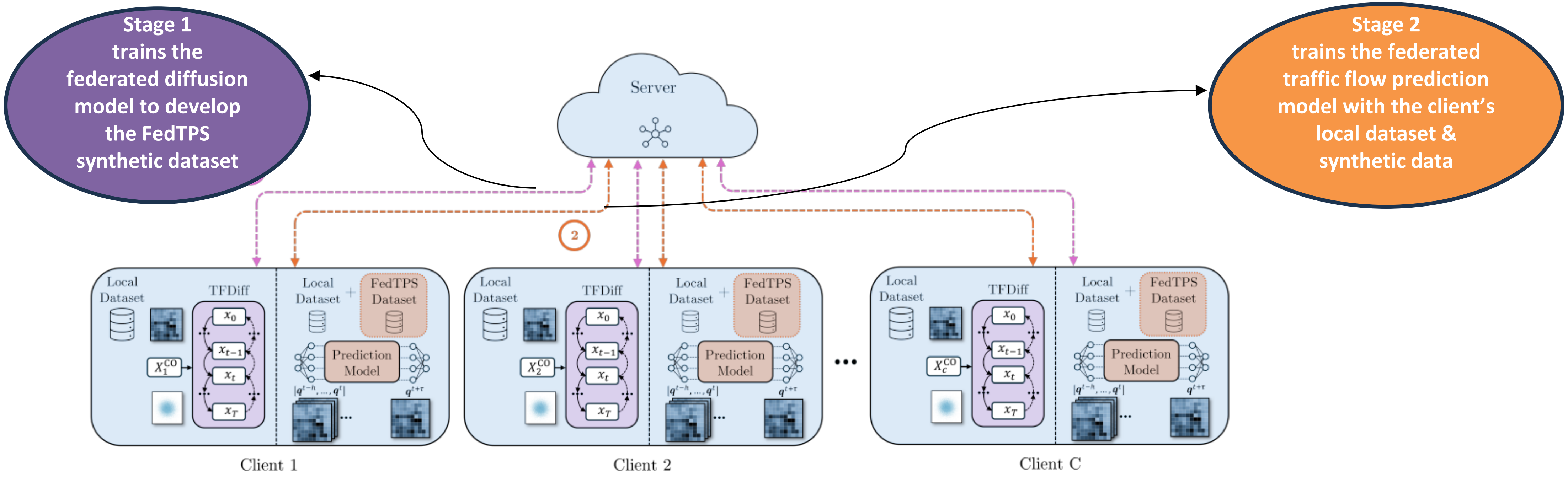


Fig.7. FedTPS Framework for training a federated generative model and subsequent traffic flow prediction model [17].

[17] F. Orozco, P. de Gusmao, H. Wen, J. Wahlstr¨ om, and M. Luo, "Federated Learning for Traffic Flow Prediction with Synthetic Data Augmentation," *arXiv preprint arXiv:2403.56789*, 2024.

Results & Discussion

- Multiple FL-based models evaluated using real-world datasets (METR-LA, PeMSD7, PeMSD4).
- Performance measured using common metrics: Mean Absolute Error, Root Mean Square Error.
- FL approaches consistently outperform centralized or baseline models.

Model	**RMSE**	**MAE**
LSTM	9.12 / 10.09 / 11.63	6.23 / 6.97 / 7.95
TGCN	8.43 / 8.93 / 9.51	5.59 / 5.95 / 6.58
DCRNN	7.86 / 8.03 / 8.22	4.89 / 5.01 / 5.32
STGCN	7.57 / 7.88 / 8.09	4.55 / 4.82 / 5.16
PLFL	7.11 / 7.63 / 8.21	4.05 / 4.79 / 4.98

COMPARISON OF PREDICTION PERFORMANCE OF DIFFERENT MODELS (RESULTS REPRESENT 5 MIN, 15 MIN, AND 30 MIN PREDICTION PERFORMANCE, RESPECTIVELY) [7].

Methods	PEMS-BAY						METR-LA					
	5min ($F=1$)		30min ($F=6$)		1h ($F=12$)		5min ($F=1$)		30min ($F=6$)		1h ($F=12$)	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
SVR	2.01	1.09	3.74	1.79	4.80	2.28	6.43	3.46	8.41	4.34	9.61	5.00
GRU	2.02	0.99	3.93	1.77	5.50	2.42	5.56	**2.91**	8.13	4.17	9.41	4.90
DCRNN	1.65	0.93	4.79	2.09	6.19	2.71	4.30	3.57	7.09	4.61	8.71	5.33
STGCN	1.46	**0.86**	3.62	1.73	4.43	2.26	5.92	3.82	8.60	4.62	10.66	5.92
MegaCRN	1.61	0.91	4.42	1.94	5.33	2.33	4.24	3.54	6.77	4.51	8.11	5.09
FedAvg	1.80	1.02	3.72	1.78	5.25	2.41	5.84	3.32	8.16	4.45	9.52	5.22
FedGRU	1.82	0.97	4.72	2.27	6.52	3.37	5.71	2.99	9.23	5.00	11.03	6.56
FCGCN	9.25	4.82	9.45	4.97	9.36	5.04	15.37	9.69	15.45	10.04	15.16	9.83
FASTGNN	5.32	2.82	6.06	3.20	6.84	3.76	11.73	7.27	12.98	8.23	12.82	8.16
CNFGNN	1.82	1.04	3.60	1.73	5.13	2.64	5.82	3.25	8.03	4.24	9.38	5.12
FedGTP	1.75	1.00	4.59	2.06	6.10	2.74	6.11	2.96	9.34	4.40	11.77	5.66
pFedCTP	5.29	2.84	6.49	3.40	7.43	3.92	8.88	5.21	10.56	6.02	12.08	7.15
REFOL	**1.00**	1.00	**1.86**	**1.61**	**2.44**	**2.08**	**3.29**	3.29	**4.87**	**4.02**	**5.29**	**4.21**

REFOL performance compared with CNFGNN on PEMS-BAY and METR-LA datasets. (a, c) Predicted traffic speed vs. ground truth. (b, d) CDFs of absolute errors, showing REFOL's lower error concentration [16].

[16] Q. Liu et al., "REFOL: Resource-Efficient Federated Online Learning for Traffic Flow Forecasting," *IEEE Trans. Intell. Transp. Syst.*, 2024.
[7] G. Bo and J. Tang, "A Short-Term Traffic Flow Prediction Method Based on Personalized Lightweight Federated Learning," *Italian Nat. Conf. on Sensors*, 2025.

REFOL vs CNFGNN - Visual Performance

REFOL Curve Dominance in both datasets

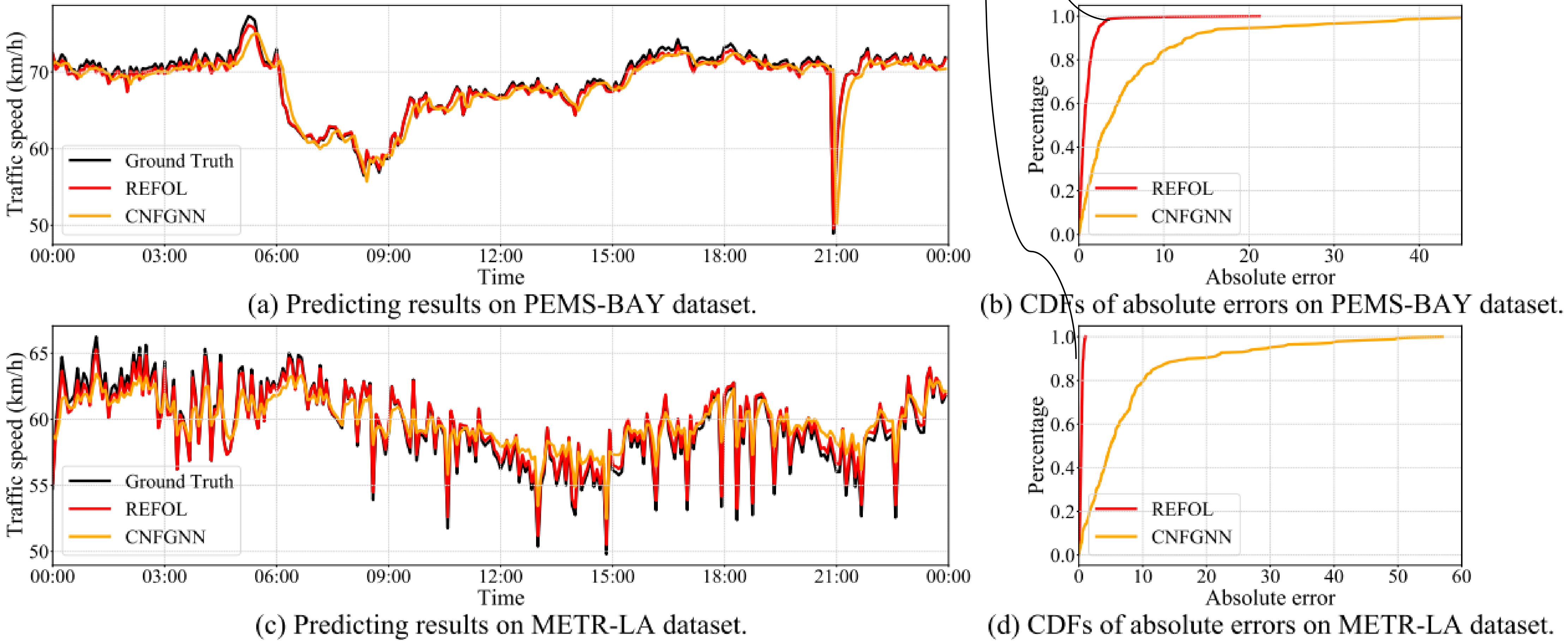


Fig. 8. Ground truth values and forecasting values of CNFGNN and REFOL [16].

[16] Q. Liu et al., “REFOL: Resource-Efficient Federated Online Learning for Traffic Flow Forecasting,” *IEEE Trans. Intell. Transp. Syst.*, 2024.

Challenges of Applying Federated Learning in Traffic Flow Prediction

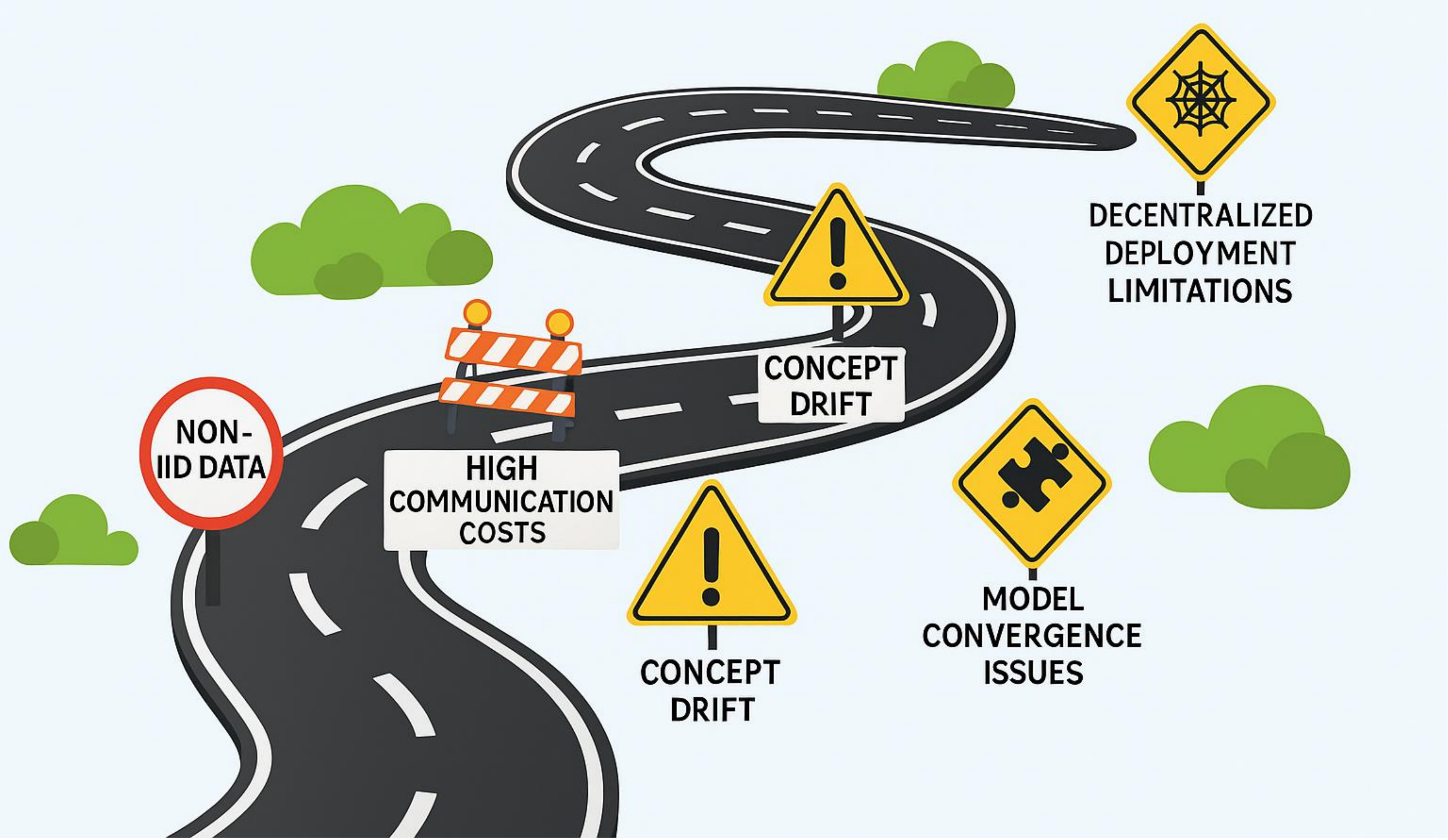


Fig. 9. Challenges of Applying Federated learning in Traffic Flow Prediction

Conclusion

Federated Learning (FL) is a promising privacy-preserving, decentralized solution for Intelligent Transportation Systems (ITS).

Effectively addresses core Traffic Flow Prediction (TFP) challenges like:
Data heterogeneity
Privacy constraints
Communication overhead

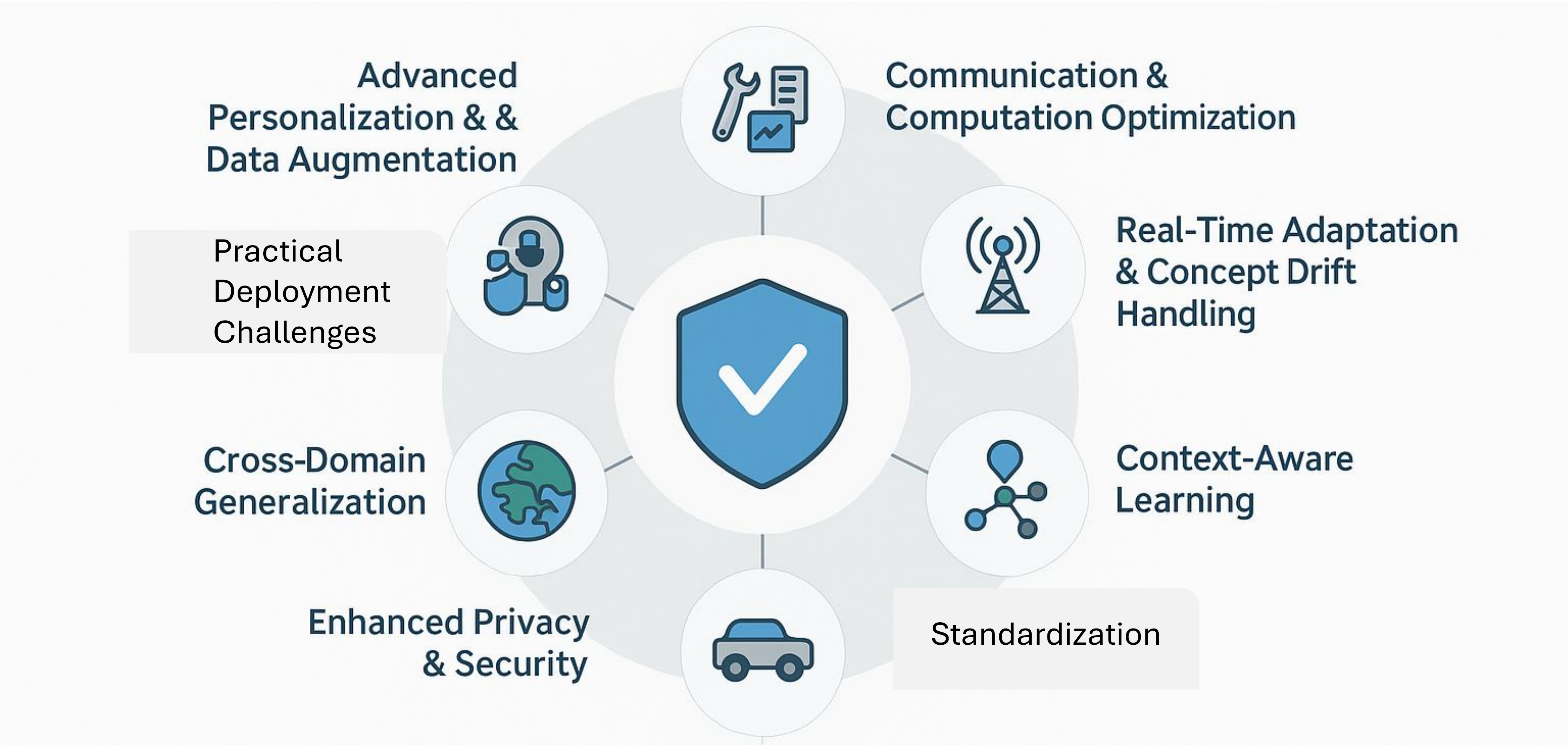
FL methods using deep spatio-temporal models (e.g., GNNs, GRUs, attention networks) achieve high prediction accuracy

Promotes ethical AI adoption by enabling collaborative model training without sharing raw data

Acts as a framework for collaborative intelligence, not just a theoretical concept.

Contributes to building smart, sustainable, and privacy-conscious urban mobility infrastructures

Future Directions and Research Gaps



THANK YOU !
Q&A

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