# AI-Enhanced Integrated Sensing and Communications: Advancements, Challenges, and Prospects

Nan Wu, Rongkun Jiang, Xinyi Wang, Lyuxiao Yang, Kecheng Zhang, Wenqiang Yi, and Arumugam Nallanathan

***Abstract*—Integrated sensing and communication (ISAC) is pivotal technology for future sixth-generation (6G) communications. It aggregates wireless sensing and communication functionalities into one system while sharing spatial, temporal, and frequency resources. In this article, a review on artificial intelligence (AI)-enhanced ISAC is provided, by introducing AI algorithms to ISAC for performance gain. We first present a general system framework for AI-enhanced ISAC, delineating its advancements from the collaboration of sensing, communication, and AI. Subsequently, several potential usage scenarios are outlined, together with the specific requirements and opportunities. Furthermore, we delve into the technical challenges that AI-enhanced ISAC must address. Finally, critical techniques and future research directions are highlighted to leverage the intelligence and adaptability of AI-enhanced ISAC within the prospective 6G ecosystem.**

## I. Introduction

As emerging services and ecosystems evolve, the performance requirements for both sensing and communication in wireless networks are escalating. To enhance spectrum utilization, sixth-generation (6G) communication systems aspire to reuse radar frequency bands, thereby achieving radar-communication spectrum sharing. Since radar and communication systems exhibit commonalities in hardware architecture and signal processing, the integrated sensing and communication (ISAC) technique [1] has been proposed to incorporate such two individual capabilities into a unified system. It enables intelligent systems to leverage radio waves to observe the physical world and construct a digital twin in a virtual realm for ubiquitous intelligent connectivity. Due to its potential of enhancing spectral-, energy-, as well as hardware-efficiency, the ISAC technique is currently receiving considerable attention from both industry and academia [2].

Despite significant progress in current research process, there are still notable shortcomings in practical applications. Firstly, existing ISAC systems exhibit limitations in information processing and analysis, especially when dealing with large-scale data. The processing latency and precision can hardly meet the demands of real-time applications. Secondly, ISAC systems struggle with resource scheduling and transmission strategy decision-making in large-scale networks and lack the capability to intelligently adapt to time-varying network environments and task requirements, which could result in resource wastage and network congestion. Additionally, ISAC systems may encounter privacy and security concerns during the data processing stage, particularly in sensitive domains like healthcare and transportation.

To overcome these limitations, artificial intelligence (AI) technologies are introduced to enhance the ISAC system performance [3]. The utilization of AI technologies, including deep neural network (DNN), convolutional neural network (CNN), and deep reinforcement learning (DRL), etc., has significantly advanced sensing and communication [4], [5], which offers potent solutions to tackle ISAC system challenges. It is envisioned that leveraging the robust data processing, learning, and reasoning capabilities of AI, ISAC systems are able to achieve improved real-time responsiveness, adaptability, and security in complex environments, better meeting the increasing demands of future novel services [6].

This paper aims to review the AI-enhanced ISAC technique, and shed lights on its future developments. The general system framework for AI-enhanced ISAC network, together with use cases and opportunities are firstly presented. Several technical challenges are then elaborated. Finally, we highlight the critical techniques and future research directions.

## II. AI-Enhanced ISAC: General System Framework and Opportunities

In this section, we introduce a general system framework for AI-enhanced ISAC network, and discuss its opportunities in diverse use cases. Note that the sensing defined in traditional ISAC systems usually refers to the ability of wireless signals to detect target and environmental features, while the generalized sensing adopted here encompasses the acquisition and understanding of information across multiple dimensions, from physical space to networks, services, and users.

### A. General System Framework

In future networks, the ISAC system is expected to adopt an endogenous design pattern to support AI functionalities, rather than a simple stacking or add-on mode. Figure 1 depicts a general system framework for AI-enhanced ISAC network, where the AI module is tightly coupled with sensing and communication modules from following perspectives.

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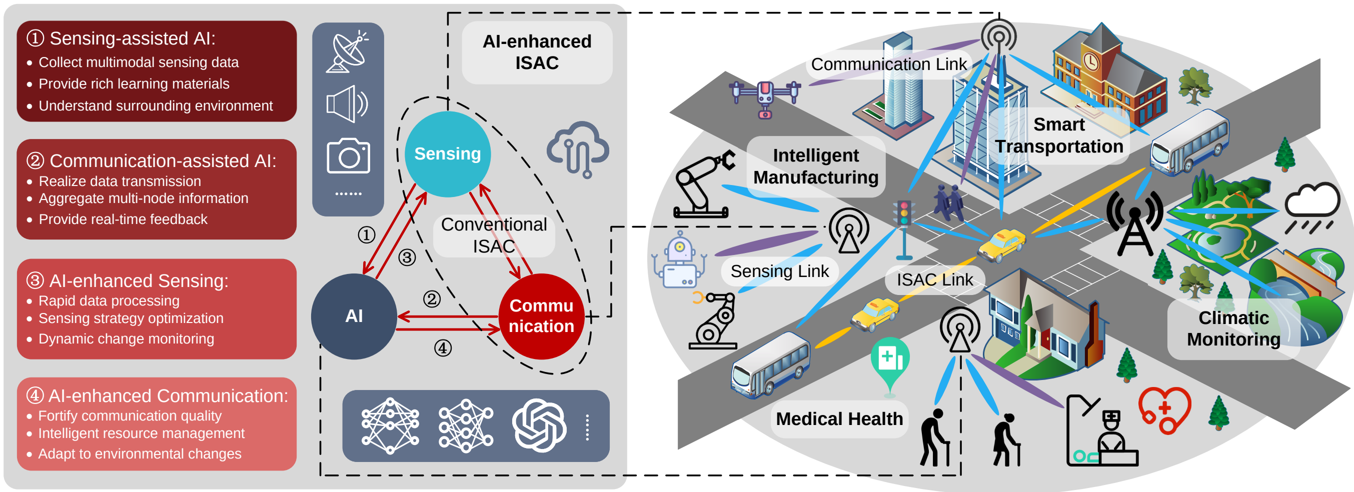


Fig. 1. General system framework and potential use cases of AI-enhanced ISAC.

*1) Sensing-assisted AI:* The sensing module is envisioned to collect massive sensing data, from various sources such as radars, microphones, cameras, and sensors. These multimodal sensing data provide rich learning materials for the AI module to train machine learning models in offline or online manners. Through extracting valuable information from the data, the AI module deepens its comprehensive understanding of intricate patterns, occurrences, and attributes present within the ambient environment, thus enhancing the intelligence of the ISAC system, i.e., the capabilities of adaptive learning, situational awareness, and autonomous decision-making derived from complex sensing data.

These intelligent capabilities help the ISAC system effectively respond to unexpected situations or rapid changes in environments, achieving a higher degree of automation and resilience. For example, AI can learn behavioral patterns of unknown targets from extensive historical and real-time sensing data to assist in informed decision-making and prediction. Moreover, sensing data can also aid AI models in anomaly detection during continuous learning. By monitoring changes and outliers in sensing data vigilantly, the AI module is poised to recognize potential crises in advance and take preventive measures to improve system robustness.

*2) Communication-assisted AI:* The primary task of the communication module is to establish bridges between different nodes in ISAC systems, achieving high-speed and stable transmission for information sharing, status updates, and synchronization. Specifically, the communication module aggregates multi-node data, including sensing, communication, and control data. It then transmits these aggregated data to the AI module via networks, thereby supporting the AI module to access richer information for learning and prediction.

Additionally, it is essential for the communication module to relay the decisions or commands from the AI module to various nodes and adapt data transmission strategies based on the AI module's needs and network conditions. For instance, in an autonomous driving scenario, network limitations might hinder real-time transmission of all node data to the AI module. If path planning is entailed, the communication module could preferentially transmit relevant data such as the vehicle's location and destination, to ensure the AI module has timely access to crucial information, thereby improving decision-making efficiency.

*3) AI-enhanced Sensing:* The applications of AI-enhanced sensing in ISAC systems are two-fold. On one hand, it helps achieve rapid processing of vast data and extract valuable features, elevating the efficiency and accuracy of sensing. Leveraging machine learning techniques, the AI module can unearth profound correlations and hidden insights in raw sensing data that are indiscernible through traditional methods. For instance, in radar applications, where traditional Fourier transform methods may struggle with time and frequency resolution trade-offs [7], employing AI methods can rapidly process high volumes of radar returns and outperform in speed and resolution for object detection and tracking. Meanwhile, AI can also unify multimodal sensing data to enhance detection accuracy and environment perception by jointly interpreting multi-source heterogeneous information.

On the other hand, after receiving the feedback from the AI module, the sensing module can intelligently optimize data collection strategies to improve data quality and efficiency. This mechanism boosts the ISAC system's ability to monitor environmental changes, including network congestion and spectrum utilization, particularly in intricate situations. For tasks like object detection, AI can dynamically adjust sensor parameter configurations in real-time based on task requirements and environmental conditions, resulting in precise localization, speed estimation, and angle measurement of targets.

*4) AI-enhanced Communication:* Wireless signals are susceptible to interferences and noise, engendering data errors or loss. The AI module, however, can exploit the inherent correlation within data series to recuperate compromised information, thereby bolstering data integrity and mitigating communication disruptions. Besides, AI techniques are also applicable to communication-centric tasks such as channel estimation and signal detection, which contribute to fortifying the communication quality in ISAC systems.

TABLE I
ADVANCEMENTS OF AI-ENHANCED ISAC NETWORK IN POTENTIAL USE CASES.

| Use Cases | Characteristics | Merits of Deploying AI-enhanced ISAC Network |
|---|---|---|
| Intelligent manufacturing | • Incorporate massive devices and machinery<br>• Entail intelligent and automatic production | • Obtain environmental information via sensing<br>• Adjust operations with environmental changes<br>• Learn environmental changes from historical data |
| Smart transportation | • Ask for real-time road monitoring<br>• Require quick access to traffic information | • Realize fast monitoring of traffic status<br>• Assist communications among vehicles<br>• Chart optimal route for autonomous vehicles |
| Climatic monitoring | • Rely on wired or wireless sensor networks<br>• Suffer from high deployment and maintenance costs | • Avoid the reliance of dedicated sensor networks<br>• Lower deployment and maintenance costs<br>• Adapt to different environments and monitoring tasks |
| Medical health | • Require wearable devices for contact-based detection<br>• Involve sensitive information in video-based monitoring | • Non-contact detection with wireless signals<br>• Detect anomalies and predict potential emergencies<br>• Safeguard individual privacy and security |

In addition, by intelligently managing spectrum resources, channel allocation, and power control, AI is able to improve the communication efficiency of the ISAC system. Specifically, resource allocation can be adjusted for more efficient transmission and utilization through using AI to analyze real-time communication data. For example, in multiuser systems, traditional optimization-based scheduling methods suffer from resource utilization degradation due to static strategies and reliance on complete channel state information (CSI). In contrast, AI-driven algorithms can automatically refine these allocations based on network conditions, user demands, and even incomplete CSI. Furthermore, AI empowers ISAC systems to swiftly adapt to environmental variations through self-learning and online reasoning.

In summary, the AI-enhanced ISAC system samples and perceives the physical world through sensing, connects to it through communication, and intelligently processes the data and resources through AI. By integrating sensing, communication, and AI functionalities, it is envisioned to achieve rapid ISAC data processing, real-time resource optimization, and intelligent decision in increasingly complex and dynamic environments.

### B. Use Cases and Opportunities

In future 6G networks, the application scenarios of AI-enhanced ISAC technology cover various domains, including intelligent manufacturing, smart transportation, climatic monitoring, and medical health, as presented in Fig. 1 and Table I.

*1) Intelligent manufacturing:* Numerous devices and machinery are typically involved in this scenario, which necessitates the processing and transmission of vast data, along with real-time monitoring of materials and equipments during production. Through collaborating communication and sensing functions, ISAC facilitates remote control and maintenance of devices. However, traditional ISAC suffers from performance degradation caused by interferences from complex electromagnetic environments and dense equipment layouts.

Integrating AI into ISAC systems can provide a solution by leveraging the DNN technology to learn and train on massive datasets. This enables intelligent modulation/demodulation of wireless signals, thereby improving the system's resistance to interferences. Furthermore, the use of recurrent neural networks (RNN) allows for prediction of production equipment failures based on sensor data in production process.

*2) Smart transportation:* In this scenario, ISAC employs wireless signals for detection, identification, positioning, and tracking of vehicles, pedestrians, and obstacles on the roads [8]. It also utilizes sensing information to enhance communication among vehicles and between vehicles and base stations (BS), thereby improving communication quality and efficiency [9]. However, traditional ISAC encounters adaptability issues in complex traffic environments.

As an effective support for ISAC, the AI technique, e.g., long short-term memory (LSTM) provides a powerful tool to model and predict time-series data such as traffic flow, vehicle speed, and road congestion. Furthermore, DRL can be employed to enable interaction between the transportation system and environment, thereby aiding autonomous vehicles in perceiving and understanding changes in the surrounding environment, as well as planning the optimal driving route and achieving safety control.

*3) Climatic monitoring:* Conventional climate monitoring methods typically rely on extensive sensors, satellites, and unmanned aerial vehicles (UAVs) to collect vast amounts of data. ISAC can reuse existing communication infrastructures, which reduces dependence on dedicated networks and lowers deployment and maintenance costs. The traditional ISAC, however, faces the challenge of limited prediction accuracy due to inadequate exploration of environmental data features.

The AI-enhanced ISAC technique, employing deep belief networks (DBN), is adept at discerning high-order statistical characteristics within environmental data for better capturing the inherent patterns. Additionally, AI-enhanced ISAC conducts model training leveraging extant climate and environmental monitoring data. The resultant model, with the use of transfer learning, can subsequently be applied to forecast future environmental events, bolstering our timely response capabilities for abrupt climate alterations, natural disasters, and environmental pollution.

*4) Medical health:* Precise medical treatment and remote healthcare services require real-time, accurate transmission of physiological signals and medical images. Traditional healthcare monitoring often hinges on contact-based detection with wearable devices, necessitating the auxiliary setup of cameras, sensors, and detectors that potentially harbor sensitive personal information. Anchored in pre-existing communication devices, ISAC techniques afford non-contact monitoring of human physiology using high-frequency signals to precisely measure

TABLE II
CHARACTERISTICS AND APPLICABLE ISSUES IN ISAC OF TYPICAL AI ALGORITHMS.

| AI Algorithms | Characteristics | Applicable Issues in ISAC |
|---|---|---|
| DNN | • Learn data representations by multilayer nonlinear transformations<br>• Optimize loss function by backpropagation | • Channel estimation<br>• Signal detection |
| CNN | • Extract local features via convolutional operations<br>• Reduce computational complexity by pooling operations | • Signal classification<br>• Object detection |
| Generative adversarial network (GAN) | • Consist of a generator and a discriminator<br>• Generate lifelike data through adversarial learning | • Data enhancement<br>• Channel modeling |
| Graph neural network (GNN) | • Learn directly from graph structured data<br>• Update node features via information exchange | • Network perception<br>• Link prediction |
| LSTM | • Control information flow through gated structures<br>• Introduce memory units to avoid gradient vanishing problem | • Resource allocation<br>• Channel prediction |
| DRL | • Learn optimal strategies through interaction with the environment<br>• Instruct to learn effective actions through rewards | • Autonomous driving<br>• Resource allocation |
| FL | • Conduct joint training of models without revealing original data<br>• Implement distributed learning with sharing model parameters | • Collective spectrum sensing<br>• Data privacy protection |
| Transfer learning | • Accelerate target domain training by knowledge transferring<br>• Tune parameters for new tasks on existing models | • Cross-scene signal processing<br>• Image classification |
| Few-shot learning | • Learn from few training samples for new tasks<br>• Accelerate convergence by prior knowledge and experience | • Anomaly detection<br>• Scene classification |
| Large language model (LLM) | • Pretrained on billions or even hundreds of billions of parameters<br>• Fine-tune for various downstream tasks with given prompts | • Resource management<br>• Inference and decision-aiding |

cardiac rhythm, respiration, and blood pressure.

However, traditional ISAC techniques confront challenges in accurately interpreting these perceived physiological parameters, leading to low diagnostic accuracy and privacy data security. Within an AI-enhanced ISAC framework, medical knowledge graph can be constructed to interpret the high-frequency signal patterns, improving the precision and dependability of non-contact vital sign monitoring. Such an AI-enhanced solution can help detect anomalies and predict potential emergencies for timely intervention. Moreover, the capability of AI to dynamically optimize data transmission, prioritize critical information, and streamline bandwidth utilization presents unique advantages in remote healthcare contexts. Additionally, implementing federated learning (FL) allows for collaborative model training without the need of raw data sharing, further mitigating data privacy risks.

## III. KEY CHALLENGES FOR AI-ENHANCED ISAC

Table II enumerates the typical AI algorithms applicable to ISAC. Due to the complexity and dynamics of wireless environments, achieving such AI-enhanced ISAC systems still faces numerous technical challenges.

### A. *Adequate and High-quality Data Collection*

As a crucial foundation, sufficient quantity and quality of data significantly influence the performance of AI-enhanced ISAC systems. Handling a wide range of complex data from diverse sources escalates the difficulty of data collection.

On one hand, model training in AI-enhanced ISAC systems necessitates gathering massive amounts of shared communication and sensing data. However, collecting wireless data requires considerable time, space, and energy resources under hardware constraints. On the other hand, AI-enhanced ISAC depends on accurate data labeling for supervised or semi-supervised learning. However, this behaviour relies on auxiliary information and expert knowledge, such as positional information, target types, and scene categories. Thus, annotating wireless data effectively in the absence or inaccuracy of auxiliary information and expert knowledge, as well as assessing, cleansing, and enhancing the data quality, pose challenging problems.

### B. *Real-time Data Processing*

To enable timely decisions and responses in AI-enhanced ISAC systems, the processing and analysis of wireless data need to be completed within extremely short timeframes, especially for autonomous driving and traffic management in smart transportation. Traditional statistical methods may not be efficient enough to process data in rapidly changing environments, due to their high computational complexity and soaring data volumes.

As 6G aims to accomplish ubiquitous intelligent connectivity in the cyber-physical world, communication and sensing data from smart terminals will be immense, while AI-enhanced ISAC needs to cope with these expanding massive data. The diversity and complexity of wireless data arising from various sensors, devices, and network infrastructures, further increase the difficulty of real-time processing. These data, including video, voice, images, and more, typically vary in formats, features, and acquisition frequencies. Consequently, AI-enhanced ISAC systems are envisioned to require increased computational capabilities compared with traditional communication systems.

### C. *Adaptive Interference Management*

In the future 6G landscape, AI-enhanced ISAC systems will encounter interference management issues [10] stemming from external and internal environments. The external interferences involve spectrum conflicts, electromagnetic disruptions, environmental noise, and signal attenuation, all exhibiting fluctuating behaviors across time, location, and environments. Traditional interference management methods, which rely on predefined strategies and empirical rules, are difficult to handle intricate and dynamic changes. Hence, AI-enhanced ISAC systems necessitate adaptive approaches to identify and locate interference sources in real time.

Constrained by limited spectrum resources, ISAC intertwines waveform, transceiver design, and signal processing, which creates an overlap in the spatiotemporal domain between sensing and communication signals. Their interaction and constraints cause internal interferences that diminish the throughput and sensing precision of AI-enhanced ISAC systems. It is challenging to guarantee both high-rate communication and high-precision sensing, especially in complex scenarios involving multiple targets and users.

### D. Low-complexity AI Model

In traditional communication systems, mature signal processing techniques have been developed to enable efficient transmission and reception. However, data analysis and processing require the utilization of various AI models to achieve intelligence and automation in ISAC systems. When dealing with multi-task problems, the parameter size of AI models grows exponentially, leading to insupportable computational burden and energy consumption. Moreover, the generalization ability of AI models in ISAC scenarios is also a bottleneck.

Due to the complexity of wireless environments, it is difficult for AI models to obtain sufficient data during the training process for effective generalization. Therefore, designing appropriate AI models with strong generalization ability to adapt to diverse complex scenarios has become a challenge. Moreover, the majority of current AI models are characterized as “black box” and lack interpretability. Establishing intelligent visualization methods to enhance the understanding of high-dimensional data features is another challenge in future research on explainable AI models.

### E. Security and Privacy

The integrated nature of the AI-enhanced ISAC system aggravates privacy and security risks, since it needs to collect, process, and transmit voluminous sensing and communication data across various nodes. These data might contain sensitive information such as personal details, location, and behavioral characteristics, heightening the threat of privacy disclosure and unauthorized access.

While relying on AI models to blend communication and sensing functions, including channel prediction, resource allocation, and target detection, the ISAC system may be affected by adversarial sample attacks, model theft attacks, and model pollution attacks, which could endanger model outputs or steal data from local devices through gradient leakage and model inversion. Meanwhile, AI-enhanced ISAC systems also depend on seamless collaboration between various nodes for optimal performance. This collaboration, however, could be disrupted by malicious nodes or external disruptors, resulting in communication breakdowns, data tampering, and even system crashes.

## IV. Critical Techniques and Future Directions

Despite numerous contributions to AI-enhanced ISAC systems, further exploration is still needed within specific requirements and scenarios. Therefore, the following outlines several critical techniques and future directions in this topic.

### A. Multimodal Data Sensing and Fusion

Fusing multimodal data is challenging for AI-enhanced ISAC systems, because of the heterogeneous and non-stationary information collected from different sensing modalities such as radars, acoustic, and visual sensors. These modalities often produce data with varying spatiotemporal resolutions, noise characteristics, and semantic interpretations. Conventional data fusion methods may falter when dealing with these complex interactions in practical scenarios.

To address this issue, one potential solution is to construct an attention-based deep learning method that coordinates multimodal heterogeneous data types into a common feature space by learning cross-modal shared representations. This approach can extract complementary features and suppress redundant information. Traditional signal processing techniques can also be used for denoising, filtering, and preprocessing operations to enhance data quality. Moreover, variational autoencoders (VAE) can synthesize missing or incomplete data modalities based on other available ones, enhancing the robustness of the fusion process. Additionally, AI-based probabilistic graphical models and Bayesian frameworks can provide a principled way to infer and fuse multimodal data, considering their dependencies and uncertainties.

### B. Collaboration between Communication and Sensing Functionalities

Facing different scenarios, communication and sensing tasks in ISAC systems manifest conflicting, complex, and dynamic characteristics. Firstly, resource conflicts such as power, time, and spectrum between these tasks may reduce the system performance and efficiency. Secondly, catering to varied objectives infuses high complexity and heterogeneity into communication and sensing tasks, complicating their coordination and alignment, thus increasing system overheads and operational burdens. Lastly, adapting to dynamic wireless environments, mobile targets, and service demands introduces temporal and spatial variability in these tasks. This variability fosters instability in task execution and may reduce the reliability and scalability of the system.

Hence, the ISAC system needs AI techniques to achieve coordination and balance between communication and sensing tasks. CNN and RNN can be employed to extract distinct features from sensing data for communication optimization. Conversely, the Informer model [11] can be exploited to derive transmission protocols from communication data for sensing optimization. Furthermore, intelligent resource allocation achieved by DRL networks and LLM (e.g., ChatGPT) enables the dynamic prioritization of communication and sensing tasks, thus optimizing overall system performance.

### C. ISAC Beamforming Design

As the wireless communication system's frequency band continues to expand, the ISAC system is anticipated to operate in higher frequency bands such as millimeter or terahertz bands. Moreover, the impact of path loss is exacerbated by the round-trip propagation in active sensing. Mitigating this high path loss necessitates beamforming design, which can be categorized into two scenarios based on whether the sensing targets are also communication users in ISAC systems.

For the scenario where the sensing targets are not communication users, there exists a trade-off between the sensing and communication functionalities. Specifically, the ISAC BS has to split the transmitted signals into multiple beams, resulting in the reduction of signal to interference plus noise ratio (SINR). Yet, the performance trade-off is diverse under different correlation between the sensing and communication channels while utilizing the communication signals to sense the target. Therefore, to improve the spectral efficiency of ISAC systems, one can employ deep learning tools to exploit such correlation and schedule the targets/users to be served, such that the targets/users with highly correlated channels are served simultaneously. For instance, the CNN was adopted in [12] to learn the inherit channel nature from the covariance matrix of the received echo signals.

In cases where the target to be sensed is also the communication user, the ISAC system is referred to as a sensing-assisted communication system. Here, the critical issue is not balancing sensing and communication performances but focusing on leveraging sensing results to facilitate communication beamforming design, particularly for high-mobility users. Dealing with fast-varying channels in complex environments has led to interest in exploiting neural network advantages in time-series prediction. Specifically, in [12], LSTM was employed to capture and predict communication channel characteristics based on received echo signals. As depicted in Fig. 2, with neural network assistance, communication channels can be accurately predicted, and peak spectral efficiency can approach the upper bound with perfect CSI. In comparison, the conventional Extended Kalman Filter (EKF)-based prediction scheme shows inferior performance, especially under low signal-to-noise ratio (SNR) corresponding to low transmit power.

### D. Environmental Adaptation

The generalization of wireless environments is an inevitable issue in AI-enhanced ISAC technology. Existing AI models are typically tailored for specific scenarios and distinct problems without universality, which may no longer be applicable to practical communication environments since they are multi-faceted and constantly changing.

To address this issue, on one hand, DRL can be employed to adaptively optimize the behavior and decision-making of the ISAC system by learning and recognizing environmental features online. On the other hand, transfer learning can be used by selecting suitable learning methods based on the specific problem. It allows to transfer the knowledge from a source domain to new target domains, facilitating efficient updating of AI models. Additionally, generative models (e.g., GAN and diffusion models) can assist in generating synthetic data to increase the diversity of training samples. Training AI models using these synthetic data helps enhance the adaptability of the ISAC system in diverse environments. Moreover, combining reconfigurable intelligent surface (RIS) to reshape wireless channels also holds promise for upgrading the environmental adaptability of AI-enhanced ISAC systems [13].

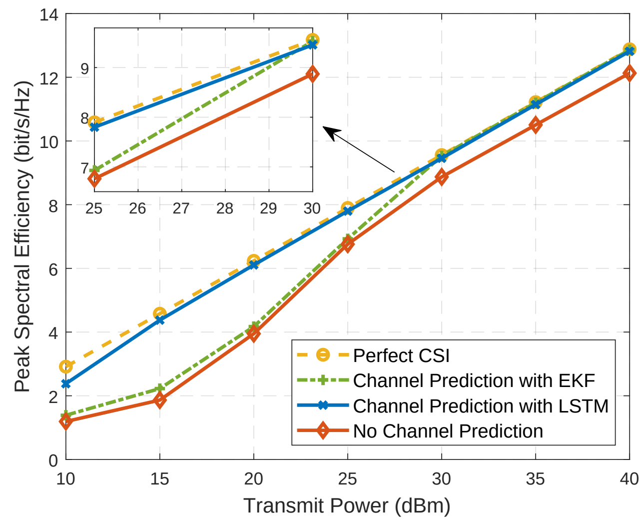


Fig. 2. Peak spectral efficiency versus transmit power of BS for AI-enhanced ISAC systems.

### E. Privacy Protection of Sensing Data

To reduce the risk of privacy leakage, feature extraction and classification based on DNN can be employed beforehand, to avoid direct sharing of raw sensing data. Meanwhile, combining DNN with encryption techniques allows for the generation and recognition of encryption patterns, rendering the contents indecipherable to attackers even with intercepted data. In particular, differential privacy deep learning methods [14] obscure sensitive information by adding artificial noise, randomly perturbing the training data and parameters, and preserving the statistical properties of the dataset while generating differential privacy data.

Furthermore, FL and edge computing [15] can enable distributed data processing and model updates without sharing raw data. Similarly, as shown in Fig. 3, optimizing the beamforming scheme of authorized users through RIS adaptively can further rise the privacy and security performance of AI-enhanced ISAC systems. On one hand, RIS allows transmitting signals to be concentrated toward the specific authorized users by smartly controlling phase shifts, thus limiting transmission sphere and reducing potential exposure to eavesdroppers. On the other hand, RIS can be programmed to actively generate destructive interferences for eavesdroppers once their locations are detected, thereby obstructing information decoding and further bolstering system security. For more details, we refer readers to [13].

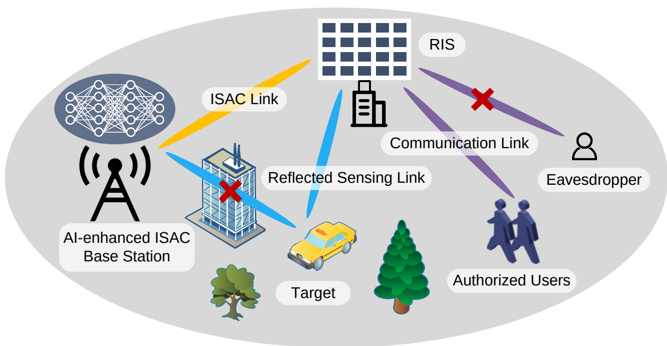


Fig. 3. RIS-assisted privacy and security for AI-enhanced ISAC systems.

## V. Conclusions

In this article, we reviewed the AI-enhanced ISAC technique, which integrates communication and sensing functionalities with AI algorithms to achieve mutual promotion and benefit. A general system framework of AI-enhanced ISAC was presented along with its advancements. Subsequently, four potential use cases were provided with the special requirements and opportunities for AI-enhanced ISAC. We also discussed the technical challenges while deploying AI-enhanced ISAC. Finally, critical techniques and future research directions were indicated. Within forthcoming 6G networks, the paradigm of AI-enhanced ISAC will further evolve from being data and model-based to being knowledge and reasoning-based.

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