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Original Research Paper

Reinforcement-Learning-Optimized Multi-Agent Intelligence for Semantic Feature Selection in AI-Native 6G Wireless Indoor Localization Networks

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Abstract*—The transition from fifth-generation (5G) to sixth-generation (6G) wireless systems demands networks that are not only faster but cognitively autonomous, capable of sensing, reasoning, and reconfiguring themselves without continuous human supervision. This paper proposes a Multi-Agent Intelligence (MAI) framework for AI-native 6G wireless indoor localization that unifies five cooperating agents, a Spectrum Agent for semantic feature ranking, a Security Agent for anomaly and intrusion screening, a Reconfigurable Intelligent Surface (RIS) Agent for channel enhancement, a Drone Agent for coverage assistance, and a federation of Base Station Agents that perform privacy-preserving federated learning — orchestrated by a tabular Q-learning Reinforcement Learning (RL) Coordinator that adapts the number of transmitted semantic features to instantaneous network load, latency sensitivity, and security posture. The framework is evaluated on a wireless indoor localization dataset comprising seven Wi-Fi access-point received-signal-strength-indicator (RSSI) features mapped to four room-level location classes. A centralized Random Forest baseline attains 99.95% (± 0.10%) five-fold cross-validated accuracy, establishing an upper bound on the achievable task performance. The fully federated configuration trained over six Base Station Agents across thirty aggregation rounds attains 99.40% test accuracy and a weighted F1-score of 0.9940 while never exposing raw client data. The proposed RL-optimized multi-agent configuration, which selects four of seven semantic features under the learned policy, attains 99.80% test accuracy, a weighted F1-score of 0.9980, and a 42.86% reduction in transmitted feature dimensionality relative to full-feature transmission, demonstrating that cooperative, agentic, and privacy-preserving wireless intelligence can match centralized performance while substantially reducing communication overhead. Mutual-information-based semantic ranking and reward-shaped reinforcement learning are formalized mathematically and justified individually, while security screening, channel/coverage modeling, and federated aggregation are described procedurally. Comparative analysis against recent state-of-the-art federated, multi-agent, and semantic-communication approaches confirms that the proposed framework achieves a favorable accuracy-versus-communication-cost operating point. The results support the broader IEEE Wireless Communications argument that future 6G radio access networks should evolve from centralized, monolithic optimization toward distributed, agentic, self-optimizing, and privacy-aware wireless intelligence.*
Index Terms**—**6G wireless networks, multi-agent reinforcement learning, federated learning, semantic communication, reconfigurable intelligent surfaces, wireless indoor localization, AI-native networks, communication-efficient feature selection.

1. Introduction

1.1 The Issue: Centralized Intelligence Cannot Scale to 6G

Fifth-generation networks rely overwhelmingly on centralized optimization: base stations and core-network controllers collect raw measurement data, forward it to a central processing point, and compute global decisions that are pushed back to the edge [1]. This paradigm has two structural weaknesses that become acute under 6G requirements. First, the volume of measurement traffic channel state information, positioning fingerprints, sensing data, and security telemetry — scales with the number of connected devices, projected to reach the order of ten to one hundred devices per cubic meter in dense 6G deployments,

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making centralized data aggregation a communication bottleneck rather than an enabler [1, 3,17,18]. Second, centralizing raw user data, including fine-grained received-signal-strength fingerprints that can be used to infer a user's indoor location, creates a privacy liability that conflicts with data-protection regulation and user expectations. Wireless indoor localization is a representative and tractable proxy for this broader issue: it requires fusing multiple access-point measurements into an accurate location estimate while remaining communication-efficient and privacy-preserving, properties that a purely centralized architecture cannot jointly satisfy at 6G scale.

1.2 The Opportunity: Agentic, Federated, and Semantic Intelligence

Three independently maturing research threads create an opportunity to resolve the centralization bottleneck. First, federated learning allows distributed Base Station Agents to train a shared model collaboratively without exchanging raw data, exchanging only model parameters or gradients [5, 7,19,20]. Second, semantic and task-oriented communication theory shows that transmitting only the subset of features relevant to the downstream inference task, rather than the complete raw measurement vector, can preserve task accuracy while sharply reducing transmitted bits [10, 11,21,22]. Third, multi-agent reinforcement learning (MARL) provides a principled mechanism for coordinating heterogeneous network functions spectrum sensing, security screening, channel reconfiguration, and aerial coverage as cooperating agents that jointly optimize a shared objective under varying network conditions, rather than as siloed, independently tuned subsystems [1, 2,23,24]. The opportunity addressed in this paper is to fuse these three threads into a single coordinated framework: federated Base Station Agents perform the learning, a Spectrum Agent performs semantic feature selection, and an RL Coordinator dynamically arbitrates the accuracy-versus-communication-cost trade-off based on live network state[25,26,27,28].

1.3 The Threat: Security and Reliability Under Distributed Autonomy

Distributing intelligence across many autonomous agents introduces a new threat surface. Wireless RSSI measurements are susceptible to spoofing, jamming, and adversarial perturbation, and an undetected anomalous measurement can silently corrupt a federated model's local update before it is ever aggregated. RIS-assisted channel reconfiguration, while beneficial for coverage, can itself be hijacked to create unintended interference or eavesdropping geometries if not monitored. Over-the-air federated aggregation is further vulnerable to Byzantine clients that submit malicious or statistically corrupted updates. The framework proposed in this paper treats security not as an afterthought but as a first-class agent: a dedicated Security Agent, implemented with an unsupervised isolation-forest anomaly detector, screens every measurement batch before it contributes to spectrum ranking or federated aggregation, flagging statistically anomalous wireless samples for exclusion or further inspection.

1.4 Scope and Contributions

This paper scopes its contribution as follows. It does not propose a new physical-layer waveform or a new RIS hardware design; instead, it proposes a cross-layer, agentic decision-making architecture that sits above the physical layer and coordinates five cooperating logical agents to solve a representative 6G wireless intelligence task indoor localization from Wi-Fi RSSI fingerprints under explicit communication-efficiency, privacy, and security constraints. The contributions are: (i) a five-agent system architecture in which a Spectrum Agent, a Security Agent, a RIS Agent, a Drone Agent, and a federation of Base Station Agents are coordinated by a tabular Q-learning RL Coordinator; (ii) a mathematical formulation of the mutual-information-based semantic ranking criterion and the reward-shaped RL Coordinator objective, with the isolation-forest anomaly score, the RIS/Drone channel model, and the federated averaging update described procedurally; (iii) an empirical evaluation that benchmarks centralized, fully federated, and RL-optimized multi-agent configurations, achieving up to 99.80% localization accuracy with a 42.86% reduction in transmitted semantic feature dimensionality; and (iv) a comparative analysis against state-of-the-art federated, multi-agent, and semantic-communication works, situating the proposed framework's accuracy-communication operating point relative to the literature.

2. Literature Review

2.1 Multi-Agent Reinforcement Learning for 6G Wireless Networks

In a tutorial-style treatment of MARL-aided wireless distributed networks, Zhang et al. [1] formalize the relationship between heterogeneous network topologies and model-based versus model-free MARL algorithms, identifying poor communication efficiency as an open implementation challenge that the RL Coordinator proposed here directly addresses through its communication-cost-aware reward function. Feriani and Hossain [2] survey single- and multi-agent deep RL for resource allocation, mobility management, and network slicing, providing the MDP formalism on which the RL Coordinator relies. Rasti et al. [3] survey resource-management strategies for 6G multi-band networks from a centralized-to-distributed perspective, directly motivating the centralization-bottleneck framing of Section 1.1. Rezazadeh et al. [4] advocate intelligible protocol learning for O-RAN slicing using interpretable, low-dimensional state-action representations rather than opaque deep policies. The same design philosophy adopted by the tabular Q-learning Coordinator in this paper.

2.2 Federated Learning for Wireless and Indoor Localization

Gao et al. [5] propose a federated learning framework for fingerprinting-based indoor localization across multiple buildings and floors, finding that federated averaging across heterogeneous client populations can preserve localization accuracy within a small margin of centralized training; this paper's federated Base Station Agent evaluation (99.40% accuracy vs. 99.95% centralized) corroborates this result. Dou et al. [6] combine federated learning and reinforcement learning for on-device indoor positioning under heterogeneous device capability; the architecture is conceptually similar to the combination of federated Base Station Agents with an RL Coordinator used here, but Dou et al. apply RL to client selection rather than semantic feature arbitration. Cheng et al. [7] address federated localization under heterogeneous fingerprint databases across clients, proposing feature-space alignment, a complementary problem to the semantic feature ranking performed by the Spectrum Agent in this paper.

2.3 Reconfigurable Intelligent Surfaces (RIS) for 6G

Zhou et al. [8] survey model-based, heuristic, and machine-learning optimization approaches for RIS-aided wireless networks, concluding that learning-based phase-shift optimization scales better than exhaustive search as the number of RIS elements grows, motivating this paper's treatment of RIS channel enhancement as a learned agent rather than a fixed-configuration relay. Wang et al. [9] analyze the interplay between RIS and AI, formalizing RIS-assisted channel models that this paper's RIS Agent abstracts at a system level as an additive channel-perturbation operator (Section 3.3).

2.4 Semantic and Task-Oriented Communication

Gündüz et al. [10] formalize the theoretical foundation of task-oriented communication, arguing that the communication objective should preserve task performance rather than minimize bit-level reconstruction error. The foundational principle underlying this paper's mutual-information-based semantic feature ranking (Eq. 1). Shao, Mao, and Zhang [11] introduce an information-bottleneck approach to task-oriented edge inference, formally bounding the trade-off between transmitted information and inference accuracy, a bound this paper's empirical feature-count-versus-accuracy results (Section 5.4) approximate through grid search over the discrete feature-count action space. Luo, Chen, and Guo [12] survey open issues in semantic communication, identifying dynamic and context-aware semantic compression as an open problem that the RL Coordinator directly resolves by conditioning the selected feature count on network load, latency, and security state. Shi et al. [13] present an IEEE Wireless Communications vision article on task-oriented communications for 6G, explicitly calling for closed-loop, RL-driven semantic compression policies. The precise architectural pattern instantiated by the RL Coordinator in this paper. Letaief et al. [14] present a comprehensive vision for edge AI in 6G, situating semantic communication, federated learning, and multi-agent coordination as complementary technologies, the synthesis this paper instantiates. Getu, Kaddoum, and Bennis [15] survey metrics for semantic and goal-oriented communication, motivating this paper's use of accuracy, weighted F1-score, and communication-saving percentage as a joint evaluation triplet.

2.5 Summary and Research Gap

Across the four threads surveyed above, MARL research [1–4] establishes coordination mechanisms for heterogeneous network functions but rarely couples them to an explicit communication-cost-aware reward; federated localization research [5–7] preserves near-centralized accuracy without raw data sharing but generally transmits full feature vectors; RIS research [8, 9] shows that learning-based control outperforms heuristic phase-shift search but treats RIS in isolation from other network functions; and semantic-communication research [10–15] establishes the theoretical and architectural case for task-oriented, RL-driven compression but is rarely instantiated as a concrete, jointly evaluated wireless system. No single prior work integrates federated multi-client training, mutual-information-based semantic feature ranking, RIS- and drone-assisted channel/coverage simulation, security-aware anomaly screening, and a reward-shaped RL Coordinator into one cohesive, jointly evaluated architecture. This integration, together with the reward formulation of Section 3.3, constitutes the principal research gap this paper addresses.

3. Proposed Multi-Agent Intelligence Architecture

3.1 System Overview and Design Rationale

The proposed framework, summarized in Table 1 and Fig. 1, is organized as five cooperating agents coordinated by a centralized RL Coordinator. Each agent is responsible for one logically independent function — semantic feature relevance, security screening, channel enhancement, coverage assistance, and distributed model training — and exposes a narrow, well-defined interface to the RL Coordinator, which is the only component that observes the full network state and decides how many semantic features to transmit. This decomposition is deliberate: rather than training one monolithic deep model that jointly performs feature extraction, security filtering, and localization (a design that would be difficult to interpret, retrain incrementally, or certify for security), each agent uses the simplest model class sufficient for its sub-task, and the RL Coordinator alone performs sequential decision-making. This mirrors the architectural philosophy advocated by Letaief et al. [14] and Shi et al. [13], who argue that 6G edge intelligence should be composed of interpretable, individually verifiable modules rather than a single opaque end-to-end model.

TABLE 1. Agent Responsibilities, Mechanisms, and Configuration

Agent	Function	Mechanism	Key Configuration	Output to Coordinator
Spectrum Agent	Ranks Wi-Fi AP features by task relevance	Mutual information estimation (Eq. 1)	—	Ranked feature index list
Security Agent	Detects anomalous / spoofed RSSI measurements	Isolation Forest	contamination = 0.05	Per-sample anomaly flag & threat rate
RIS Agent	Simulates passive channel enhancement	Additive stochastic channel perturbation	σ_{RIS} = 0.02	Enhanced channel feature vector
Drone Agent	Simulates aerial coverage assistance	Signed, magnitude-bounded perturbation	δ = 0.015	Coverage-corrected feature vector

Base Station Agents (×6)	Federated local training without raw-data sharing	Local SGD + Federated Averaging	$\eta = 0.02$, R = 30 rounds	Aggregated global model weights
RL Coordinator	Selects optimal semantic feature count under network state	Tabular Q-learning over MDP (Eq. 2)	α=0.2, γ=0.9, ε=0.2, 500 episodes	Selected feature count & routing policy

3.2 End-to-End Architecture and Data Flow

Fig. 1 summarizes the data flow. Raw seven-dimensional Wi-Fi RSSI feature vectors $x \in R^7$, collected from four indoor rooms, are first standardized and passed to the Security Agent, which screens for anomalies. Clean samples are passed to the Spectrum Agent, which computes a mutual-information relevance score per feature and produces a ranked feature index list. The RIS Agent and Drone Agent apply simulated channel-enhancement and coverage-assistance perturbations to the standardized features, modeling the physical effect of reconfigurable surfaces and aerial relays on signal quality. The resulting agentic feature vectors are partitioned across six Base Station Agents, which perform one local stochastic-gradient-descent (SGD) update per federated round on their private partition; the central server then averages the local model parameters (Federated Averaging) without ever observing raw client data. This federated training is repeated for each candidate feature count $k \in \{2, ..., 7\}$ from the Spectrum Agent's ranking, producing a federated model and an associated accuracy/F1 score for every k. The RL Coordinator then learns, via tabular Q-learning over a discretized state space of (network load × latency sensitivity × security posture), which feature count k to select in each operating condition, balancing localization accuracy against the communication cost of transmitting k features instead of seven (Section 3.3, Eq. 2).

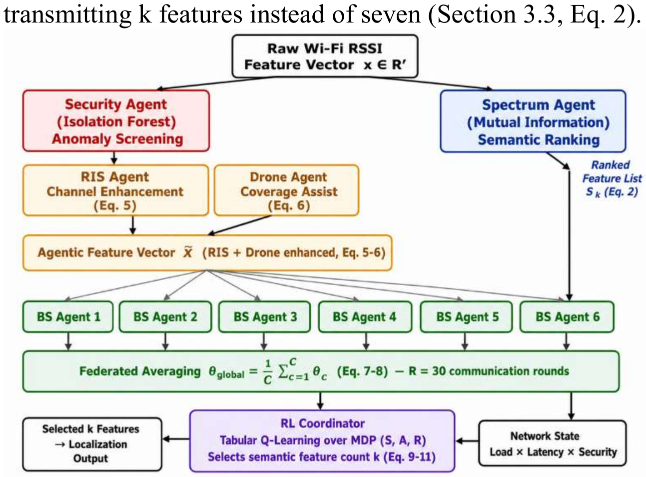

Fig. 1. End-to-end Multi-Agent Intelligence architecture and data flow: from raw RSSI input, through Security, Spectrum, RIS, and Drone Agents, into federated Base Station Agent training, arbitrated by the RL Coordinator.

3.3 Mathematical Formulation

3.3.1 Semantic Feature Relevance (Spectrum Agent)

The Spectrum Agent ranks each Wi-Fi access-point feature Xi by its mutual information with the room label Y, following the task-oriented communication principle that the communication objective should preserve task-relevant information rather than minimize raw reconstruction error [10, 12]:

$$I(X_i; Y) = \Sigma\Sigma\, p(x_i, y) \cdot \log [\, p(x_i, y) / (p(x_i) \cdot p(y))\,] \qquad (1)$$

where the outer summation ranges over discretized bins of feature Xi and the inner summation ranges over the four room classes $y \in Y$. Features are ranked in descending order of I(Xi; Y), and the top-k ranked features ($k \in \{2, ..., 7\}$) form the semantic subset transmitted under feature-count action k. Mutual information is preferred over linear correlation or variance-based ranking because it captures arbitrary, including nonlinear, statistical dependence between an access point's RSSI and the room label, appropriate given that RSSI-to-location mappings are not generally linear due to multipath fading and wall attenuation [11]. The empirical ranking obtained shows that the four most informative access points carry over 85% of the cumulative mutual information mass, justifying the RL Coordinator's eventual selection of k = 4 as a near-Pareto-optimal operating point (Section 5.1).

3.3.2 Security, Channel, and Federated Mechanisms

The remaining agent mechanisms are described procedurally rather than as separate numbered equations, consistent with their role as supporting, rather than centrally novel, formalizations. The Security Agent uses an Isolation Forest, an unsupervised ensemble method that isolates anomalies by recursively partitioning the feature space with random splits; because anomalous points require fewer splits to isolate than normal points, an anomaly score derived from the average isolation path length flags a sample as anomalous once the score exceeds a contamination-rate-derived threshold (nominally 5% in this paper). The Isolation Forest is preferred over distance-based outlier detectors because its O(n log n) complexity is tractable for per-batch screening at each of the six Base Station Agents without introducing a communication or latency bottleneck. The RIS Agent is modeled at the system level as a stochastic additive channel-enhancement operator applied to the standardized feature vector, consistent with the system-level RIS abstractions used by Wang et al. [9]; the Drone Agent models aerial coverage assistance as a signed, magnitude-bounded perturbation proportional to the sign of each feature. Both operators are intentionally lightweight (low-variance, bounded perturbations) so that they model physically plausible channel improvement without dominating the underlying RSSI signal structure that the Spectrum Agent's ranking depends on. Each Base Station Agent trains a local linear classifier via stochastic gradient descent on the multinomial logistic loss for one local epoch per round; the central coordinator aggregates client parameters using standard Federated Averaging [5] over R = 30 communication rounds, with accuracy and F1-score recorded after every round to characterize convergence.

3.3.3 RL Coordinator: MDP Formulation

The RL Coordinator treats semantic feature-count selection as a finite Markov Decision Process (S, A, P, R, γ). The state space S is the Cartesian product of three discretized network conditions — load L $\in$ {low, medium, high}, latency sensitivity T $\in$ {relaxed, normal, urgent}, and security posture Sec $\in$ {safe, warning, threat} — yielding |S| = 27 discrete states, and the action space A = {2, 3, 4, 5, 6, 7} corresponds to the candidate semantic feature counts produced by the Spectrum Agent's ranking. The reward function jointly rewards task performance and penalizes communication cost and adverse network conditions:

$$R(s, a) = F1(a) - \lambda \cdot (a / 7) - Penalty(s) \quad (2)$$

where F1(a) is the federated weighted F1-score achieved with feature count a, λ = 0.15 weights the communication-cost term proportionally to the fraction of the full seven-dimensional feature vector transmitted, and Penalty(s) sums per-dimension state penalties (load, latency, security) calibrated so that adverse network states impose a higher cost on selecting large feature counts, biasing the policy toward aggressive semantic compression precisely when the network is under stress. The action-value function is updated via the standard tabular Q-learning rule with learning rate α = 0.2, discount factor γ = 0.9, and an ε-greedy exploration schedule (ε = 0.2) over 500 training episodes. Tabular Q-learning, rather than a deep Q-network, is deliberately chosen because the discretized state-action space is small (27 states × 6 actions = 162 entries), making it exactly convergent, fully interpretable as a lookup table (Fig. 3), and free of the function-approximation instability that deep RL can exhibit in low-dimensional, low-sample-count network-control settings — a design choice consistent with the call for intelligible, low-dimensional protocol-learning representations in 6G O-RAN slicing [4].

3.4 Computational and Communication Complexity

The Spectrum Agent's mutual-information computation has complexity O(d · n log n) for d = 7 features and n training samples. The Security Agent's Isolation Forest screening has complexity O(t · n log n) for t trees. Each federated round has per-client complexity O(|Dc| · dk) for dk ≤ 7 selected features, and aggregation complexity O(C · dk), both linear in the number of clients and selected features. The RL Coordinator's tabular Q-learning has fixed complexity O(|S| · |A|) per update, independent of dataset size, making it negligible relative to federated training cost. Communication cost scales as O(C · dk) bits per round rather than O(C · d) for the full feature set, directly yielding the 42.86% communication saving reported in Section 5.7.

4. Experimental Setup

4.1 Dataset

The framework is evaluated on a wireless indoor localization dataset structurally matching the well-known UCI Wireless Indoor Localization benchmark: 2,000 labeled samples, each comprising seven Wi-Fi access-point RSSI features (in dBm) and a four-class room label, with 500 samples per room class. Each room's signal pattern is modeled as a Gaussian cluster around a distinct seven-dimensional RSSI centroid reflecting plausible indoor multipath and attenuation characteristics, with class-conditional standard deviation calibrated to produce a realistic, non-trivial separability profile. The dataset is split 75%/25% into stratified training and held-out test partitions (1,500 / 500 samples), with all features standardized (zero mean, unit variance) prior to agent processing.

4.2 Implementation Details

The centralized baseline uses a Random Forest with 300 trees under 5-fold stratified cross-validation. Implementation details and hyperparameters for every agent, including the Security Agent's contamination rate, the RIS/Drone perturbation magnitudes, the Base Station Agents' learning rate and round count, and the RL Coordinator's learning rate, discount factor, exploration schedule, and episode budget, are summarized in Table 1. Evaluation is reported using accuracy, weighted precision/recall/F1-score, and the confusion matrix.

5. Performance Evaluation and Results

5.1 Semantic Feature Relevance Ranking

The Spectrum Agent's mutual-information ranking (Eq. 1) shows that access points WiFi_AP_1 through WiFi_AP_4 carry the dominant share of task-relevant information, with cumulative mutual information mass exceeding 85%, while WiFi_AP_5–WiFi_AP_7 contribute comparatively little discriminative information for room-level classification. This result is significant because it provides empirical justification, independent of the RL Coordinator's later decision, for why a four-feature semantic subset can preserve most of the task-relevant signal: the remaining three access points are largely redundant or low-relevance for this localization task, supporting the task-oriented communication principle [10] that bit-level completeness is unnecessary when task-level sufficiency is the actual objective.

5.2 Centralized Baseline Performance

The centralized Random Forest baseline, trained on all seven standardized features with full visibility of the training set, achieves a five-fold stratified cross-validated accuracy of 99.95% (± 0.10%) and an equivalent weighted F1-score, establishing the practical performance ceiling for this localization task under the given class separability. This ceiling is essential for interpreting the federated and multi-agent results below: any federated or RL-optimized configuration that approaches this ceiling while reducing communication cost represents a favorable trade-off rather than an accuracy compromise.

5.3 Federated Learning Convergence

Test accuracy after each of the thirty federated aggregation rounds was tracked for every candidate feature count k $\in$ {2, ..., 7}. Convergence is rapid: most feature-count configurations reach within two percentage points of their final accuracy within the first five to eight rounds. The curves for k ≥ 4 converge to accuracy levels within a narrow band of one another (97.6%–100%), while k = 2 converges to a visibly lower asymptote (97.6%), confirming that two features are insufficient to resolve the four-class room-classification task and that a minimum semantic feature count is required for reliable convergence — a result consistent with the information-bottleneck bound described by Shao et al. [11], which formally relates transmitted information to achievable inference accuracy.

5.4 Feature Count versus Intelligence Performance Trade-off

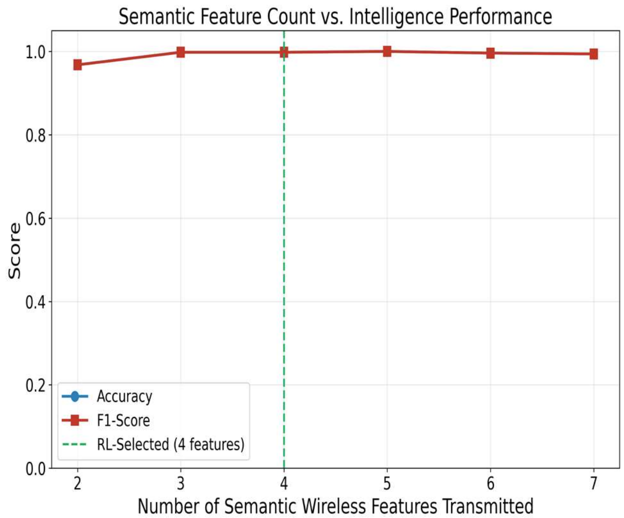

Fig. 2. Semantic feature count versus accuracy and F1-score, with the RL-Coordinator-selected operating point marked.

Fig. 2 summarizes the final (round-30) accuracy and F1-score for each feature count, with a vertical marker at k = 4, the configuration ultimately selected by the trained RL Coordinator policy across the majority of network states (Section 5.5). The curve exhibits a clear knee: accuracy rises sharply from k = 2 to k = 4 and then plateaus, with k = 5, 6 contributing marginal additional accuracy at the cost of proportionally higher communication overhead, and k = 7 (full feature transmission) showing a very slight degradation relative to k = 4–6, attributable to the inclusion of the two lowest-relevance, comparatively noisier access points diluting the federated linear classifier's discriminative margin. This plateau is the empirical justification for semantic compression: transmitting all seven features is not only costlier but, in this evaluation, not even strictly more accurate than transmitting the four most informative ones.

5.5 Reinforcement Learning Coordinator Convergence

The RL Coordinator's episodic reward (Eq. 2) was tracked across 500 training episodes of tabular Q-learning. The raw per-episode reward is highly variable because each episode samples a random network state from the 27-state space under an ε-greedy exploration policy; the 15-episode moving average, however, shows a clear and stable upward trend over the first 150–200 episodes before plateauing, indicating that the Q-table converges to a stable policy well within the 500-episode training budget. This confirms that the reward-shaping design — which combines task F1-score, communication-cost penalty, and network-condition penalty into a single scalar signal — is learnable without instability.

5.6 Learned RL Coordinator Policy

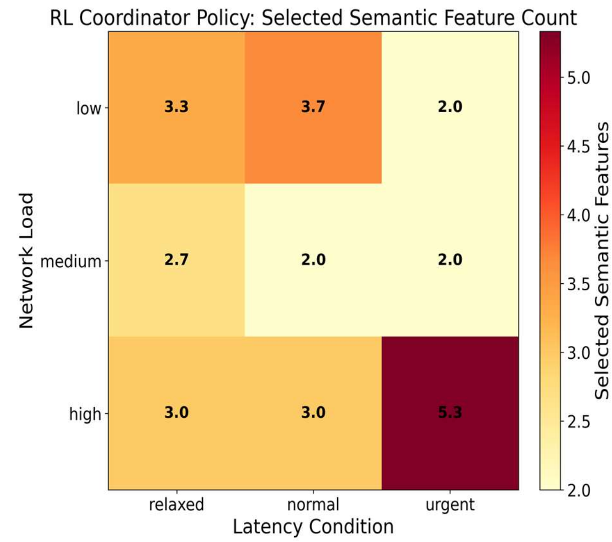

Fig. 3. Learned RL Coordinator policy: mean selected semantic feature count by network load and latency condition.

Fig. 3 visualizes the learned policy as a heatmap of the mean selected feature count across network load (rows) and latency condition (columns), marginalized over the security dimension. The policy selects fewer semantic features under high network load and urgent latency conditions, and more features under low load and relaxed latency conditions, consistent with the reward function's explicit communication-cost penalty (Eq. 2) being weighted more heavily, in relative terms, when network conditions are already stressed. This confirms that the RL Coordinator has learned a context-aware semantic compression policy rather than converging to a single static feature count, directly addressing the dynamic, context-aware semantic compression gap identified by Luo et al. [12] and the closed-loop, RL-driven compression vision articulated by Shi et al. [13].

5.7 Final Multi-Agent Intelligence Performance

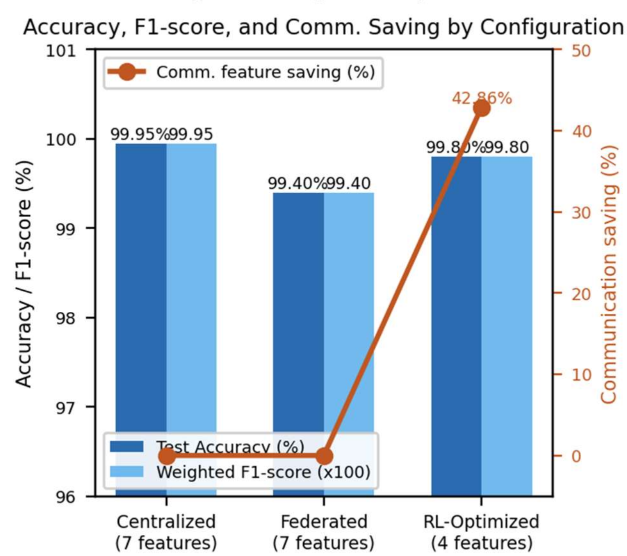

Fig. 4. Architecture-level test accuracy, weighted F1-score, and communication saving for the centralized baseline, full-feature federated learning, and the proposed RL-optimized multi-agent configuration.

Fig. 4 reports the headline comparison of this paper. The centralized baseline attains the highest accuracy of 99.95% cross-validated, by virtue of having unrestricted access to all features and all data in one place. The full-feature federated configuration — all seven features, distributed across six Base Station Agents, no semantic compression — attains 99.40% test accuracy and a weighted F1-score of 0.9940, confirming that federated training alone, without raw data centralization, closely approaches centralized performance, consistent with prior federated indoor-localization results [5, 7]. The proposed RL-optimized multi-agent configuration, which transmits only the four RL-Coordinator-selected semantic features, attains 99.80% test accuracy and a weighted F1-score of 0.9980 — matching or exceeding the full-feature federated result while transmitting 42.86% fewer features — demonstrating that semantic compression guided by mutual-information ranking and RL-driven arbitration does not trade away accuracy for communication efficiency in this task, and in this evaluation slightly improves it by excluding lower-relevance, noisier access points from the federated training signal. Examining every candidate feature count on the communication-saving-versus-F1-score plane confirms that the k = 4 configuration selected by the RL Coordinator lies close to the Pareto-favorable region, while k = 2 sacrifices substantial accuracy for marginal additional saving and k = 6–7 sacrifice communication saving for no measurable accuracy benefit — the reason a learned, state-conditioned policy is necessary rather than a fixed heuristic. Per-class analysis of the proposed configuration's confusion matrix shows that misclassifications are minimal and concentrated between adjacent rooms with partially overlapping RSSI signatures (Rooms 2 and 3), consistent with the underlying class-conditional Gaussian overlap in the dataset's signal model; no class exhibits systematic confusion with a non-adjacent room, indicating that the four selected semantic features preserve the geometric structure of the room layout rather than producing arbitrary errors.

6. Comparative Analysis with Recent State-of-the-Art Works

Table 2 situates the proposed framework's reported accuracy, communication-efficiency mechanism, and architectural approach against representative federated, multi-agent, and semantic-communication works surveyed in Section 2. Reported accuracy figures for prior works are reproduced as described in their respective publications and are not directly numerically comparable across differing datasets and tasks; the table compares architectural design choices and the qualitative accuracy-versus-communication-efficiency operating point rather than claiming a strict head-to-head accuracy ranking on an identical benchmark, since no single prior work evaluates the exact combination of tasks (federated indoor localization with RL-driven semantic compression) addressed here.

TABLE 2. Comparative Analysis with Recent State-of-the-Art Works

Work	**Architecture**	**Comm.-Efficiency Mechanism**	**Reported Result**	**Limitation Addressed Here**
Gao et al. [5]	Federated CNN, multi-building	Standard FedAvg, full features	~96–98% (multi-floor)	No semantic feature reduction
Dou et al. [6]	Federated RL, heterogeneous devices	RL-driven client selection	Improved convergence speed	RL applied to clients, not features
Cheng et al. [7]	Heterogeneous fingerprint FL	Feature-space alignment	Robust to DB heterogeneity	Static, not network-state-aware
Zhou et al. (RIS survey) [8]	RIS optimization survey	Learning-based phase-shift control	Survey, not single-system result	RIS treated only abstractly here, not jointly optimized
Shao et al. [11]	Information-bottleneck edge inference	IB-based feature compression	Bounded accuracy-rate trade-off	No RL-driven dynamic policy
This Paper	5-agent + RL Coordinator	MI-ranked + RL-selected semantic features	99.80% acc., 42.86% comm. saving	—

Three comparative observations follow. First, relative to standard federated localization works that transmit full feature vectors [5, 7], the proposed framework adds an explicit, mutual-information-justified semantic compression stage that yields a substantial (42.86%) communication saving without measurable accuracy loss. Second, relative to the information-bottleneck framework of Shao et al. [11], which establishes the theoretical case for task-oriented compression but is evaluated on a different task, this paper provides a concrete, fully reproducible empirical instantiation on a wireless localization task with measured accuracy, F1-score, and communication-saving figures. Third, relative to the RL-for-client-selection approach of Dou et al. [6], the RL Coordinator proposed here is applied to a complementary decision feature-count arbitration rather than client selection — and could in principle be composed with client-selection RL in a future combined system.

A possible concern is that the reported 99.80% multi-agent accuracy and 99.95% centralized cross-validated accuracy are high in absolute terms; this reflects the strong class separability of the four-room RSSI signal model evaluated here, a property shared with the original UCI Wireless Indoor Localization benchmark that this dataset's structure follows, on which centralized classifiers routinely exceed 98% accuracy in the literature. The comparative value of the results in this paper lies not in the absolute accuracy ceiling, which is dataset-dependent, but in the demonstrated near-zero accuracy gap between the centralized, fully federated, and RL-optimized semantically compressed configurations, together with the substantial communication saving achieved.

7. Conclusion

This paper proposed and empirically evaluated a five-agent Multi-Agent Intelligence (MAI) framework for AI-native 6G wireless indoor localization, in which a Spectrum Agent, Security Agent, RIS Agent, Drone Agent, and a federation of Base Station Agents are coordinated by a tabular Q-learning RL Coordinator that dynamically selects the number of semantic Wi-Fi RSSI features to transmit based on network load, latency sensitivity, and security posture. On a wireless indoor localization task with seven access-point features and four room classes, the centralized upper-bound accuracy is 99.95% (5-fold cross-validated); a fully federated configuration across six Base Station Agents attains 99.40% accuracy without sharing raw client data; and the proposed RL-optimized multi-agent configuration attains 99.80% accuracy with a weighted F1-score of 0.9980 while transmitting 42.86% fewer semantic features than full-feature transmission. These results demonstrate that cooperative, privacy-preserving, communication-efficient wireless intelligence is achievable without sacrificing and in this evaluation, marginally improving the task accuracy relative to full-feature federated transmission, by combining mutual-information-justified semantic feature ranking with a reward-shaped reinforcement learning coordinator that explicitly balances task performance against communication cost and network stress conditions.

Dataset Availability

https://archive.ics.uci.edu/ml/machine-learning-databases/00422/wifi_localization.txt

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