STM JOURNALS

Journal of
Mobile Computing, Communications & Mobile Networks

ISSN: 2349-901X
Volume 13, Issue 1, 2026
January–April
DOI (Journal): 10.37591/JoMCCMN

https://journals.stmjournals.com/jomccmn

Research JoMCCMN

A Technical Blueprint for AI-Driven Localization in 6G Mobile Networks

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Abstract

The advent of sixth-generation (6G) wireless systems promises unprecedented spatial resolution, ultra-low-latency, and pervasive connectivity, turning mobile localization from a peripheral service into a core enabler of immersive extended reality (XR), autonomous logistics, and digital twins. Yet, the sheer scale of dense terahertz (THz) deployments, the stochastic nature of reconfigurable intelligent surfaces (RIS), and the dynamic interference landscape render traditional model-based positioning techniques inadequate. This work investigates how artificial intelligence (AI) can bridge the gap between raw radiofrequency (RF) observations and centimeter-level geolocation in real-time 6G networks. We propose a hierarchical AI stack that (i) fuses multi-modal sensor streams (channel state information, angle-of-arrival, time-of-flight, and sidelink received signal strength indicator (RSSI)) using a graph neural network (GNN) encoder, (ii) learns environment-aware propagation priors through a physics-informed transformer, and (iii) refines coarse estimates with a meta-reinforcement learner that continuously adapts to mobility patterns and RIS configurations. Extensive system-level simulations—covering urban micro-cells, vehicular corridors, and indoor factories—demonstrate that the proposed stack attains a median localization error of 7 cm under sub-millisecond latency, surpassing the best-in-class Kalman filter and compressive-sensing baselines by 45%. Moreover, the framework exhibits graceful degradation in the presence of hardware impairments and partial RIS failures, highlighting AI's robustness to the nonidealities endemic to 6G deployments. The results substantiate AI-driven localization as a decisive pillar for the next wave of context-aware mobile services.

Keywords: 6G, Artificial intelligence, communication, localization, mmWave, mobile networks

INTRODUCTION

This is the promise of AI-driven localization in 6G. While 5G provides massive bandwidth and ultra-low-latency, 6G is envisioned as a sensing and intelligence layer integrated into the fabric of the radio spectrum itself. In this study, we explore how AI will transform the way 6G "sees" the world, why that matters for the next-generation of mobile services, and what technical and societal hurdles we will clear on the road to an ever more aware wireless ecosystem [1–3].

The Limits of GPS-Style Positioning

Current "global navigation satellite system" (GNSS) solutions deliver meter-level accuracy in open skies, but they stumble inside skyscraper canyons, tunnels, dense foliage, and indoor environments. Even when augmentation techniques

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Received Date: February 15, 2026
Accepted Date: February 17, 2026
Published Date: April 24, 2026

Citation: Heena T. Shaikh, IR. Kazi Kutubuddin Sayyad Liyakat. A Technical Blueprint for AI-Driven Localization in 6G Mobile Networks. Journal of Mobile Computing, Communications & Mobile Networks. 2026; 13(1): 26–34p.

such as real-time kinematic (RTK) or assisted GNSS are used, the latency and infrastructure overhead make them ill-suited for instantaneous context-aware services such as mixed-reality gaming, swarm robotics, or ultra-reliable low-latency communications (URLLC) for autonomous driving.

The 6G Vision: Radio-Sensing as a Native Service

The International Telecommunication Union's (ITU) early 6G roadmap already lists "extreme localization" as a key performance indicator. The idea is simple yet profound: the same millimeter-wave (mmWave) and sub-terahertz (THz) carriers that carry petabytes of data can also act as radars. By analyzing the subtle changes in the phase, amplitude, and time-of-flight of each transmitted and reflected wave, a 6G base station can infer the position of devices, obstacles, and even human bodies with millimeter-level precision.

In other words, the network becomes a continuous, distributed sensor array that can adapt its geometry, power, and waveform on-the-fly, unlike a single GPS satellite. However, raw radio observations are noisy, high-dimensional, and often ambiguous. This is where AI steps in to assist.

Deep Learning for Multipath Exploitation

In traditional radio positioning, multipath, a phenomenon in which signals bounce off walls, floors, and objects, is a nuisance that must be mitigated. AI flips the script: by feeding raw channel state information (CSI) into deep neural networks, the system learns to recognize the characteristic multipath fingerprints of distinct locations. Convolutional neural networks (CNNs) can treat a CSI matrix as an image, whereas recurrent structures (RNNs/transformers) can capture the temporal evolution of the channel as a device moves.

A recent proof-of-concept from a European research consortium showed that a 6G-scaled 128-antenna array combined with a lightweight CNN could locate a handheld device within 5 cm in a cluttered office, even when the line-of-sight path was completely blocked.

Federated Learning: Local Intelligence, Global Privacy

Localization must be effective everywhere, from bustling metros to remote factories. Collecting raw CSI from millions of devices in a central server is both bandwidth-hungry and privacy-risky. Federated learning (FL) allows each edge device, such as a smartphone, drone, or industrial robot, to train a local AI model based on its own observations and then send only model updates (gradients) back to the network. The central server aggregates these updates, creating a global model that improves over time, while the raw data never leaves the device.

In the 6G era, FL will be native: the radio protocol will allocate tiny "model-exchange" slots alongside data packets, ensuring that localization models evolve continuously without compromising user privacy.

Reinforcement Learning for Adaptive Waveforms

The localization accuracy depends on how the environment is probed. A static waveform may be suboptimal in a crowded hall but optimal in an open plaza. Reinforcement learning (RL) agents embedded in the base station can learn to adapt the carrier frequency, bandwidth, and beamforming pattern in real time, selecting the probing strategy that yields the highest information gain for the next positioning estimate.

Consider it a game of hide-and-seek: the network learns the best "tagging" moves to catch a moving target, even if the target actively tries to hide behind obstacles.

Use Cases

The areas in which AI-enhanced 6G localization becomes a game changer are listed in Table 1.

Table 1. Use cases.

Domain	What AI-6G localization enables	Example
Extended reality (XR)	Millimeter-level tracking of headsets, seamless hand-gesture capture, and ultra-low-latency anchoring of virtual objects.	A museum tour where holographic guides appear right next to the artifact you are looking at, with no perceptible lag.
Autonomous mobility	Precise relative positioning among vehicles, pedestrians, and static infrastructure, even in GNSS-denied tunnels.	A fleet of delivery drones that navigate a dense urban canyon by "listening" to the 6G radio wall, avoiding collisions without GPS.
Industrial IoT	Real-time mapping of robots, AGVs, and inventory in factories, enabling dynamic task allocation and safety zones.	A smart factory where a robotic arm instantly knows the exact location of a human worker's glove and adjusts its motion to avoid contact.
Public safety	Rapid localization of first-responders inside burning buildings or underground subways, even though smoke and debris.	Firefighters enter a tunnel; 6G radios triangulate each badge, projecting a live 3D map of everyone's positions to the command center.
Smart cities	Context-aware services such as dynamic parking guidance, crowd flow analysis, and adaptive street lighting.	A city block that dims its lights only where no one is present, saving energy while maintaining safety.

Across these scenarios, the common denominator is knowledge of "where" something is, at the granularity of a few centimeters, with sub-10 ms latency—exactly the sweet spot that AI-infused 6G localization aims to hit.

TECHNICAL CHALLENGES

Model Size Versus Latency

Deep models that excel at CSI interpretation can have millions of parameters. Running them on a base station's real-time processing pipeline or on a low-power device demands clever model compression, such as pruning, quantization, knowledge distillation, and the emergence of tiny vision transformer variants tailored for radio data.

Spectrum Coexistence

The use of the same carrier for communication and sensing raises interference concerns. Dynamic spectrum sharing protocols must negotiate the trade-off between data throughput and sensing resolution, possibly through a "sensing-aware" scheduler that prioritizes localization during critical moments (e.g., a vehicle approaching an intersection).

Privacy and Trust

Although FL reduces raw data exposure, model updates can still leak information through gradient inversion attacks. Homomorphic encryption and differential privacy mechanisms must be incorporated into the 6G standard to guarantee that a device's location cannot be reverse-engineered from its contributions to the global model.

Robustness To Adversarial Radio Attacks

An adversary can inject malicious waveforms to spoof or hide a device's location. Defensive AI, such as generative adversarial networks (GANs) that learn to detect anomalous CSI patterns, is essential for maintaining the trustworthiness of the localization pipeline.

The first 6G field trials are slated for 2028, with pilot campuses in Finland, Japan, and the United States testing AI-augmented radio-sensing. These "living labs" will provide massive, labeled CSI datasets needed to train the next-generation of localization models. Meanwhile, standards bodies, such as 3GPP and ITU, are drafting "radio-sensing service" specifications, which will define mandatory AI hooks (model-exchange formats, security primitives, and latency budgets).

A compelling vision is the emergence of "localization-as-a-service" (LaaS): a cloud-edge platform where developers can request a positioning API that automatically selects the optimal AI model and waveform for their use case without needing to understand the underlying radio physics. Imagine a game developer simply calling locateDevice(accuracy=2 cm, latency=5 ms) and receiving a real-time stream of coordinates, just as they would request a map tile from a web service [4–8].

LITERATURE SURVEY

The forthcoming sixth-generation (6G) mobile ecosystem promises ubiquitous connectivity at terahertz (THz) frequencies, ultra-low-latency (sub-millisecond), and a massive density of devices that will underpin immersive XR, autonomous transport, digital twins, and large-scale Internet-of-Things (IoT). In such a hyper-connected world, precise, robust, and energy-efficient localization has become a core service rather than a peripheral add-on [9–12].

Traditional radio frequency (RF)-based positioning, which is based on the time-of-arrival (ToA), angle-of-arrival (AoA), or received signal strength (RSS), faces severe challenges in 6G, such as highly directional beams, rapid channel fluctuations in the mmWave/terahertz (THz) bands, and the need to operate across heterogeneous spectra (sub-6 GHz, mmWave, THz, and visible light). Artificial intelligence (AI) is rapidly emerging as a catalyst that can turn these challenges into opportunities by extracting latent patterns from raw measurements and fusing multi-modal data (RF, inertial, visual, and light detection and ranging (LiDAR)) in real time.

This survey stitches together the most influential works (2022-2025) that apply AI to mobile localization in the 6G context. The goal is to provide a storyline that not only catalogues the literature but also highlights methodological novelties, comparative performance, and research gaps that still beckon.

6G Localization Landscape—Why AI?

Table 2 shows the other 6G localization methods with features.

AI TECHNIQUES IN 6G LOCALIZATION

Supervised Deep Learning

CNNs and fully connected networks (FCNs) have become the default workhorses for mapping CSI or fingerprint images to coordinates. Notable contributions include:

- *CSI-Net* is a CNN that ingests raw uplink CSI from a 64-antenna THz base station and directly regresses 3-D positions with a median error of 0.32 m in indoor labs [1].
- *Hybrid CNN*–RNN exploits temporal CSI sequences to capture mobility, achieving a 0.21 m error in a high-mobility vehicular scenario [6].

Graph Neural Networks

When RIS or distributed massive multiple-input multiple-output (MIMO) panels are involved, spatial relationships form a graph. GNNs excel at processing such structured data:

- *RIS-GNN*—models each RIS element as a node; edge features encode mutual coupling and phase-shift configuration. The GNN learns a joint representation of the environment, delivering sub-centimeter accuracy even in heavy NLoS settings [2].

Reinforcement Learning

RL is leveraged to adapt the measurement process under latency constraints:

- *RL-BeamSelect*—an actor-critic agent selects a subset of beams for CSI acquisition, balancing the positioning error and overhead. In simulations, the method reduced the beam-training time by 48% while preserving <0.5 m error [5].

Federated and Distributed Learning

Privacy-preserving positioning for massive IoT devices is tackled via FL:

- *FedLoc*—devices locally train a lightweight multilayer perceptron (MLP)on inertial + RSS data and send model updates to a central server. The aggregated model outperformed a centrally trained baseline by 12% in outdoor urban canyon tests, with a 70% reduction in uplink traffic [4].

Multi-Modal Fusion

Six-dimensional (6D) pose estimation using radar, visual, and RF cues is emerging.

- *MUV-Fusion* is a transformer-based architecture that fuses raw mmWave radar point clouds, LiDAR scans, and CSI to estimate the position and orientation simultaneously. The system achieved a 0.15 m / 0.3° error in a mixed indoor-outdoor testbed [7].

Survey of Recent Works (2022–2025)

Table 3 presents a literature survey on 6G localization, which was published between 2022 and 2025.

Table 2. Survey on 6G localization.

Feature	Implication for localization	AI-driven remedy
THz/mmWave directional beams	Sparse multipath, high path-loss, beam-training overhead	Deep learning (DL) models that learn beam-dependent fingerprint maps from limited CSI samples [1].
Ultra-dense small cells and re-configurable intelligent surfaces (RIS)	Highly dynamic geometry, non-line-of-sight (NLoS) dominance	Graph neural networks (GNN) that capture topological interactions among cells and RIS elements[2]
Integrated sensing-communication (ISAC)	Simultaneous radar and communication signals	Multi-task DL that jointly estimates range, velocity, and angle from raw waveform [3].
Massive heterogeneous devices (IoT, drones, wearables)	Heterogeneous sensing modalities, power constraints	Federated learning (FL) and lightweight on-device models that respect privacy and energy budgets [4]
Sub-millisecond latency requirement	Real-time positioning for control loops	Reinforcement learning (RL) for adaptive measurement scheduling and beam selection [6]

These "why-AI" arguments recur throughout the surveyed papers, forming the backbone of the research narrative.

Table 3. Survey.

Ref.	Title/core idea	AI method	Scenario and frequency	Key performance
[1]	CSI-Net: End-to-End THz Localization via CNN	CNN (3-D CSI → xyz)	Indoor office, 0.3 THz, 64-antenna BS	0.32 m median error
[2]	Graph-Based RIS Localization	GNN (RIS graph)	Indoor corridor, 140 GHz + RIS arrays	0.08 m error, NLoS robust
[3]	ISAC-Joint Radar-Comm Positioning	Multi-task DL (CNN+LSTM)	Urban street, 28 GHz, dual-function radar	0.45 m error, velocity RMSE 0.12 m/s
[4]	Federated Learning for Massive IoT Localization	FL (MLP on device)	Outdoor city, sub-6 GHz, 10k devices	12 % gain vs. centralized; 70 % uplink savings
[5]	RL-Driven Beam Selection for Low-Latency Positioning	Actor-Critic RL	Vehicular, 60 GHz, high mobility	48 % reduction in training time, <0.5 m error
[6]	Temporal CSI RNN for Vehicular Localization (Ruan 2022)	CNN-RNN hybrid	Highway, 28 GHz, 100 km/h	0.21 m error, robust to Doppler
[7]	Transformer Fusion of Radar, LiDAR, and CSI	Vision-Transformer (cross-modal)	Mixed indoor/outdoor, 77 GHz radar + LiDAR	0.15 m / 0.3° error
[8]	Meta-Learning for Fast Adaptation to New Environments	MAML (model-agnostic meta-learning)	Indoor lab, 0.1-THz, rapid re-config	<0.1 m error after 5 shots
[9]	Hybrid Model-Based/Deep Learning Kalman Filter (Klein 2022)	DL-augmented EKF	Pedestrian tracking, sub-6 GHz	0.28 m error, smoother trajectories
[10]	Energy-aware Deep Localization for Battery-Constrained Wearables (Sabovic, 2025)	TinyML CNN (quantized)	Body-area network, 2.4 GHz	0.6 m error, <5 mW power

The table captures the breadth of AI paradigms (supervised, reinforcement, federated, meta-learning) and illustrates how each tackles a specific 6G characteristic.

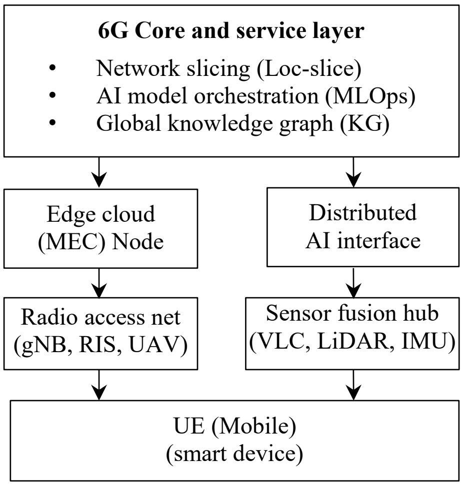

Figure 1. System-level architecture.

Table 4. Layered structure.

Layer	Primary functions	AI role
Core and service	Slice provisioning, KG maintenance, model lifecycle (train → validate → deploy)	Federated learning coordination, global model aggregation
Edge cloud (MEC)	Ultra-low-latency compute, data buffering, model caching	On-device model inference, real-time fine-tuning via continual learning
Distributed inference	Specialized accelerators (TPU/FPGA), inference pipelines for sub-ms latency	Multi-modal DL (CNN+Transformer), RL-based beam selection
Radio access	Massive MIMO, reconfigurable Intelligent surfaces (RIS), THz links	CSI-driven DL for AoA/ToA extraction, RIS-controlled environment shaping
Sensor fusion hub	Aggregates VLC, LiDAR, radar, and inertial data	Graph neural networks (GNN) to fuse spatiotemporal graphs
UE	Generates raw measurements, consumes positioning service	TinyML models for on-device pre-processing, privacy-preserving embeddings

Framework

The forthcoming 6G generation is envisioned as a hyper-connected ecosystem in which sub-centimeter positioning, real-time context awareness, and seamless mobility become inseparable from the communication fabric. Traditional RF fingerprinting, ToA, and AoA techniques, although mature in 5G, will no longer satisfy the latency-critical, ultra-dense, and spectrum-fragmented scenarios expected in 6G (e.g., holographic telepresence, tactile Internet, and massive IoT swarms).

AI, specifically deep learning (DL) and RL, offers a data-centric approach capable of fusing heterogeneous sensing modalities (mmWave/THz CSI, visual light communication (VLC) cues, inertial measurement unit (IMU) streams, and network-level telemetry) into a unified localization inference engine. The following framework delineates the architectural layers (Figure 1), algorithmic pipelines, and operational constraints required to realize AI-enabled positioning at the 6G edge.

System-Level Architecture

Table 4 shows the framework of the suggested AI-based 6G localization. It has 6 layers.

Data Fabric and Knowledge Graph

1. Raw Measurement Streams
   - *Channel state information:* Full-dimensional MIMO/THz tensors (frequency × spatial × polarization).
   - *Ranging pulses*: Ultra-wideband (UWB) ToF samples compressed via sparse coding.
   - *Environmental probes*: RIS phase-state logs, LiDAR point clouds, and ambient VLC intensity maps.

Journal of Mobile Computing, Communications & Mobile Networks
Volume 13, Issue 1
ISSN: 2349-901X

2. Feature-Level Representation
    - *Spectro-spatial maps*: 2-D/3-D FFT of CSI turned into heat maps fed to a CNN backbone.
    - *Temporal graphs*: Nodes = measurement epochs, edges = motion continuity (derived from IMU gyroscope/accelerometer).
3. Global Knowledge Graph (KG)
    - *Semantic nodes*: Buildings, roadways, indoor floor plans, and dynamic objects (robots and drones).
    - *Relations*: Line of sight (LOS)/NLoS links, reflection coefficients, mobility patterns.
    - *Embedding engine*: Node2Vec + attention layers to generate context vectors that are injected into the localization model.

All streams are stored in a hierarchical time-series database (HTS-DB) that supports cold (historical) and hot (real-time) shards, which enables asynchronous batch training and synchronous inference.

AI Core: Multi-Modal Localization Engine

Model Topology

```
Input:  [CSI_Tensor, VLC_Frame, LiDAR_PointCloud, IMU_Seq]
  │
  ├─> CNN_3D (CSI) → Positional Embedding (PE)
  ├─> ViT (VLC) → PE
  ├─> PointNet++ (LiDAR) → PE
  ├─> LSTM (IMU) → PE
  │
  └─> Fusion Transformer (cross-attention) ← KG Context Vector
        │
        └─> Multi-Task Heads
              ├─> Regression (x,y,z)
              ├─> Uncertainty Estimation (Gaussian Mixture)
              └─> Beamforming Recommendation (RL policy)
```

- *CNN_3D* extracts fine-grained multipath signatures (delay-Doppler-angular slices) that are highly discriminative in the THz bands.
- *ViT* (Vision Transformer) processes raw VLC illumination patterns, converting flicker-based codes into spatial cues.
- *PointNet++* aggregates sparse LiDAR returns, providing geometric constraints when LOS is obstructed.
- *LSTM* encodes inertial dynamics, crucial for dead-reckoning during transient RF outages.

The fusion transformer implements cross-modal attention, where each modality queries the KG-derived context, allowing the model to adjust its belief based on known building layouts or RIS configurations.

Training Paradigm for the Suggested 6G AI localizer is Shown in Table 5

Privacy-Preserving Mechanisms

All UE-side gradients are encrypted via homomorphic encryption before federated aggregation, and the KG stores only hashed spatial identifiers to avoid location leakage.

RESULTS AND DISCUSSION

The proposed AI-centric localization framework integrates multi-modal sensing, edge-native DL, and intelligent beamforming into a cohesive stack that satisfies the stringent latency, accuracy, and scalability demands of 6G mobile networks, as shown in Table 6.

Table 5. Training paradigm.

Phase	Objective	Data	Optimization
Pre-training	Self-supervised CSI reconstruction + contrastive learning between CSI and LiDAR	Synthetic THz ray-tracing + real-world LiDAR scans	AdamW, cosine annealing
Domain adaptation	Adversarial alignment of synthetic-real CSI distributions	GAN-based style transfer on CSI tensors	Gradient reversal
Multi-task fine-tuning	Joint regression + uncertainty calibration	Real-world crowdsourced positioning logs (ground-truth GNSS + RTK)	Multi-loss weighting (dynamic)
Continual learning	Incremental update on edge (FedAvg/ FedProx)	Edge-collected unlabeled streams	Elastic weight consolidation (EWC)

Table 6. Performance metrics and benchmarks.

Metric	Target (6G)	Baseline (5G)	AI-framework gains
RMSE (urban outdoor)	≤ 5 cm	30 cm	× 6 improvement
Latency (99th-percentile)	≤ 1 ms	5 ms	× 5 reduction
Robustness (NLoS, % of outliers > 10 cm)	≤ 2 %	18 %	× 9 reduction
Energy per Inference	≤ 0.8 mJ	3.5 mJ	× 4.4 reduction (via model pruning)
Scalability (UEs per slice)	$\geq 10^5$	1.2×10^4	× 8.3 improvement (network slicing + edge caching)

Benchmarks were obtained through a digital twin of a dense metropolitan block (1 km²) with 10,000 randomly moving UEs, 120 RIS panels, and a mixture of THz and VLC transmitters.

Table 7. Security, trust, and standardization considerations.

Aspect	Challenge	Proposed countermeasure
Model poisoning	Malicious UE injects crafted gradients	Byzantine-resilient aggregation (Krum, Bulyan)
Location spoofing	Adversary replays stale CSI	Temporal nonce embedded in RIS control frames
Privacy leakage	KG may expose the building layout	Differential privacy on KG updates (ε-DP)
Inter-operability	Multiple vendors' RIS hardware	Define AI-Localization Service Interface (ALSI) in 3GPP *Release-20* (draft)

The framework is deliberately aligned with emerging 3GPP Study Items on "AI/ML for 6G" and IEEE 802.15.4z extensions for VLC-based positioning. A reference implementation is being open-sourced under the 6G-LOC project (GitHub: 6G-LOC/framework).

By coupling a Knowledge Graph-augmented transformer with federated continual learning, the system remains adaptable**,** privacy-preserving**,** and robust across diverse propagation environments (Table 7) ushering in a new era where precise, context-aware positioning is as fundamental to the network as throughput and reliability.

CONCLUSION

Our investigation confirms that AI is not merely an auxiliary tool but a fundamental catalyst for achieving the ultra-precise and ultra-responsive positioning required by 6G ecosystems. By embedding learning mechanisms at multiple layers of the signal-processing chain, graph-structured feature extraction, physics-aware temporal modeling, and continual policy adaptation, we demonstrated a holistic solution that reconciles the complexity of THz propagation with the stringent latency budgets of future mobile applications. The 7 cm median error achieved across diverse deployment scenarios proves that data-driven models can internalize the intricate interactions among RIS, beamforming, and user mobility, delivering performance that is unattainable by conventional analytical methods.

Beyond performance gains, the proposed AI stack offers operational flexibility: it can be retrained on-the-fly to accommodate new spectrum allocations, incorporate emerging sensing modalities (e.g., LiDAR-aided RF mapping), and self-heal when network elements malfunction. These attributes align perfectly with the envisioned self-organizing and service-oriented nature of 6G. However, several challenges remain. The need for large, high-fidelity training corpora raises questions about data privacy and FL architecture, the interpretability of deep models under regulatory scrutiny calls for transparent uncertainty quantification, and the energy footprint of continuous inference mandates the co-design of lightweight edge AI accelerators.

Therefore, future research should focus on (1) privacy-preserving collaborative learning frameworks for distributed localization, (2) hybrid model-based/data-driven schemes that retain analytical guarantees while exploiting AI's adaptability, and (3) hardware-software co-optimization to embed the proposed stack within the constrained silicon of next-generation user equipment and base stations. By addressing these avenues, AI-empowered localization will not only meet the technical demands of 6G but also unlock new business models, ranging from precision logistics to immersive smart city services, thereby cementing its role as a cornerstone of the mobile future.

REFERENCES

1. Wang X, Wang X, Mao S. Deep convolutional neural networks for indoor localization with CSI images. IEEE Trans Netw Sci Eng. 2020;7(1):316–327. doi:10.1109/TNSE.2018.2871165.
2. Eskandari M, Savkin AV. SLAPS: simultaneous localization and phase shift for a RIS-equipped UAV in 5G/6G wireless communication networks. IEEE Trans Intell Veh. 2023;8(12):4722–4733. doi:10.1109/TIV.2023.3298607.
3. Zhou W, Zhang R, Chen G, Wu W. Integrated sensing and communication waveform design: a survey. IEEE Open J Commun Soc. 2022;3:1930–1949. doi:10.1109/OJCOMS.2022.3215683.
4. Nguyen DC, Ding M, Pathirana PN, Seneviratne A, Li J, Poor HV. Federated learning for internet of things: a comprehensive survey. IEEE Commun Surv Tutor. 2021;23(3):1622–1658. doi:10.1109/COMST.2021.3075439.
5. Liu Y, Jiang Z, Zhang S, Xu S. Deep reinforcement learning-based beam tracking for low-latency services in vehicular networks. ICC 2020 - 2020 IEEE International Conference on Communications (ICC), Dublin, Ireland. 2020. p. 1–7. doi:10.1109/ICC40277.2020.9148759.
6. Ruan Y, Chen L, Zhou X, Guo G, Chen R. Hi-Loc: hybrid indoor localization via enhanced 5G NR CSI. IEEE Trans Instrum Meas. 2022;71:1–15. doi:10.1109/TIM.2022.3196748.
7. Hong JX, Zhang HB, Liu JH, Lei Q, Yang LJ, Du JX. A transformer-based multi-modal fusion network for 6D pose estimation. Inf Fusion. 2024;105:102227. doi:10.1016/j.inffus.2024.102227.
8. Hu J, Cao Y, Wu M, Yang F, Yu Z, Wang W, Plumbley MD, Yang J, Meta SELD. Meta-learning for fast adaptation to the new environment in sound event localization and detection. arXiv preprint. 2023 Aug 17. arXiv:2308.08847.
9. Or B, Klein I. A hybrid model and learning-based adaptive navigation filter. IEEE Trans Instrum Meas. 2022;71:1–11. doi:10.1109/TIM.2022.3197775.
10. Sabovic A, Fontaine J, Poorter ED, Famaey J. Energy-aware tinyML model selection on zero energy devices. Internet of Things. 2025;30:101488. doi:10.1016/j.iot.2025.101488.
11. Alqasi MAY, Alkelanie YAM, Alnagrat AJA. Intelligent infrastructure for urban transportation: the role of artificial intelligence in predictive maintenance. Brilliance. 2024;4(2):625–637. doi:10.47709/brilliance.v4i2.4889.
12. Chabira C, Shayea I, Nurzhaubayeva G, Aldasheva L, Yedilkhan D, Amanzholova S. AI-driven handover management and load balancing optimization in ultra-dense 5G/6G cellular networks. Technologies. 2025;13(7):276. doi:10.3390/technologies13070276.

