AI-Enabled Integrated Sensing, Communication, and Computation Survey: Techniques, Status, and Perspectives

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***Abstract*—The rapid advancement of 6G technology has driven extensive research on integrated sensing, communication, and computation (ISCC), enabling applications in smart transportation, digital twins, and edge intelligence. ISCC aims to integrate communication, sensing, and computation functions to enhance system performance (e.g., energy efficiency, spectrum efficiency, and reduced latency) by designing an integrated architecture that comprehensively considers system resources and energy consumption. This article provides an overview of key ISCC technologies, research contents, challenges, and prospects. It starts by analyzing key technical points, introducing their development history and metrics, and then discusses the reasons for integrating these key technologies to lay the groundwork for ISCC research. Subsequently, this article categorizes and discusses existing ISCC research, ranging from different computational paradigms to emerging communication paradigms, highlighting the current research trends in ISCC. Additionally, it explores the interaction between ISCC and artificial intelligence (AI) and how they can be mutually beneficial in research. Finally, we propose challenges for future ISCC research based on existing studies and suggest potential directions and ideas for research combining new technologies. The integration of ISCC and AI is expected to offer strong support for intelligent 6G by enabling intelligent resource management, reducing AI task handling latency, and improving AI inference accuracy.**

***Index Terms*—6G, artificial intelligence (AI), integrated sensing, communication, and computation (ISCC).**

Received 2 August 2024; revised 17 February 2025 and 3 June 2025; accepted 4 June 2025. Date of publication 23 June 2025; date of current version 8 August 2025. This work was supported in part by the National Key Research and Development Program of China under Grant 2023YFE0107900; in part by the National Natural Science Foundation of China (NSFC) under Grant 62071306; and in part by the Shenzhen Science and Technology Program under Grant JCYJ20241202124219023 and Grant JSGG20210420091805014. *(Corresponding author: Yejun He.)*

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Digital Object Identifier 10.1109/JIOT.2025.3579940

I. Introduction

A. Background and Motivation

With the rapid development of mobile communication technology, there has been an update approximately every ten years, with each generation significantly transforming our lives [1], as shown in Fig. 1. Currently, mobile communication has progressed through five generations, with 5G being commercialized, and both academia and industry are gradually researching 6G [2]. 6G is aimed at the needs of an intelligent society, transitioning from mobile interconnectivity to ubiquitous connectivity, thereby enabling intelligent production and living [3]. Consequently, 6G has higher requirements for transmission speed, latency, and the number of connections compared to 5G. It will utilize higher frequency bands to achieve greater bandwidth, thus increasing communication speeds. Additionally, it requires more advanced computing power to reduce latency, ensuring efficient intelligent interconnection. This necessitates intelligent sensing to accurately and in real-time capture the current state of the physical world [4]. Thus, the future of 6G highlights several key areas of focus: "communication," "sensing," "computation," and "artificial intelligence (AI)."

In the future, spectral resources, being expensive, are becoming increasingly scarce, and the rational and effective use of these resources has become a primary focus. Meanwhile, communication and radar systems are advancing toward higher frequency bands, wider bandwidths, and miniaturization, driving the development of integrated communication and sensing (ISAC) [5]. The simultaneous realization of communication and sensing functions within the same frequency band can significantly improve spectrum efficiency. At the hardware level, using the same set of equipment for both communication and sensing can greatly reduce hardware costs and support miniaturization. At the signal processing level, both communication and sensing utilize electromagnetic waves for information transmission and object sensing, making the integration of signal processing feasible [6]. Therefore, the integration of communication and sensing offers substantial advantages in enhancing spectrum efficiency, reducing hardware costs, and achieving efficient signal processing. This makes it a crucial area of research for realizing the 6G vision of "inclusive intelligence" [7].

Computation is the core pillar for building an intelligent 6G society. Whether in intelligent transportation, smart homes, or

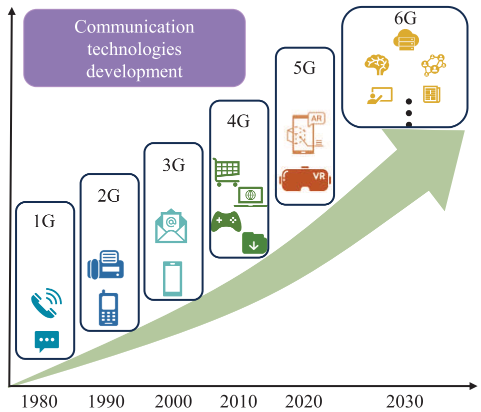

Fig. 1. Evolution of communication technologies.

smart cities, all rely on powerful computing capabilities to process the massive amounts of data generated by end devices while meeting stringent requirements for network latency and real time performance [8], [9]. Looking back at the evolution of computation, in the 4G era, tasks that end devices could not handle were offloaded to cloud computing [10]; 5G introduced mobile-edge computing (MEC), effectively reducing latency caused by distance [11], [12]; 6G demands even more efficient and flexible collaborative computing to address the dual challenges of massive data and ultra low latency [13]. By deeply integrating communication and computation (ICAC), the network can schedule computing resources on demand and maximize utilization. In other words, if the network is reachable, computation is reachable, thereby providing the computing foundation for an intelligent 6G network [14].

In recent years, the development of AI technology has accelerated, demonstrating performance in information processing [15], [16] and intelligent management [17], [18] that rivals or even surpasses human capabilities. AI is now applied in many fields. In the communication field, integration with AI was proposed during the 5G era, leading to the development of relevant standards for architectural convergence and business applications, as well as extensive academic research [19], [20], [21]. Introducing AI into the communication ecosystem can enable self-operation, self-configuration, and self-optimization of networks. A highly autonomous communication network exemplifies the core of "intelligence" in the 6G vision of "inclusive intelligence" [22], [23].

ISAC, ICAC, and integrated communication and AI (ICAA) are the three major components of the 6G network vision, each contributing to multidimensional integration, ubiquitous connectivity, and intelligent endogeneity from different perspectives [24]. If the future 6G network can intelligently integrate sensing, communication, and computation capabilities—referred to as integrated sensing, communication, and computation (ISCC)—it will enable the wireless network to perceive its environment anytime and anywhere, while efficiently processing vast amounts of sensory data in real time. This integration will facilitate the mapping of the physical world to the digital world [25]. Incorporating AI further deepens this integration. Embedding AI technology from the initial stages of system design—covering aspects from waveform design and resource allocation to signal processing—enables the 6G network to achieve truly intelligent connectivity of everything [26]. Fig. 2 illustrates some application scenarios of ISCC.

B. Related Work

Several review articles focusing on ISCC are available. Xu et al. [27] focused on edge learning (EL) research in wireless communications, emphasizing the interaction between distributed EL and communication design. It summarizes typical EL and communication metrics, discusses the future role of EL in wireless communications, identifies challenges, and examines openness from an information-theoretic perspective. Xing et al. [28] centered on task-oriented ISCC systems in EL scenarios, outlining key technologies and using case studies to demonstrate the advantages and challenges of these systems. Wen et al. [29] and Zhu et al. [30] also focused on EL. Wen et al. [29] discussed the design motivation and principles of ISCC systems from the perspectives of resource management and waveform design, studied the coupling mechanisms among sensing, communication, and computation, and further investigated related physical-layer technologies. In [30], EL is classified into three types: 1) centralized EL; 2) federated EL (FEEL); and 3) edge inference, with an analysis of resource management in these scenarios. Moke et al. [31] addressed federated learning (FL) in EL, introducing the concept and research trends of FL, demonstrating the FL framework, and exploring its implementation within the ISCC framework. It analyzes challenges and proposes solutions, highlighting future research directions. Li et al. [32] focused on over-the-air computation (AirComp)-assisted ISCC systems for the Internet of Things (IoT), introducing and analyzing key technologies, such as space-division multiplexing, target estimation, waveform design, and security, and identifying specific application scenarios. Ren [33] investigated key technologies of ISCC, establishing system models based on different objectives and introducing performance optimization strategies. Feng et al. [34] proposed an ISCC framework where perceptual information enhances communication performance and reduces latency while improving computational performance. It presents key ISCC technologies, research challenges, and validates the proposed framework with a smart manufacturing example. Different from the aforementioned reviews, this article provides a comprehensive overview of ISCC technology. It includes related key technologies and explains the advantages and research content of each technology fusion step by step, from separation to integration. Additionally, it categorizes ISCC research in detail. Unlike the literature that primarily focuses on ISCC-assisted EL, this article also analyzes AI-assisted ISCC from a reverse perspective, offering readers references for studying ISCC.

C. Key Contributions

With the development of wireless communication technologies in recent years, ISCC research has gradually become a hot topic, leading to a surge in related research articles. Thus, it is crucial to conduct a comprehensive review and summary of existing studies. Currently, there are few studies on the

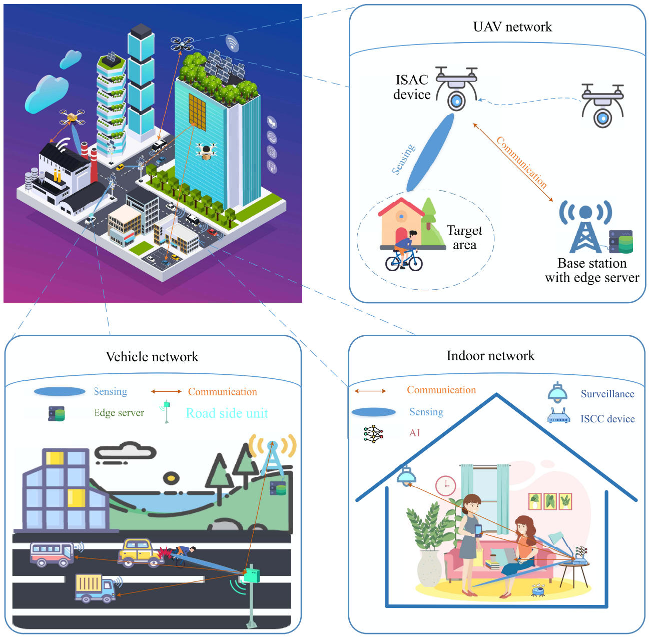

Fig. 2. Some application scenarios of ISCC.

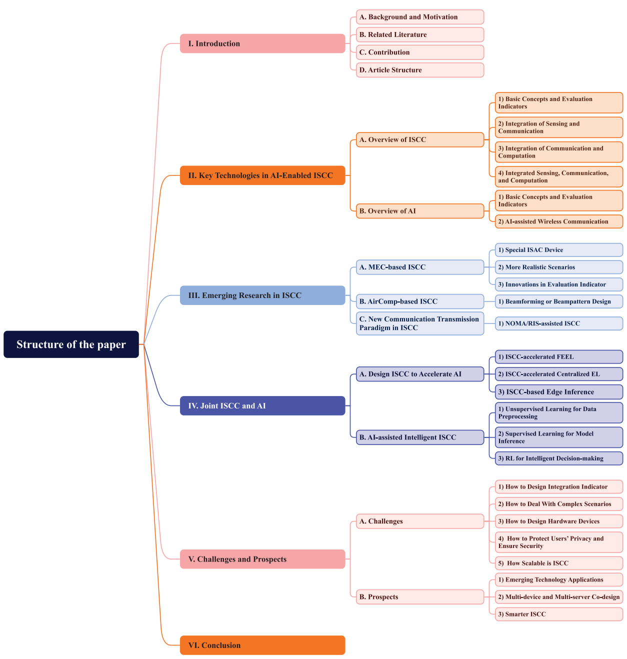

Fig. 3. Structure of this article.

interaction between AI and ISCC. This article provides an in-depth summary of key technologies, research contents, and their interactions with AI in ISCC, offering new research perspectives for future ISCC researchers. The main contributions of this survey are summarized.

Overview of Key Technologies in ISCC: We provide an overview of the key technologies in ISCC, including the basic concepts and development history of its three important elements: 1) communication; 2) sensing; and 3) computation. We also cover evaluation metrics to lay the foundation for subsequent ISCC research. Additionally, we introduce ISAC, ICSC, and ISAA technologies, illustrating the advantages of technology integration and highlighting the key research focuses by presenting their concepts, reasons for integration, and research content. This provides guidance for ISCC research.

Classification and Analysis of Existing ISCC Research: We classify existing ISCC research articles into MEC-based ISCC, AirComp-based ISCC, and new communication transmission paradigm in ISCC. We analyze the characteristics of each category, summarize the relevant research articles in a table, and include metrics of interest, optimization objectives, optimization methods, evaluation criteria, and techniques employed. This breakdown of ISCC research into tangible metrics and methods allows researchers to understand and further investigate them intuitively.

Interaction Between ISCC and AI Technologies: We present an analysis of the interaction between ISCC and AI technologies. First, we analyze the advantages of improving FEEL and centralized EL performance by designing ISCC systems based on existing research articles, essentially accelerating AI through ISCC. Second, we specifically analyze papers related to AI-assisted ISCC systems, identifying the stages in which AI is used and its roles. This examination of the interrelationship between ISCC and AI provides a basis for further intelligent and deep integration.

Challenges and Future Research Directions in ISCC: We identify the challenges in existing ISCC research and propose future research directions. Since most current ISCC research is in its early stages and involves relatively simple scenarios, achieving ultimate intelligent integration remains a long-term goal. We point out specific problems in ISCC research and suggest potential areas for future investigation based on current research.

D. Organization

The structure of this article is shown in Fig. 3. In Section II, we explore the key techniques integral to ISCC. Section III then delves into the emerging research of ISCC. Following that, Section IV examines the interaction between ISCC and AI. Section V addresses the challenges and prospects of the research. Finally, Section VI provides a comprehensive summary of this article. The abbreviations used in this article are summarized in Table I.

II. Key Technologies in AI-Enabled ISCC

A. Overview of ISCC

1) Basic Concepts and Performance Metrics: *Communication:* Communication involves the use of basic signals to transmit complex information. In a communication system, information is sent from the sender through a transmission channel to the receiver. Channels can be divided into wired and wireless channels based on the transmission medium [35]. Nowadays, wireless communication, which uses wireless channels, is the primary method of communication. In this article, communication generally refers to wireless communication [36]. Wireless communications have undergone explosive changes in the last few decades, with each generation

TABLE I
LIST OF ABBREVIATIONS

Abbreviation	Definition
ISCC	Integrated sensing, communication, and computation
AI	Artificial intelligence
ISAC	Integrated communication and sensing
ICAC	Integrated communication and computation
ICAA	Integrated communication and AI
EL	Edge learning
FL	Federated learning
FEEL	Federated edge learning
AirComp	Over-the-air computation
IoT	Internet of Things
MEC	Mobile edge computing
ITU	International Telecommunication Union
BER	Bit error rate
SER	Symbol error rate
SNR	Signal-to-noise ratio
MSE	Mean square error
FLOPS	Floating-point operations per second
MIPS	Million instructions per second
LFM	Linear frequency modulated
OFDM	Orthogonal frequency division multiplexing
JRC	Joint radar communications
JCR	Joint communications radar
JCAS	Joint communications and sensing
DFRC	Dual-functional radar and communications
CRB	Cramér-Rao bound
PAPR	Peak-to-average power ratio
SDR	Semi-definite relaxation
RIS	Reconfigurable intelligent surface
AO	Alternating optimization
AR/VR	Augmented reality/virtual reality
DQN	Deep Q-network
UAV	Uncrewed aerial vehicle
RL	Reinforcement learning
PCA	Principal component analysis
SVM	Support vector machines
DRL	Deep reinforcement learning
DNN	Deep neural network
CNN	Convolutional neural network
RNN	Recurrent neural network
MAE	Mean absolute error
RMSE	Root mean square error
FP	Fractional programming
SCA	Successive convex approximation
NOMA	Non-orthogonal multiple access
AoI	Age of information
SIC	Successive interference cancellation
MLP	Multilayer perceptron
DDQN	Double DQN
DDPG	Deep deterministic policy gradient
TD3	Twin delayed deep deterministic policy gradient
QCQP	Quadratically constrained quadratic programming

of change driven by new technologies. Therefore, it is vital that communication systems are designed according to the needs of users and the development of society [37]. Aligned with the "one generation of use, one generation of research" trend in network development, ongoing research into 6G is underway as per plan. The International Telecommunication Union (ITU) Wireless Communication Sector, in its 6G White Paper, mentions new technologies that may be applied to 6G in the future, such as ISAC, ICAC, and ICAA. These new technologies will help meet the needs of 6G, enabling ultralarge range connectivity, ultralow latency services, and a wider range of applications [38].

TABLE II
COMMUNICATION PERFORMANCE METRICS

Classification of metrics	**Specific parameter**	**Calculation formula**
Reliability	Bit error rate(BER)	$BER = N_e/N_t$
	Symbol error rate(SER)	$SER = N_{se}/N_s$
	Signal-to-noise ratio(SNR)	$SNR = P_s/P_n$
Effectiveness	Latency(L)	$L = T_t + T_p + T_q + T_r$
	Transmission rate	Symbol Rate: $R_B = 1/T_s$ Bit Rate: $R_b = R_B \log_2 M$
	Spectral efficiency(η_{se})	$\eta_{se} = R_b/B$
	Energy efficiency(η_{ee})	$\eta_{ee} = R_b/P_t$

where N_e is the number of bit errors, N_t is the total number of transmitted bits.N_{se} is the number of symbol errors, and N_s is the total number of transmitted symbols. T_t: transmission delay,$T_t = D/B$, T_p: propagation delay, $T_p = d/s$, T_q: queuing delay, T_r: processing delay, D: data block length, B: bandwidth, d: distance, s: signal propagation rate. T_s: symbol time length, M: carry system, P_t: signal transmission power.

Performance Metrics: In communication, evaluation revolves around two primary aspects: 1) effectiveness and 2) reliability. Reliability metrics focus on parameters, such as bit error rate (BER), symbol error rate (SER), and signal-to-noise ratio (SNR). Effectiveness, on the other hand, is assessed through metrics, such as latency, transmission rate, spectral efficiency, and energy efficiency. Specific metrics are summarized in Table II.

Sensing: The realm of sensing encompasses a broad array of methodologies, including environment sensing based on electromagnetic wave reflections, visual sensing through image–video processing, and sensor-based systems, collectively categorized under sensing. Radar sensing technology, which is based on electromagnetic waves, is primarily used for distance and speed measurement. It is now widely applied in emerging fields, such as autonomous driving [39], [40]. The development of communication systems has facilitated the smooth transmission of large data volumes, such as images and videos. This enables image- and video-based visual perception technology to provide users with more detailed and informative perceptual content. Sensor-based sensing finds widespread application in professional information gathering, particularly in targeted areas, such as air humidity, environmental smoke, displacement, and speed measurement. Typically, such applications entail collaboration between a known observation object and the observer [41]. In alignment with the developmental trajectory of 6G, extensive sensing forms the cornerstone of intelligence. However, achieving extensive sensing necessitates a substantial number of sensing equipment, entailing significant costs. Addressing this, electromagnetic wave-based sensing leverages the existing communication system's shared propagation medium, enabling the use of the same equipment for both communication and radar sensing purposes. WiFi sensing, currently a subject of widespread study, capitalizes on this concept. Given the ubiquitous use of WiFi technology for indoor communication, repurposing existing WiFi devices for target sensing not only reduces costs but also safeguards user privacy [42].

Performance metrics: Sensing evaluation metrics can be categorized into three main groups: 1) detection; 2) estimation;

TABLE III
SENSING PERFORMANCE METRICS

Classification of metrics	Specific parameter		Calculation formula
Detection category	Probability of detection		$P_D = \int_{\mathcal{R}_1} p_y(\mathbf{y}\|H_1)d\mathbf{y}$
	Probability of false alarm		$P_{FA} = \int_{\mathcal{R}_1} p_y(\mathbf{y}\|H_0)d\mathbf{y}$
Estimation category	Estimated mean square error	Distance	$\sigma_R = c/2B\sqrt{2SNR}$
		Speed	$\sigma_\nu = \lambda/2\tau\sqrt{2SNR}$
		Angular	$\sigma_\theta = \theta_{3dB}/1.6\sqrt{2SNR}$
	Resolution	Distance	$\Delta R = c/2B$
		Speed	$\Delta\nu = \lambda\Delta f_d/2$
		Angular	$\theta_{3dB} = 0.886\lambda/D$
	Maximum unambiguous range	Distance	$R_{\max} = cT_r/2$
		Speed	$\nu_{\max} = \lambda/4T_r$
		Angular	$\theta_{\max} = \sin^{-1}(\lambda/2d)$
Recognition category	Recognition accuracy		$Accuracy = C/N$

where $\mathcal{R}_1$: region, y : measured data values. $p_y(\mathbf{y} \mid H_1)$: the probability density function (PDF) of y given that a target was present, $p_y(\mathbf{y} \mid H_0)$: the PDF of y given that a target was not present. c: the speed of light, B: signal bandwidth, λ: wavelength, τ: signal duration, θ_{3dB}: 3dB beam width, T_r: pulse repetition interval. C: the number of correctly classified instances, N: the total number of instances.

TABLE IV
COMPUTATION PERFORMANCE METRICS

Classification of metrics	Specific parameter	Calculation formula
Computing performance	FLOPS	/
	MIPS	/
Network performance	Latency(L)	$L = T_t + T_p + T_q + T_r$

where T_t: transmission delay, $T_t = D/B$, T_p: propagation delay, $T_p = d/s$, T_q: queuing delay, T_r: processing delay, D: data block length, B: bandwidth, d: distance, s: signal propagation rate.

and 3) recognition. The detection category primarily assesses whether a target exists or not, including detection probability and false alarm probability. Estimation class metrics are mainly used to measure the distance, velocity, and orientation of the target. The mean-square error (MSE) is the primary metric for evaluating the accuracy of these estimations. The recognition class is primarily utilized for detecting the state of the target and is assessed based on recognition accuracy, as shown in Table III.

Computation: Computing power refers to the capability of a computer to process data and produce a target result, which drives the advancement of the digital age. The communication industry's ongoing progress led to the emergence of new technologies, such as cloud computing. This innovation enabled large-scale data to be processed and transmitted over networks to computationally capable devices, offering high-performance and cost-effective computation [43]. The advent of MEC in the 5G era allowed computational tasks to be processed at edge servers, distributing some cloud computational power to the edge, thereby reducing computational latency [44]. As we move toward 6G, there are stricter requirements for lower latency and increased data processing capabilities due to intelligent applications, demanding higher computing power. Research into new computing technologies and effective utilization of existing computational resources to meet 6G requirements has become a focal point. ISCC has emerged as a key research area, offering solutions for the efficient and rational use of computing resources to fulfill these demands.

Performance Metrics: Computing performance is typically measured by a computer's ability to perform operations, such as floating-point operations per second (FLOPS) and million instructions per second (MIPS). For online computing, network performance is also commonly assessed in terms of communication latency, as shown in Table IV.

2) *Integration of Sensing and Communication:*

What Is ISAC? ISAC integrates communication and sensing systems at multiple levels, including waveform design, signal processing, and hardware systems [45]. This integration effectively utilizes spectrum resources and reduces hardware costs. The concept dates back to 1963, when Mealey [46] proposed adding communication information to the ranging radar pulses of a missile. This early prototype allowed radar systems to not only perform basic functions like range and speed measurement but also to facilitate simple communication, forming a rudimentary network. In 1978, the NASA Space Shuttle Orbiter achieved both radar and communication functions. It could search and track to provide space data while enabling two-way communication with the ground via the tracking and data relay satellite system [47]. In 2003, Roberton and Brown suggested using linear frequency-modulated (LFM) signals for dual-function communication and radar waveforms. However, LFM signals had limitations, particularly their low communication rates [48]. With technological advancements, orthogonal frequency-division multiplexing (OFDM) technology has gained prominence in communications. In 2011, Sturm and Wiesbeck [49] explored using OFDM waveforms to achieve both wireless communication and radar functions, significantly improving communication rates compared to LFM. In 2017, the concept of perceptive mobile networks was proposed [50]. By 2020, although studies on radar and communication integration had continued, the number remained relatively small. Most research still focused primarily on adding communication functions to radar systems [51]. With the advent of 5G, ISAC has garnered renewed academic interest, resulting in a surge of related research papers. Subsequently, standardization efforts for WIFI sensing have been gradually progressing [52]. Early academic terms for ISAC research included joint radar communications (JRC), joint communications radar (JCR), joint communication and sensing (JCAS), and dual-functional radar and communications (DFRC). Today, ISAC is the preferred term for communication–sensing integration.

Reasons for Integration: In the last five years, more researchers have focused on ISAC for several reasons. Initially, ISAC research aimed to add communication functions to radar systems, reducing costs and hardware consumption. Recently, phased array radar technology, which uses multiple antenna arrays for signal transmission and reception, has become prominent. Similarly, multiple-input–multiple-output (MIMO) technology, essential for 5G communication, utilizes MIMO antenna systems. The convergence of these hardware developments increases the feasibility of integrated devices, reducing costs and physical footprint [53]. From a signal processing perspective, both communication and radar systems employ digital circuits and share many signal processing methods, such as channel characterization and signal processing flow. This commonality facilitates the integration of these systems [45]. In terms of spectrum resources, achieving higher communication rates necessitates operating in higher frequency bands, such as millimeter-wave and terahertz bands. For radar systems, higher frequency bands are required to meet the growing demand for higher resolution in an intelligent society. Consequently, both fields are advancing toward high-frequency bands and large bandwidths. Spectrum resources are expensive, and communication operators must invest heavily to acquire operational frequency bands. Given the increasing overlap in the working frequency bands of communication and radar systems, ISAC offers a solution to alleviate spectrum congestion. Integrated technology can effectively optimize the use of spectrum resources [5]. From a business-driven perspective, the continuous development of communication technology and AI has led to more intelligent devices connecting to the Internet. This trend, coupled with the growing demand in areas, such as smart homes, smart cities, and smart healthcare, increases the need for end-to-end information processing capabilities. The integration of communication and sensing networks can significantly enhance the development of an intelligent society.

How to Study ISAC? It is clear that there are many reasons to promote ISAC, and the advantages of integration are obvious. However, to truly realize these benefits, a thorough understanding of the main points of integration technology is necessary. According to the IMT-2030(6G) Promotion Group's communication and sensing integration research report, the development of ISAC can be divided into three stages: 1) service coexistence; 2) capacity mutual assistance; and 3) network reciprocity. In the first stage, the primary research focus is achieving the coexistence of communication and sensing services within a single system, enabling both functions to operate simultaneously. Once this stage is achieved, the second phase explores how shared information can enhance their respective performances. This means that communication and sensing functions can work concurrently, with shared information aiding in performance enhancement for either communication or sensing. The third phase builds on the second phase, where integrated devices are not restricted to their respective scenarios. Networked connectivity facilitates device reciprocity across the entire network, and the introduction of AI allows for intelligent co-management. This progression leads to the realization of the 6G vision of "inclusive intelligence."

Currently, ISAC research primarily focuses on the first phase, the service coexistence stage. Specific research includes a comprehensive analysis of performance boundaries from a theoretical perspective to guide subsequent integrated designs. At the signal level, research involves designing integrated waveforms, channel estimation and prediction, and beam assignment. At the resource allocation level, it includes RF resource allocation and power allocation.

At the theoretical analysis level, Xiong et al. [54] investigated the point-to-point ISAC system under the Gaussian channel model. They analyzed the ISAC performance of specific points in the region using the Cramér–Rao bound (CRB)-rate region as a tradeoff between ISAC sensing and communication functions. Ouyang et al. [55] explored the performance of uplink and downlink ISAC systems, using mutual information metrics for both communication and sensing. They defined the basic performance constraints of ISAC and evaluated the communication and sensing performance based on this framework. In terms of waveform design, Zhu et al. [56] created ISAC waveforms to reduce interference among multiple users in MIMO communication and enhance MIMO radar target detection capability. They optimized communication and radar performance weights under constant mode constraints using the coordinate descent-Dinkelbach iteration algorithm, achieving a tradeoff between communication and sensing performance. Another study [57] proposed a waveform design to minimize interuser interference and maintain radar signal similarity under peak-to-average power ratio (PAPR) constraints, exploring the impact of PAPR on communication and sensing performance, even considering imperfect CSI scenarios. For the ISAC beamforming problem, Dong et al. [58] considered precoder communication and radar waveforms for secure transmission, formulating a nonconvex optimization problem that integrates radar, communication, and security performance. They used a low-complexity semi-definite relaxation (SDR) algorithm to address nonconvexity and proposed a robust beamforming design to handle practical scenarios with imperfect estimation, including uncertain or unattainable target direction. Wang et al. [59] addressed hardware impairment in ISAC beamforming, focusing on radar-centered and communication-centered beamforming design problems, highlighting in-phase/quadrature imbalance as a key metric of hardware impairment. Regarding signal estimation, a two-stage scheme is proposed in [60] for channel estimation, target detection, and frequency guidance optimization. The first stage involves the base station performing target detection and channel estimation based on the received signal, and the second stage optimizes frequency guidance based on the first stage's results. Liu et al. [61] examined the channel estimation problem in reconfigurable intelligent surface (RIS)-assisted ISAC systems, dividing the problem into three phases: 1) direct path communication and sensing; 2) RIS reflective path communication; and 3) RIS reflective path sensing channel estimation, utilizing a deep learning framework with convolutional neural network (CNN) for training and estimation. Resource allocation is also a significant issue in ISAC. Li et al. [62] investigated temporal resource allocation and precoding in RIS-assisted ISAC systems to maximize the average achievable capacity under perceptual performance and interference constraints, using the alternating optimization (AO) algorithm. Dong et al. [63] designed a resource allocation framework for ISAC that flexibly allocates system resources based on the quality of communication and sensing, exploring the tradeoff between these services. It addresses power and bandwidth allocation within a single cellular network, taking into account the fairness and comprehensive coverage of each sensing task. It is evident that many scholars have studied various aspects of ISAC systems. In waveform design and beamforming, most studies focus on optimizing communication or sensing parameters, typically using classical optimization algorithms. For channel estimation and resource allocation, recent studies have incorporated advanced deep learning algorithms, enhancing the intelligent system's capabilities.

3) Integration of Communication and Computation:

What Is ICAC? ICAC on a large scale aims to achieve the integration of network and computing through mutual collaboration, real-time arithmetic discovery, and flexible service scheduling. This ensures a reasonable distribution of computing resources and user sensing, thereby improving the utilization of network and computing resources. On a smaller scale, for a limited range of users in a single scenario, when users have high functional requirements for communication and computation, collaborative design can optimize performance. This enhances data processing efficiency, reduces system delay, and improves overall performance. The advantages of combining communication and computation have been studied for decades. In the 1980s, El Gamal [64] raised an open question about the communication complexity problem of distributed computation in broadcast networks. In 1988, Gallager [65] discussed the scenario where each node in a broadcast network has a binary state, highlighting the construction of distributed algorithms to determine the parity of the set of states, given reliability constraints. In 1998, Akamai [66] launched the first generation of content delivery networks (CDNs) to address network congestion, an approach later applied to MEC. In 2005, Giridhar and Kumar [67] investigated the maximum rate at which sensor measurements can be computed and communicated to transmit them to sink nodes. In the 21st century, the rise of cloud computing, fog computing [68], MEC, and AirComp [69], [70], [71] has addressed higher computing requirements. Cloud computing addresses insufficient computing power on the user side. However, with the development of IoT technology and higher latency requirements from users, cloud computing cannot meet the demand for low-latency services. MEC emerged to sink computing resources closer to the user side, addressing the needs of users with higher latency requirements and improving the quality of experience through joint optimization of communication and computing performance. Users can dynamically interconnect distributed computing and storage resources via a mobile computing network, scheduling applications to distributed computing power resources on demand and achieving global optimization of resources by considering transmission latency. AirComp, another form of ICAC, leverages the inherent superposition characteristics of the wireless communication channel to enable parallel transmission of multiple sensors. This facilitates the superposition of computational characteristics during communication, making large-scale data collection and processing more efficient and improving system performance [72].

Reasons for Integration (Increased Demand for Computing Power in 6G Networks): Compared to 5G, 6G will utilize higher frequency bands, which entail higher signal loss and require each base station to cover a smaller area. Consequently, a denser network of base stations will be necessary. Additionally, 6G networks will support a wider array of complex applications, such as IoT, augmented reality/virtual reality (AR/VR), and autonomous vehicles, all of which demand significant data processing capabilities. The combination of high-density base stations and complex application services will necessitate robust information collaboration capabilities. Thus, 6G networks must enhance their computing power to meet the service demands of 6G with ubiquitous, flexible, and efficient collaborative arithmetic.

The Vision of 6G Intelligent Endogenous: Intelligence is a prominent trend in social development. From the outset, 6G has embraced Intelligent Endogenous as a core vision. This intelligence extends beyond network design and optimization to include network management and operation. It enables dynamic configuration of network resources and automatic adjustment of configurations and services based on user needs and environmental changes. Computing power is crucial for realizing this intelligence. ISCC provides a reliable transmission network and distributed, efficient computing power, thereby supporting the intelligent capabilities envisioned for 6G.

Mismatch Between Computing Power Demand and Computing Power Growth: The 6G network will underpin the intelligent needs of smart homes, smart cities, and smart societies, all of which require processing vast amounts of data, leading to a significant increase in computing power demand. AI computing power is set to gradually replace traditional computing power to support extensive intelligent services. According to OpenAI predictions, by 2030, the computing power required for AI-related fields will be about 400 times greater than in 2018. However, the growth in computing power from chips will not suffice to meet this enormous demand. Consequently, computing networks must effectively utilize existing computing power resources and improve their utilization rates to address this challenge.

How to Study ICAC? To address the resource management problem of ICAC, Ren et al. [73] investigated the resource management of joint communication and computation in nonterrestrial networks, focusing on resource management models and optimization. In another study [74], open radio access network resource slicing was examined, enabling flexible sharing of communication and computation resources to meet requirements, including ultrareliable and low-latency communication services. This resource partitioning problem was transformed into a Markov decision-making process and solved using a deep Q-network (DQN). Liu et al. [75] studied the resource scheduling problem for uncrewed aerial vehicle (UAV)-assisted vehicular networking scenarios. They aimed to maximize the system's computational capacity under communication and computational resource constraints, solving the optimization problem using second-order convex approximation. Similarly, Cui et al. [76] investigated allocating communication and computational resources in vehicular networking scenarios. They used the K-nearest neighbor method for selecting computational layers, including cloud computing, MEC, and local computing layers. A reinforcement learning (RL) approach was used for resource allocation in the MEC layer. For the application delay problem of virtual reality, MEC can alleviate the issue, but the selection of MEC nodes affects computation and communication delays. Liu et al. [77] studied joint graph-based computation and communication resource models to find the optimal MEC nodes. Energy efficiency is also a crucial direction for communication and computation. Mo and Xu [78] enhanced the energy

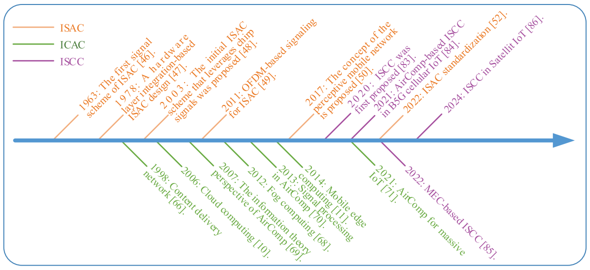

Fig. 4. Brief development history of ISCC, ISAC, and ICAC.

efficiency of FEEL systems by jointly designing communication and computation to optimize transmission power and rate of edge devices and balance the frequencies of edge devices and the central processor. Cao et al. [79] investigated energy efficiency in MEC systems for large-scale computation tasks with latency constraints, minimizing total energy consumption through joint resource allocation. Fog computing, similar to MEC, is another solution for achieving communication and sensing integration. Zhou et al. [80] proposed a network architecture for heterogeneous communication and hierarchical fog computing, better utilizing communication and computation resources compared to traditional networks. AirComp is also a technique for combining communication and computation. It achieves efficient data aggregation through waveform superposition characteristics of wireless multiple access channels and parallel transmission by multiple users. Cao et al. [81] proposed a model aggregation method based on over-the-air computing to alleviate communication delay in FEEL, addressing limitations of current communication–computing separation designs. Evaluation metrics are a key direction for communication and computation convergence. Addressing timeliness in communication and computation, Chen et al. [82] introduced the concept of computational age to evaluate computational freshness in networks where communication and computation collaborate. This study investigated the communication-computation tradeoff and the computational age-delay tradeoff.

4) Integrated Sensing, Communication, and Computation: In the previous section, we introduced the concepts, development, and performance metrics of communication, sensing, and computing. Additionally, we elaborated on the integration of communication with sensing and computing, including the concepts, reasons for integration, existing research directions, and some research results. ISAC and ICAC have laid the foundation for the integration of communication, sensing, and computing. The development of ISAC and ICAC has laid the foundation for the advancement of ISCC. The progress of the three developments is shown in Fig. 4.

Reasons for Integration: Network vision of 6G. To realize the overall vision of 6G's pervasive intelligence and ubiquitous connectivity, meet the high-quality development needs of future society, and achieve the intelligent interconnection and collaborative coexistence of humans, machines, and objects, it is necessary to deeply converge communication, sensing, and computing. At the World 5G Convention, China Mobile and others released a white paper on ISCC [83], discussing how the integration of communication, sensing, and computation can bring new capabilities and services to 6G. Since then, an increasing number of researchers have focused on ISCC, exploring it from different perspectives [84], [85], [86].

Application Requirements for Smart Cities, Smart Transport, and Smart Factories: Smart cities require large-scale connectivity and intelligent control. In future smart cities, interconnected smart devices, such as autonomous robots, IoT sensors, mobile devices, and AI-driven infrastructure, will collaboratively optimize urban operations through real-time data sharing and adaptive decision-making. In such large-scale connectivity environments, signal interference is a common issue. The addition of sensing capabilities while maintaining communication exacerbates this problem further, making timely data computation and processing difficult. Therefore, rational scheduling of resources, such as spectrum, and intelligent decision-making from a system-level perspective is essential. Smart transportation demands low latency and high security. From the residents' perspective, autonomous driving requires real-time access to and processing of road condition information. From the government's perspective, intelligent roadside units must perceive local traffic data and enable intelligent scheduling and decision-making. Therefore, an efficient and secure ISCC transportation system must be designed from a global perspective. Smart factories have high demands for precision, reliable connectivity, and intelligent decision-making. In smart factories, the primary focus is on machine collaboration, requiring high-precision sensing to improve product quality, reliable communication to ensure large-scale device interconnectivity, and intelligent decision-making to address production issues in real time. These smart applications need to integrate communication, sensing, and computing functions to achieve very low latency, high reliability, large bandwidth, and massive access.

Existing Network Architecture Is Not Suitable: The existing network architecture cannot meet the above network vision and application requirements. The independent functions of current systems make it difficult to exchange information quickly and accurately. Therefore, it is necessary to research the convergence of communication, sensing, and computing architectures. This includes the acquisition of environmental information, information interaction, information processing, and control of information distribution, to achieve efficient global resource use and intelligently adapt to the needs of different applications.

Integrated Logic of Communication, Sensing and Computation: Communication and Computation Enhance Sensing Performance: For large-scale sensing nodes, communication functions can transfer and converge multinode sensing information, enabling interaction among nodes and supporting multinode collaborative sensing. This helps expand the dimension of sensing. Additionally, distributed computing can process sensing data from each node in real time, and advanced AI models can transform this data into actionable information according to the task, achieving environmental cognition capabilities.

Sensing and Computation Enhance Communication Performance: Sensing functions can provide information obtained from the environment (e.g., user information and environmental information) as a priori information to the communication system, helping reduce communication overhead. Distributed computing can assist in achieving efficient channel estimation and fast beam alignment. Large-scale computing can simulate the physical environment in digital space, construct accurate channel information, and plan optimal transmission methods, thereby enhancing communication performance.

Communication and Sensing Enhance Computing Performance: Enhanced communication functions can help realize a ubiquitous computing power network, providing computing resources to intelligent devices in the network as needed. Enhanced sensing functions provide a priori information about the environment to the computing function, enabling fast and optimal resource scheduling.

Prospects for ISCC Applications (Indoor Intelligent Networks): Indoor intelligent networks include scenarios, such as smart homes and smart factories. As technology advances and peoples quality of life expectations increase, smart homes are gradually becoming a reality. ISCC helps connect intelligent home devices and enables indoor positioning and gesture recognition while protecting user privacy. It also aids in building an indoor IoT to gather a priori information about the environment, thereby reducing communication overheads. Smart factories need to handle large-scale data, including machine scheduling and multimachine collaboration. ISCC provides an intelligent platform for smart factories, enabling multinode collaborative communication, environmental awareness, and intelligent scheduling operations. This improves the flexibility and operability of factory operations, ensuring the stability and efficiency of large-scale machine work.

Intelligent Transport: In recent years, autonomous driving has become a major research focus, and intelligent transport can greatly enhance the driving experience. Intelligent transport requires high communication, sensing, and computation capabilities. Specifically, it needs ultralow latency and ultrahigh transmission rates for communication, high-precision and real-time sensing of the surrounding environment, and the ability to process large amounts of perception data and make intelligent decisions. Deploying roadside units with passive sensing and computing capabilities can help vehicles obtain more information and form queues for intelligent decision-making, addressing issues like high communication latency and unsynchronized information in long queues. Therefore, ISCC can help build an efficient intelligent traffic network.

Drone Network: Drones are increasingly integrated into daily life. UAVs with ISCC functions can serve as aerial base stations in emergency scenarios, providing communication and sensing services for rescue operations. The flexibility of UAVs can also address communication and computation needs in densely populated areas. An all-in-one design reduces UAV equipment size and lowers energy consumption. Furthermore, the ISCC network can optimize resource allocation to further reduce resource consumption. It enables intelligent decision-making for UAVs and provides globally optimal scheduling and control for UAV clusters, ensuring the safe operation of low-altitude networks.

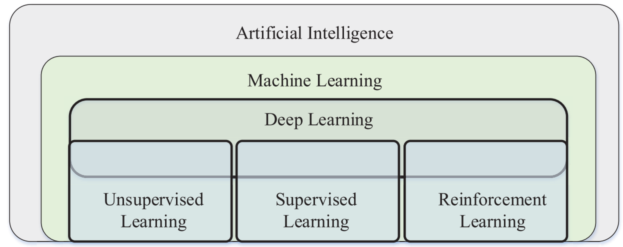

Fig. 5. AI relationship diagram.

B. Overview of AI

1) Basic Concepts and Performance Metrics:

AI: AI refers to the ability to make rational judgments in response to environmental changes, enabling machines to "hear" and "see" like humans to achieve specific goals [87]. AI has achieved amazing results in many application areas, such as automatic speech recognition [88], image processing [89], intelligent manufacturing [90], the IoT [91], and natural language processing [92]. It integrates knowledge from multiple disciplines, including computer science, mathematics, biology, psychology, and logic. Enhanced computing power has accelerated AI development in recent years. The recent explosion of generative models like ChatGPT [93] has marked a new climax in AI development, with real-time interactive operations making the presence of intelligence even more evident. As a crucial productive force in modern society, AI is now widely applied across various aspects of daily life. In fact, the development of AI is mainly summarized as the development of machine learning [94]. Deep learning is a special type of machine learning that achieves more complex learning by using multilayer networks to complete intricate tasks [95]. The relationship between AI and machine learning is shown in Fig. 5. Machine learning can be divided into three categories: 1) unsupervised learning [96]; 2) supervised learning [97]; and 3) RL [98].

Unsupervised Learning: Unsupervised learning involves mining data information without labels [99]. In clustering tasks, classification is mainly based on the inherent characteristics of the data. Methods include principal component analysis (PCA) [100] and K-means [101].

Supervised Learning: Supervised learning refers to predicting new data (classification and regression) through training on labeled data [102]. It adjusts the model's weight parameters by minimizing the error between predictions and actual data, ultimately finding a prediction model within an acceptable error range. Methods include K-Nearest Neighbor [103], support vector machines (SVM) [104], random forests [105], and logistic regression [106].

Reinforcement Learning: RL studies how to maximize rewards through interactions between agents and the environment. By sensing the state of the environment and responding to the agent's actions, better actions can be taken to maximize final benefits [107]. For high-dimensional state spaces, RL

TABLE V
AI PERFORMANCE METRICS

Classification of metrics	Specific parameter	Calculation formula
Classification tasks	Accuracy	$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$
	Precision	$Precision = \frac{TP}{TP+FP}$
	Recall	$Recall = \frac{TP}{TP+FN}$
	F1-score	$F1 = \frac{2*Precision*Recall}{Precision+Recall}$
Regression tasks	MSE	$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i))^2$
	MAE	$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid y_i - f(x_i) \mid$
	RMSE	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i))^2}$
where TP: True positive, FN: False negative, FP: False positive, TN: True negative N: Sample size, y_i: Actual value, $f(x_i)$Predicted value.		

training is more complex. Deep RL (DRL) extends deep learning into RL, effectively solving high-dimensional state-space problems [108].

Common Deep Learning:

Deep Neural Network (DNN): A neural network with multiple hidden layers, consisting of input, hidden, and output layers. The layers are fully connected, forming a feedforward neural network [109].

CNN: A basic deep learning network consisting of input, convolution, pooling, fully connected, and output layers. Its training process is equivalent to convolution, and compared to fully connected neural networks, CNNs are more flexible [110].

Recurrent Neural Network (RNN): Mainly used to process sequential data, or data with correlations in sequence. RNNs include input layers, neural network units, and output layers, with an additional looping connection. Compared to feedforward neural networks, RNNs have a "memory" capability, which can effectively process time-series data [111].

Performance Metrics: The evaluation metrics of AI can be mainly divided into classification tasks and regression tasks according to the task types. For classification tasks, the primary evaluation metrics include accuracy, precision, recall, F1-score, and so on. For regression tasks, the primary evaluation metrics include MSE, mean absolute error (MAE), root MSE (RMSE), and so on, as shown in Table V.

2) AI-Assisted Wireless Communication:

What Is AI-Assisted Wireless Communication? Wireless networks are increasingly integrated with AI, leading to the development of intelligent wireless networks that encompass intelligent wireless architecture, intelligent wireless airports, and intelligent wireless applications utilizing wireless data and models. For instance, intelligent new airports will revolutionize the traditional modular airport design. By leveraging AI, these airports can mine and utilize multidimensional characteristics, such as resources, services, and users, enhancing the real-time performance, reliability, and security of the wireless network. Moreover, these systems will have the ability to self-learn and self-evolve in response to environmental changes. Intelligent wireless architecture will fully exploit the communication, sensing, and computing capabilities of nodes. By deploying these capabilities on the cloud and at the edge, the architecture will achieve robust network intelligence, thereby supporting a wide range of intelligent applications.

Reasons for Integration (The Demand for Network Efficiency and Security): 6G networks will involve large-scale device connections and massive data processing, necessitating real-time data management. This creates a demand for dynamic network management. AI, as a powerful data analysis tool, can handle large-scale and complex data, aiding in efficient network management [23].

Transformation of Resource Management: Resource management in future wireless networks will undergo a significant transformation. Traditional resource management approaches will be inadequate to meet the stringent quality of service requirements in increasingly complex networks. AI offers a critical means for bottom-up resource coordination, enabling automated resource allocation from lower to upper network layers in 6G [20], [112].

The Enormous Potential of AI: AI is a key technology for 6G, essential for achieving "smart connectivity." Its application in wireless communications shows immense potential, particularly in solving complex, hard-to-model problems. AI will support ubiquitous AI services from the core to the network edges [113]. AI can significantly contribute to the design and optimization of 6G architectures, protocols, and operations. AI-assisted physical layers demonstrate substantial potential in future wireless systems, including areas like channel coding and intelligent signal recognition [114].

How to Study AI-Assisted Wireless Communication? There is extensive research on AI-assisted communication, covering areas, such as network design, resource management, and allocation [115]. For instance, Dogra et al. [116] implemented user-optimal power allocation using RL. They optimized the power allocation process based on application requirements, achieving intelligent allocation and enhancing network energy efficiency. Lee et al. [117] applied machine learning for channel selection in underwater IoT. Given the harsh environment of underwater communication compared to terrestrial communication, machine learning helps intelligently select the medium and bandwidth for communication through training, thereby improving performance. In beam management, Chen et al. [118] explored a deep-learning-based partial codebook scanning beam training method to reduce the overhead associated with traditional beam selection. Their method directly outputs beamforming weights by maximizing attention metrics (e.g., received SNR), thus improving beamforming gain. Bai and Peng [119] addressed the guide frequency overhead problem in massive MIMO systems by proposing a deep-learning-based channel estimation framework for millimeter-wave massive MIMO systems. They designed an unlabeled loss function and demonstrated its convergence. Lu et al. [120] applied deep learning to a relay-assisted communication collaboration system, introducing DNNs into the communication system design to represent transmit and receive functions. This approach interprets the entire system as a self-encoder and optimizes it through data training.

Different AI algorithms offer solutions for various wireless communication challenges. Deep learning provides new approaches for network channel modeling in wireless

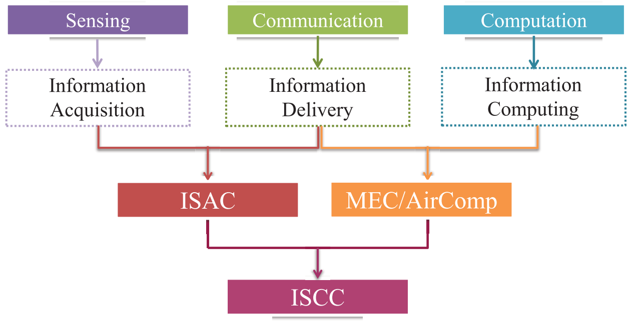

Fig. 6. Schematic of the functions and interactions of ISCC internal elements.

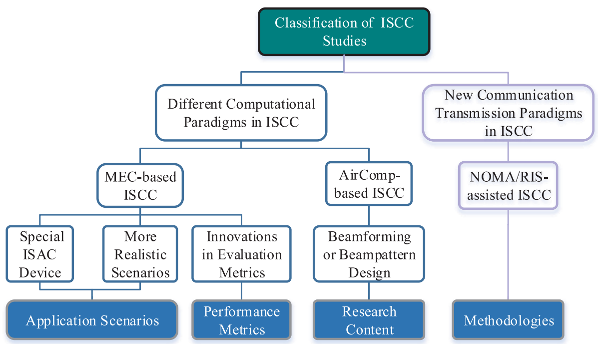

Fig. 7. Classification of ISCC studies.

communication, helping to meet the requirements for unknown channel modeling and low latency [21]. CNNs can handle complex signal-processing tasks [19]. RL has significant advantages in resource management and access control, offering autonomous decision-making capabilities for complex and dynamic wireless networks [121]. AI fully leverages its intelligent capabilities in wireless networks, progressively transforming traditional communication into intelligent communication.

III. Emerging Research in ISCC

In Section II, we have described the components and key technologies of ISCC. Fig. 6 illustrates the functions and interactions of ISCC internal elements. The ideal ISCC network of individual intelligent devices achieves collaborative communication, multidimensional sensing, and deep integration of computational functions through the collaborative sharing of hardware and software resources. This enables the network to interact and process information intelligently, ultimately realizing the connected intelligence of 6G. To achieve these capabilities, frontier practitioners have conducted extensive ISCC-related research. In Section II, we discuss the key technologies (ISAC and ICAC) that constitute ISCC, with MEC and AirComp being essential technologies for ICAC and critical to the realization of ISCC. Nonorthogonal multiple access (NOMA) and RIS, as emerging communication transmission paradigms, can enhance the communication performance within ISCC and provide new insights for future 6G research by integrating these novel technologies. In ISCC research, different computational paradigms lead to distinct

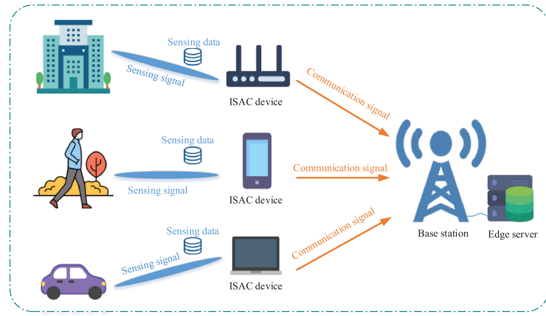

Fig. 8. Schematic of MEC-based ISCC.

optimization focuses. Therefore, this section first discusses MEC-based ISCC and AirComp-based ISCC, differentiating them according to their respective computational paradigms. Second, it explores research on new communication transmission paradigms within ISCC systems. As shown in Fig. 7, discussions are made from different dimensions according to the research characteristics of each paradigm, providing a reference for future researchers adopting relevant technologies in their studies. The types of studies and performance metrics are summarized in Table VI.

A. MEC-Based ISCC

MEC technology can leverage the computing power distributed at the edge of the network to assist mobile devices with limited computational resources. In a MEC-based ISCC system, MEC technology aids ISAC devices with insufficient computational power to process sensory data or assists other users in the region with computational tasks. Research in this system focuses on computation offloading strategies and system resource allocation. The MEC-based ISCC system is illustrated in Fig. 8. The main workflow of the system is as follows. First, devices with communication and sensing functions sense the surrounding area and gather relevant data. Second, computational tasks are allocated based on the offloading strategy (binary offloading and partial offloading). Finally, the communication function of the ISAC device is used to send tasks that require computation by the edge server to the base station where the edge server is located.

1) Special ISAC Device: The UAV equipped with an ISAC system can provide greater flexibility for the ISCC system. For communication and sensing, the UAV can adjust its position to obtain better sensing information and enhance communication performance. For computation, the UAV's mobility allows it to offload tasks to the edge server more efficiently. However, the system faces more stringent energy consumption constraints due to the UAVs. To balance the energy consumption of UAVs and the performance of the ISCC system, relevant research has been conducted in [122] and [123].

Liu et al. [122] investigated the joint optimization problem of beamforming precoding design (including both communication and perception components) and UAV positioning in ISCC systems to minimize sensing pattern error and the weighted sum of UAV energy consumption. The performance of communication (computational offloading capability) and sensing is enhanced by beamforming precoding design, which

TABLE VI
TYPES OF RESEARCH AND METRICS OF CONCERN

Reference		[122]	[123]	[85]	[124]	[125]	[126]	[84]	[127]	[128]	[129]	[130]
Classification	Precoding design	✓		✓								
	Sensing scheduling		✓									
	Computation resource allocation			✓							✓	
	Bandwidth resource allocation				✓							
	Device association					✓						
	Subchannel assignment					✓						
	UAV trajectory optimization	✓	✓									
	User selection				✓							
	Beamforming design							✓	✓	✓	✓	✓
	Computation policy				✓		✓					
Communication Metrics	Achievable data rate	✓		✓	✓	✓	✓	✓			✓	✓
	Throughput		✓									
	Data transmission delay	✓				✓	✓					
	Transmission energy consumption	✓	✓	✓	✓		✓					
Sensing Metrics	Beampattern	✓								✓		
	Minimum radar detection range	✓										
	Estimation information rate		✓									
	Sensing data size	✓	✓	✓	✓	✓						
	Average interference-to-noise ratio			✓								
	Mutual information					✓						
	Sensing MSE								✓			
	Sensing SINR										✓	✓
	Weighted sum-rate of sensing signals							✓				
	Successful sensing possibility						✓					
	Sensing time						✓					
	Sensing energy consumption	✓	✓	✓	✓		✓					
Computation Metrics	Computation delay	✓		✓	✓	✓	✓					
	CPU cycles	✓		✓	✓						✓	
	Task processing density	✓		✓								
	Computation frequency	✓		✓	✓						✓	
	Data ratio	✓		✓								
	Model training error		✓									
	Computation rate										✓	✓
	Computation energy consumption		✓	✓	✓		✓				✓	✓
	Computation MSE							✓	✓	✓		

is correlated with the system's transmit energy consumption. To solve the joint optimization problem and balance sensing performance with computational energy consumption, the authors decompose the original optimization problem into a data offloading subproblem and a sensing subproblem to be solved separately. For the data offloading subproblem, an AO algorithm is employed to solve the communication precoding and UAV positions, transforming the nonconvex optimization problem using fractional programming (FP) and successive convex approximation (SCA). The solution process for the sensing subproblem is similar to that of the data offloading subproblem. This article focuses on UAV signal transmission energy consumption and computational energy consumption, while ignoring UAV flight energy consumption, and it considers perception for a single sensing target.

Similarly focusing on the balance between UAV energy consumption and sensing performance, Huang et al. [123] considered flight energy consumption but do not account for UAV computational energy consumption, as the data obtained from sensing is only sampled without further processing. The authors focus on scenarios with multiple perception targets, selecting one target for sensing in each time slot. The selection of a sensing target is an optimization metric due to this single-target selection per time slot. Additionally, the collection time of sensing data (number of time slots) is considered, as it affects the amount of sensing data and the error in the final model training. The metric for evaluating sensing performance is the radar estimation information rate, suitable for scenarios where sensory data is used for machine learning training. The optimization problem aims to minimize the weighted sum of UAV energy consumption and data collection time, and optimize system performance by jointly optimizing the scheduling of sensing, the energy consumption of sensing and communication, and the UAV's trajectory. This nonconvex optimization problem is solved using vertical decomposition, horizontal decomposition, and block coordinate descent methods.

Summary: UAVs as ISAC devices, combined with MEC technology, can realize ISCC systems. Their flight trajectory (position) and energy consumption are critical factors that can affect the performance of the ISCC system. MEC technology aids UAVs in processing sensory data, thereby reducing their energy consumption. Depending on the computational offloading methods, UAV energy consumption includes different elements (full offloading to the base station does not include local computational energy consumption, while partial offloading includes local computational energy consumption). The components of UAV energy consumption and the evaluation metrics for sensing performance are chosen based on the application scenarios.

2) More Realistic Scenarios: With the advantages of low cost and small size brought by ISAC, an increasing number of intelligent devices, such as cell phones, robots, automobiles, and drones, will adopt this technology in the future. In areas covered by a base station with multiple users, the overall system performance can be enhanced through comprehensive design, making the study of multiuser scenarios practically significant. Additionally, base stations equipped with edge servers offer extra computing power to assist users in processing sensory data. Similar to [122], Ding et al. [85] focused on optimizing transmit signal precoding. In a multiuser scenario, designing precoding can mitigate signal interference between users while allocating communication and sensing power. Additionally, both users and edge servers have computational power, making the effective allocation of these resources crucial for processing sensed data. The authors consider a multiobjective optimization problem aimed at minimizing radar beampattern error and offloading energy consumption. This is done to jointly optimize communication and sensing transmission precoding as well as computational resources. The optimization problem is nonconvex, and the authors use an iterative approach to obtain a suboptimal solution. The quadratic transform method is employed to address the nonconvex fractional term during the solution process, and the first-order Taylor expansion method is utilized to solve the variable coupling problem in the Frobenius-norm term.

In the above multiuser scenario, each user has their own sensing tasks, necessitating the processing of sensing data individually. In contrast, Li et al. [124] investigated the mobile crowdsensing scenario, where for a specific sensing task, the base station selects a portion of users to participate. In this scenario, the users are mobile, allowing them to cover a larger area. Similarly, in scenarios involving UAVs, mobile devices can adjust the UAVs' trajectories to achieve better perception. In the mobile crowdsensing scenario, user selection is a critical optimization index for completing the required perception task by selecting participating users. To effectively utilize limited bandwidth resources, an efficient bandwidth allocation strategy for the selected users is also necessary. Furthermore, the duration of different functions (sensing, communication, and computation) and transmit power are considered as optimization parameters in this article. This article examines two computational offloading methods: 1) binary offloading and 2) partial offloading, corresponding to different optimization equations. The optimization goal is to maximize the weighted sum of the amount of data processed by the task. For partial offloading, the optimization problem involves discrete variables and nonconvex optimization challenges. The authors simplify the optimization parameters based on the association between variables and decompose the problem into internal and external subproblems. They separate the discrete and continuous variables and solve the internal subproblems using an iterative algorithm. The binary offloading case follows a similar process but involves handling binary parameters. The authors address this parameter case-by-case, decomposing the optimization problem into subproblems similar to partial offloading.

Summary: In multiuser scenarios, interference between users is a key issue, which can be mitigated through precoding designs at the signaling level. Resource allocation between different users is crucial at the resource allocation level. In special multiuser scenarios like mobile crowdsensing, user selection also needs to be addressed. Ding et al. [85] focused on partial offloading, while Li et al. [124] considered both partial and binary offloading methods.

3) Innovations in Evaluation Metric: The integrated design in ISCC introduces competition between different functions, making it crucial to effectively utilize system resources to balance these functions. Each function in ISCC has distinct evaluation metrics, necessitating an evaluation metric that meets the overall requirements of the ISCC system. Zhao et al. [125] and Chen et al. [126] designed their own system evaluation metrics based on the specific needs of their scenarios.

Zhao et al. [125] employed utility theory from microeconomics, specifically using the Cobb–Douglas utility function to evaluate the system. This utility equation can capture conflicts between multiple optimization objectives and transform a multiobjective situation into a single-objective one, effectively solving the system evaluation problem in ISCC. The ISCC scenario studied in this article includes multiple base stations and multiple IoT devices, each with an intelligent application task requiring base station assistance for processing sensory data. To avoid interference between wireless channels, each device can only access one base station and one subchannel at most. Effective scheduling in this scenario is crucial for the system's final performance. The authors optimize the scheduling strategy (device association and subchannel assignment) with the goal of maximizing the utility function. They use matching theory, which can converge quickly, to solve the optimization problem.

Also focusing on IoT scenarios, Chen et al. [126] addressed the state update of the system. Given that state update tasks are computationally intensive and IoT devices have limited computational resources, the use of MEC techniques can help IoT devices overcome these challenges. Additionally, measuring the timeliness of system state updates is crucial. The Age of Information (AoI), a popular metric in recent research, is used to measure the freshness of generated state information. The smaller the average AoI, the fresher the information. The authors derive the AoI formula in this ISCC system in detail, aiming to minimize the weighted system average AoI and energy consumption. They achieve a tradeoff between AoI and energy consumption by optimizing the sampling interval, sensing time, and computation offloading.

Summary: Zhao et al. [125] used a unified metric (utility equation) to measure the performance of the ISCC system, incorporating three functional metrics: 1) communication; 2) sensing; and 3) computation. This allows for effective tradeoffs among these functions. In contrast, Chen et al. [126] proposed using AoI as a performance metric, tailored to the specific needs of their research scenario. The authors classify the sensing situation into sensing success and sensing failure, where failures require resensing or using the next stage's sensing information, making AoI more appropriate compared to the delay metrics used in other studies. Although the above articles have selected evaluation metrics suitable for their scenarios, a unified evaluation metrics remains a key focus in ISCC research. The applicability of this unified metric needs to be analyzed at a theoretical level.

The above papers are summarized in Table VII.

B. AirComp-Based ISCC

AirComp helps ISAC devices process massive amounts of computational data. Unlike MEC, which sends data to the

TABLE VII
SUMMARY OF LITERATURE ON MEC-BASED ISCC

Optimization problems	Constraint	Methods	Scenario	Reference
Joint optimization of radar beampattern and UAV energy consumption	Maximum transmit power constraint; minimum radar detection range constraint; the task processing delay constraint	FP, SCA	UAV-assisted	[122]
Minimize UAVs energy consumption and the data collecting time	Model training error, radar sensing performance	Block coordinate descent, SCA	UAV-assisted	[123]
Minimize radar beam pattern error and the offloading energy consumption	Power constraint, delay constraint, computing resource constraint	FP, first-order Taylor expansion, Lagrangian dual method, multidimensional quadratic transform method, interior point method	Multi-user	[85]
Maximize utility function	The respective performance limits of communication, sensing, and computation, each IoT device can only be matched with at most one unique and unused BS-subchannel pair.	Matching theory	Multiple base stations	[125]
Maximize the total number of bits processed in the task, or weighted sum of computation bits	Time sensitive sensing tasks, energy limitation, wireless bandwidth, user selection constraint, the transmit power constraint.	Iterative algorithm, dynamic programming	Mobile Crowdsensing	[124]
Maximize the average AoI and energy consumption	Sensing time, sampling interval, successful sensing probability, data size.	Block coordinate descent, game theory	Mobile Crowdsensing	[126]

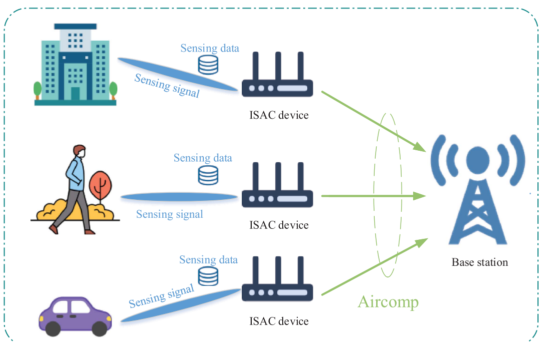

Fig. 9. Schematic of AirComp-based ISCC.

edge server for processing, AirComp utilizes the additive property of analog waveforms in multiple access channels. This allows the transmission signals of multiple ISAC devices to be superimposed over the air and aggregated into a weighted sum at the receiving end. As future intelligent applications increasingly emphasize data aggregation, the superposition characteristics of AirComp align well with the data processing needs of these applications. Additionally, the parallel transmission characteristics of AirComp can significantly reduce transmission delay, particularly when there are a large number of devices, making this advantage even more pronounced. In the AirComp-based ISCC system, the primary focus is on minimizing the error in the data received by the receiver after AirComp-based transmission. The schematic is shown in Fig. 9.

1) Beamforming or Beampattern Design: In order to minimize the error of data transmitted through AirComp technology, [84] and [127] investigate beamforming design at both the transmitter of the device and the receiver of the base station, as the calculated distortion can be represented by the transmit and receive beamforming matrices. Additionally, [128] focus on radar beampattern design in the ISCC system, and also examines the AirComp receive beamforming matrix design.

Qi et al. [84] focused on AirComp-based ISCC systems, where IoT devices send sensing and computing signals, and the base station receives both. The superposition characteristics of the channel affect these two types of signals differently. For sensing signals, the data from a single device needs to be separated from the mixed signals, and the overlay characteristic introduces interference. For computation, the base station requires aggregated data from multiple devices to compute the signal, making the overlay characteristic beneficial. Similar to [85] and [122], the authors study the beamforming design of the system to mitigate interference. For AirComp functionality, MSE evaluation between transmitted and received signals is used, while for the sensed signal, weighted sum-rate evaluation is applied. The authors address two optimization problems: 1) minimizing computational error and 2) maximizing weighted sum rate, with optimization parameters for transmit and receive beamforming for computed and sensed signals, respectively. They use the AO algorithm to decompose the original nonconvex optimization problem containing coupled variables.

In the AirComp-based ISCC system studied in [127], the IoT device has transmitting and receiving antennas. The transmitting antenna sends sensing and computational signals, while the receiving antenna captures signals reflected from the sensing target. The sensed and computed signals share the transmitting beamformer, and the beamformer at the access point reception is used for data aggregation. The authors investigate minimizing the computational MSE and optimizing the transmit and receive beamformers under constraints of perceptual performance and transmit power. Unlike [84], which measures perceptual performance from the perspective of the signal, this article measures it in terms of the estimation error of the response matrix of the sensed target.

Summary: In the above AirComp-based ISCC studies, the beamforming matrix at the AirComp signal reception is optimized to reduce the transmission error of AirComp. The difference lies in the focus of the sensing performance concern.

TABLE VIII
SUMMARY OF LITERATURE ON AIRCOMP-BASED ISCC

Optimization problems	**Constraint**	**Methods**	**Scenario**	**Reference**
Minimize AirComp error	Power constraint, sensing quality constraint	SDR, gaussian randomization algorithm	AirComp, MIMO	[127]
Minimizing the AirComp error	Covariance matrix constraint	AO, projected gradient descent method	AirComp	[128]
Minimize calculation error and maximize weighted sum rate	The rate requirements of the sensing signals; the requirement of the computation error	SDR	AirComp, IoT	[84]

Qi et al. [84] analyzed the SINR and the weighted sum rate of the sensed signals from the perspective of signal transmission, using the weighted sum rate as the sensed performance index. Li et al. [127], on the other hand, approach from the perspective of the sensing target, using the response matrix of the sensing target to analyze the specific target and minimizing the estimation error of this matrix as the sensing performance index. Wang et al. [128] examined the beampattern in radar perception, analyzing both omnidirectional and directional radar beampatterns. Although these articles focus on different sensing metrics, these metrics can all be represented by the transmit beamforming matrix, emphasizing that the research on sensing performance centers on the transmit beamforming design. In summary, the transmit and receive beamformers are the key parameters for optimization in AirComp-based ISCC studies. The above papers are summarized in Table VIII.

C. New Communication Transmission Paradigm in ISCC

The future ISCC system will be deployed in a 6G-based wireless communication network, where it will need to address challenges, such as spectral resource shortages and energy constraints. Existing wireless communication research has proposed various new techniques to mitigate some of these 6G problems. ISCC researchers have analyzed and incorporated these advancements into their work. For instance, Qi et al. [84] and Wang et al. [129] addressed resource shortages during large-scale connectivity by conducting NOMA-assisted ISCC research. Additionally, Xu et al. [130] explored RIS-assisted ISCC to achieve user-side lightweight solutions.

1) NOMA/RIS-Assisted ISCC: In future 6G communication, existing multiple access technologies cannot meet the requirements of large-scale connections and low-latency communication simultaneously for certain application scenarios. NOMA technology is one solution to these challenges, achieving ultrahigh spectral efficiency. RIS, an emerging wireless communication technology, can dynamically control wireless signal propagation using programmable electromagnetic units. RIS can address signal fading and blind area coverage problems through its reflective properties and can also use its electromagnetic units to dynamically control wireless signal propagation and serve as a platform for signal transmission. By utilizing the arrayed electromagnetic units as information carriers (similar to quick response codes), RIS can further propagate information. Both NOMA and RIS are new transmission paradigms in wireless communication, which can be applied in ISCC systems to enhance their performance.

In NOMA-assisted systems, multiple users sharing a single resource block creates an interference problem. The NOMA-assisted ISCC system studied in [129] addresses this by organizing the system into three layers: 1) a terminal layer; 2) an edge layer; and 3) a cloud layer. In the terminal layer, users need to offload computational tasks while also sensing a target. The edge layer involves the base station emitting signals to sense the target, receiving computational tasks from users, and offloading these tasks to the cloud layer when it lacks sufficient computational power. The cloud layer performs the computational tasks offloaded by the base station. The user–BS link utilizes the uplink NOMA technique. To mitigate the interference problem, superposition coding (SC) is used at the user transmitter side, and successive interference cancellation (SIC) is used at the base station side. The SIC technique allows the base station to decode each user's computational task progressively before decoding the sensed echo signal. This approach ensures that the sensed active signal is not affected by the computational offload signal, thus reducing interfunctional interference. For the NOMA-assisted ISCC system with AirComp technology discussed in [84], the interference issue is addressed on a case-by-case basis. In terms of the sensing function, the co-channel interference from NOMA's resource multiplexing is detrimental because sensing requires extracting individual device perceptual signals from the mixed signals. However, for AirComp, this interference is advantageous since the computation function relies on aggregated data. To resolve the interference problem for the sensing function, the authors optimize the beamforming design at both the transmitter and receiver. This optimization aims to maximize sensing performance while meeting computational error requirements.

Xu et al. [130] studied the RIS-assisted ISCC system, where the RIS acts as a carrier of information, replacing the user's function of transmitting via the RF chain. Instead of the user sending communication information using the RF chain, the base station sends electromagnetic waves without information. These waves are then modulated by the RIS connected to the user. The base station receives the signal and reads the information modulated by the RIS. The information received by the base station from the user includes the data that the user needs to compute. Additionally, the signal sent by the base station performs the sensing of the target. In this system, the authors measure performance based on the data collection capability, indicating how much useful information the system can extract from the environment. To maximize the system's data collection capability, the authors optimize beamforming at the RIS, the transmit beamforming, and sense-receive beamforming at the base station, along with the computation and communication times. The final simulation results show that RIS performs well as an information carrier in terms of communication performance.

TABLE IX
SUMMARY OF LITERATURE ON NEW TECHNOLOGY-ASSISTED ISCC

Optimization problems	Constraint	Methods	Scenario	Reference
Maximize the computation rate	Communication-computation causality, sensing quality, total power	Weighted minimum mean square error (WMMSE)-based AO algorithm, alternating direction method of multipliers (ADMM)-based AO algorithm	NOMA assisted	[129]
Maximize weighted throughput capacity	Transmitting power budget, the complex reflection coefficient, receiving beamforming, energy, time, user scheduling	Linear programming, FP, integer programming and AO	RIS assisted	[130]

Summary: In NOMA-assisted ISCC systems, research has focused on how to effectively mitigate or utilize the interference problem caused by resource sharing. This problem can be mitigated through beamforming design or transformed into a benefit by employing AirComp technology. In RIS-assisted ISCC systems, research aims to make the system performance of RIS as a message carrier comparable to that of users transmitting their own messages. This involves optimizing the beamforming design of both the RIS and the base station. Besides being a message carrier, the reflective function of RIS can also enhance communication performance in ISCC, as investigated in the corresponding article in Section IV. The above articles are summarized in Table IX.

IV. Joint ISCC and AI

ISCC and AI can leverage their respective strengths to mutually enhance performance. On one hand, the intelligence requirements of 6G necessitate AI to analyze vast amounts of data to achieve environmental intelligence. AI performance hinges on computational power and data quality, where computational power is tied to resource allocation, and data quality depends on both sensing and communication functions (data offloading). Hence, the communication, sensing, and computation aspects of the entire system need to be considered comprehensively. By addressing issues, such as resource allocation and computation offloading in ISCC systems, AI performance can be significantly improved. On the other hand, intelligent data processing and decision-making are crucial for realizing a fully intelligent system. In ISCC systems, resource allocation and computation offloading decisions can be driven by AI, such as using RL to optimize these processes, leading to AI-assisted intelligent ISCC. Therefore, this section is divided into two parts: 1) design ISCC to accelerate AI and 2) AI-assisted intelligent ISCC. The focuses of these two directions are summarized through the analysis of specific papers.

A. Design ISCC to Accelerate AI

Due to the proliferation of IoT devices, a large amount of data is generated at the edge of the network. To achieve intelligent systems with high reliability and low latency, the training and inference tasks traditionally handled in the cloud are moved to the network edge, known as EL. This section focuses on enhancing edge AI performance by holistically designing the ISCC system. Depending on the AI training structure, EL can be categorized into distributed training and centralized training. FL, a model of distributed training, involves training the model on the device and uploading the model parameters to a server for aggregation. When implemented at the edge of the network, this approach is known as FEEL. On the other hand, centralized training involves uploading local data to an edge server for unified training and inference, known as centralized EL when implemented at the network edge. This section will present studies on ISCC-facilitated FEEL and centralized EL, respectively. The schematic is shown in Fig.10.

1) ISCC-Accelerated FEEL: The model training of FEEL is executed cooperatively by the edge device and the edge server. First, the edge server broadcasts the global model. Then, the edge device uses the local data for model training and uploads the updates to the edge server. Finally, the edge server performs the model aggregation, completing one round of training. The training process concludes when the required minimum error is achieved through multiple rounds of training. In previous FEEL studies, the data acquisition has often been assumed to be a given. However, the acquisition of sensory data is also a crucial process in future intelligent systems. Tang et al. [131] and Liu et al. [132] analyzed this process from the perspectives of sensing success probability and perceived power, respectively. Additionally, model aggregation is vital for FEEL, and Qi et al. [133] and Zheng et al. [134] have combined AirComp technology to explore relevant research.

The wireless transmission environment, such as the presence of occlusion, affects the success of sensing. Tang et al. [131] investigated the impact of the probability of successful sensing on FEEL training. The convergence of the FL model is related to the number of participating devices; only successfully sensed devices can be locally trained and participate in global model aggregation. In this study, the devices are UAVs, which facilitate data collection for the FEEL model. In a UAV-assisted FEEL system, the success of sensing and communication performance is influenced by the deployment of UAVs, making the location of UAVs one of the optimization objectives. The time required for model training in FEEL is an important metric for measuring model performance. The authors aim to minimize FEEL training time by optimizing the batch size, communication bandwidth, and UAV locations. The resource allocation in the ISCC system affects FEEL model performance, but there is a lack of corresponding theoretical analysis. Liu et al. [132] analyzed the impact of perceived signal transmit power on perceived quality and provide guidance for the rational use of system resources. The case study focuses on human motion recognition, using spectrograms to analyze Micro-Doppler features of motion. The authors find that spectral quality is related to perceived

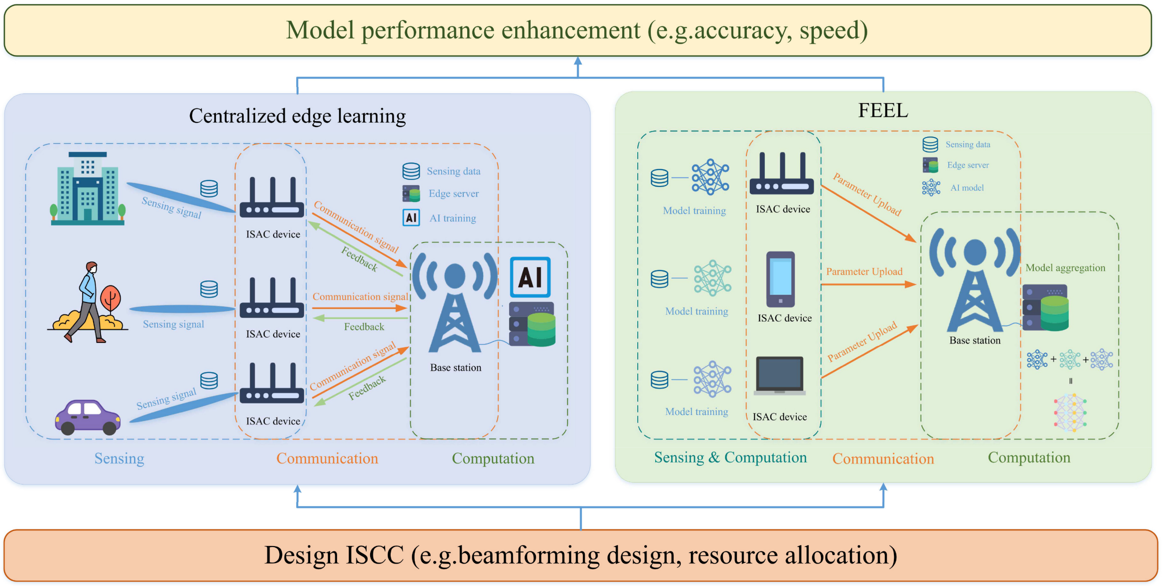

Fig. 10. Improve AI performance by designing ISCC.

transmit power; higher transmit power results in more useful information in the spectrogram. However, due to higher order clutter, there is a threshold for the effect of transmit power on spectral quality. Beyond this threshold, increasing power results in minimal enhancement, so transmit power should be kept below this threshold to avoid unnecessary energy consumption. The goal of training in FEEL is to seek a model that minimizes the objective loss function, but there is no exact expression for this problem. Therefore, the authors convert the problem to an upper bound on the mean gradient paradigm. They derive an upper bound on the error related to batch size; a larger batch size results in a smaller upper bound on the error, indicating faster convergence. The problem of minimizing the objective loss function is solved in two steps: first, maximizing the total batch size given power and delay constraints, and second, maximizing convergence speed by optimizing the batch size of each round when the optimal total batch size is known.

The technique that combines AirComp and FL is called AirFL. FL trains models on edge devices that require uploading model parameters for aggregation, a key step in achieving FL. AirComp, with its unique properties, can be used as a framework for fast model aggregation in FL because the computation functions it implements, such as weighted sums, are required on average by FL models. To minimize FL function distortion, AirComp aggregation errors need to be minimized. The scenario studied in [133] involves multiple sensors and a base station with multiple antennas to achieve multitarget sensing, multiuser communication, and AirFL. Target sensing parameter estimation is performed at the base station, in the form of bi-static sensing. The estimated MSE of the target reflection coefficient is used as the evaluation index for sensing, and images are used to demonstrate the importance of MSE on target imaging quality. For communication information transmission, SINR is selected as the evaluation metric. In AirFL, multiple sensors cooperate to train a global model, and the aggregated MSE of AirComp is used as the evaluation metric, demonstrating its impact on computational accuracy in AirFL image recognition. In this integrated system, different types of signals interfere with each other, but signals of the same type may assist each other. Therefore, the authors design the transmit and receive beamforming of the system to reduce interference between different functions and increase the mutual aid gain of similar signals, ultimately maximizing the performance of the integrated system. The issue of user participation in FL is addressed in [134]. For FL, more user participation improves the model's training effect, but communication performance limitations mean only a portion of users can participate in each training round. AirComp can transmit simultaneously and utilize the principle of wireless channel superposition to alleviate this issue. Additionally, RIS is added to address channel fragility and improve FL performance. The authors maximize the number of participating users by optimizing beamforming and RIS phases under the constraints of AirComp error and sensing error.

Summary: To make FEEL converge faster and more effectively, it is essential to systematically analyze the sensing, communication, and computation processes during training and identify the performance indexes related to FEEL for optimization. For instance, the sensing probability is related to the number of participating users, the perceived transmit power affects sensing quality, the communication bandwidth influences the upload speed of the model, and AirComp impacts the aggregation performance. By optimizing these relevant metrics within the ISCC system, such as reducing training time, increasing convergence speed, or minimizing aggregation error, the performance of FEEL can be improved under power and delay constraints. Through careful design, ISCC helps reduce latency and energy consumption during FEEL training and deployment, which is crucial for real-time autonomous driving systems and energy-efficient IoT applications. Additionally, FEEL enhances user data privacy protection.

2) ISCC-Accelerated Centralized EL: Centralized EL training via edge servers is a common research framework where edge devices send sensed data to edge servers via a communication link for AI model training and inference. Compared to FEEL, the centralized EL architecture can alleviate the computational pressure on edge devices, but it requires higher communication performance because a large amount of sensed data needs to be uploaded. In addition to edge devices performing sensing, the base station can also emit sensing signals. The data sensed by the base station can be processed directly in the edge server equipped in the base station, eliminating the need for sensing data transmission. The base station equipped with an edge server can provide computation services to users in the area. Therefore, it is important to analyze and optimize the processes in ISCC for centralized EL training.

The ISCC system studied in [135] realizes the sensing function through the base station and simultaneously provides computational services to edge devices. The authors design a new sensing framework based on the characteristics of sensing tasks to help the system reduce resource consumption. Specifically, for the task of detecting the motion state of a target, to reduce resources consumed by subsequent data processing, static object data will not participate in the CNN-based target classification process. The increase of high-frequency components in the signal can indicate object motion, and the power of these components can be obtained by FFT transforming the sensed signal. Whether the target is in motion can be determined by setting a power threshold. Sensing accuracy and delay are used as metrics for evaluating system performance. The authors derive expressions for perception accuracy and delay in terms of the sampling rate, related to the power threshold, in probabilistic form. In addition to sensing tasks that consume base station computational resources, edge devices also have computational tasks that require base station assistance, making resource allocation important. The authors propose an optimization problem aimed at maximizing sensing accuracy to optimize the sensing threshold, sampling rate, and computational resources under delay and resource constraints. Unlike other articles that verify algorithm performance through simulation, this study uses real experimental data to validate the framework and the effectiveness of the algorithm.

Summary: In the centralized EL system, AI models need to be trained at edge servers. The accuracy of the trained model and the training latency are the key metrics for evaluating the system. The quality of sensory data and computational resource allocation affect the model's accuracy. From the sampling perspective, the sampling rate influences the quality of sensed data. From the power allocation perspective, higher perceived transmit power results in higher data quality. From the resource allocation perspective, more computational resources lead to higher model accuracy and lower training latency. These are common optimization directions in ISCC system optimization. Additionally, designing the ISCC framework according to the characteristics of specific AI training tasks can further improve system performance.

3) ISCC-Based Edge Inference: Previously, we introduced how ISCC accelerates FEEL and Centralized EL, with a primary focus on the model training phase. However, ISCC also plays a crucial role in the model inference phase. Studies, such as [136] and [137], investigate AirComp-based edge inference systems, while [138] and [139] focus on device selection and inference method selection in ISCC-based edge inference, respectively.

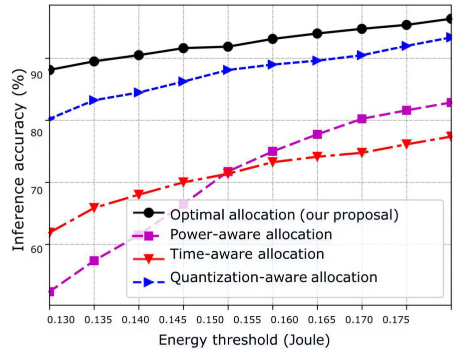

Fig. 11. Performance comparison of SVM among different schemes [140].

Wen et al. [136] investigated an AirComp-based edge inference system. To achieve real-time and high-precision inference tasks, the study designs an ISCC system comprising multiple ISAC devices that enable multiview sensing. The sensed data undergoes feature extraction and quantization at the device level before being simultaneously transmitted using AirComp technology. The aggregated data is then processed at the edge server for inference. In Section III, MSE is used as the evaluation metric for AirComp-based ISCC research. However, [136] focuses on maximizing inference accuracy and formulates an optimization problem to maximize discriminant gain by optimizing both transmit and receive beamforming. While [137] follows a similar architecture to [136], it selects the minimization of pair-wise discriminant gain as the inference performance metric. This metric measures the minimum distance between any pair of classes in the feature space, ensuring a more balanced inference accuracy across all classes.

Wang et al. [138] investigated multitask edge inference with the goal of maximizing overall inference accuracy. In this ISCC framework, multiple ISAC devices are selectively assigned to different tasks based on their sensing perspectives. Consequently, device scheduling emerges as a key optimization challenge. The three edge inference paradigms (on-device inference, on-server inference, and edge-device co-inference) offer distinct advantages and are suitable for different application scenarios. To address the limitations of fixed inference approaches, Liu et al. [139] proposed an ISCC-based edge inference framework that dynamically selects the optimal inference strategy based on varying network conditions. By adaptively choosing the most appropriate inference model, the framework seeks to optimize energy efficiency while maintaining the required inference accuracy and resource constraints.

Summary: Designing an ISCC framework for efficient edge inference tasks is feasible. In this scenario, the primary focus is on optimizing resource allocation within ISCC to achieve the best inference performance in terms of inference time, energy consumption, and accuracy. Since these studies

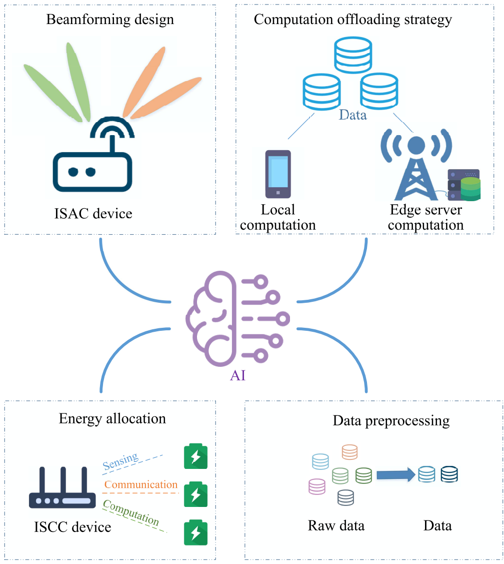

Fig. 12. Schematic of AI-assisted intelligent ISCC.

target general AI inference tasks, discriminant gain is selected as the evaluation metric. Additionally, the aforementioned studies assess the correlation between inference accuracy and discriminant gain, demonstrating the effectiveness of this metric for evaluating inference performance. By optimizing ISCC resource allocation or beamforming design, low latency and low energy intelligent services can be realized at the network edge. As shown in Fig. 11, the results in [140] demonstrate the superiority of the proposed ISCC framework and algorithms, laying the foundation for future deployment of intelligent 6G edge networks.

The above-mentioned literature related to ISCC-accelerated AI is summarized in Table X.

B. AI-Assisted Intelligent ISCC

In the pursuit of high-precision perception, efficient communication, and precise computational capability in ISCC systems, dynamic and complex environments make manual management difficult, and AI becomes an enabling technology to ensure the capability of ISCC systems. AI algorithms, including unsupervised learning, supervised learning, and RL, have achieved outstanding results in many fields due to their respective advantages. By applying these different AI algorithms to various parts of the ISCC system, the overall performance can be significantly improved. The following three sections introduce the different AI methods and their roles in ISCC: 1) unsupervised learning for data preprocessing; 2) supervised learning for model inference; and 3) RL for intelligent decision-making. The schematic is shown in Fig. 12.

1) Unsupervised Learning for Data Preprocessing: Unsupervised learning is a method for exploring the intrinsic properties of data. Typical unsupervised learning techniques include dimensionality reduction and clustering, both of which simplify the overall data into a smaller number of representative parts, albeit through different mechanisms. When data dimensionality is high, not all dimensions contain useful information. Therefore, we aim to find a set of low-dimensional data that retains as much information as possible from the original datałthis process is known as dimensionality reduction, with PCA being a common tool for this purpose. Clustering, on the other hand, identifies subgroups within a dataset. The process of clustering involves partitioning the dataset into distinct groups, where data points within the same group are very similar, and data points from different groups are very different. K-means is a fundamental method used in clustering.

Wen et al. [140] and Zhuang et al. [141] utilized PCA to process raw data and reduce data dimensionality. Specifically, the scenario studied involves an edge inference task where edge devices and edge servers collaborate. In this ISCC system, the edge device acquires raw sensory data through the sensing function, which needs to be uploaded to the edge server for inference tasks. Since the subsequent inference task focuses on the features of the data rather than the raw data, sending the raw data directly to the edge server incurs significant communication overhead. Given the advantages of unsupervised learning, applying the PCA method at the edge device and transmitting smaller sized feature data instead of raw data to the edge server for inference can reduce communication overhead and protect the privacy of the edge device.

Liu et al. [144] employed the K-means method for task categorization to increase the efficiency of ISCC system task processing. The study focuses on the fusion of sensory data from RSUs and vehicles in Telematics. Originally, the fusion task was performed on the vehicle side, but due to limited computational resources, an offloading strategy (local computation or offloading to available nodes) must be determined based on the task. To improve task processing efficiency, the authors use K-means for task classification to determine whether to offload the data fusion task based on the computational and latency constraints of each task.

Summary: Unsupervised learning is suitable for ISCC system optimization preprocessing. After the sensing stage, the acquired sensing data undergo dimensionality reduction, reducing both communication transmission overhead and later computation overhead. Additionally, unsupervised learning can be applied to categorize computational tasks before they are processed, enabling the system to allocate resources more efficiently according to task types.

2) Supervised Learning for Model Inference: Supervised learning involves model training using labeled data, typically class labels in classification problems, enabling the trained model to classify unlabeled data. Mathematically, this process is about finding a mapping relationship between input and output variables to predict the output of unknown data. Widely used supervised learning methods include SVM and multilayer perceptron (MLP). In ISCC systems, classifying perceptual data is an important research goal, and models trained with supervised learning methods can achieve this classification effectively.

Wen et al. [140] and Zhuang et al. [141] used SVM and MLP as inference models to verify the effectiveness of their proposed algorithms. Specifically, these articles investigate AI

TABLE X
SUMMARY OF LITERATURE ON ISCC-ACCELERATED AI DESIGN

Optimization Metrics	Optimization Objectives	Calculation Type	AI method	Algorithm	Reference
Beamforming and phase-shift matrix of IRS design	Maximization problem of the number of participating clients	AirComp	FL	AO and difference-of-convex	[134]
Beamforming design	Weighted overall performance maximization; total transmit power minimization	AirComp	FL	AO, QCQP, inter-point method, SDR	[133]
UAV deployment and resource allocation	FEEL training time minimization	MEC	FEEL	AO	[131]
Resource allocation	Maximize the convergence speed of FEEL	MEC	FEEL	One-dimensional grid search	[132]
Resource allocation	Sensing accuracy maximization	MEC	CNN	AO	[135]
Beamforming design	Maximize discriminant gain	AirComp	SVM, MLP	SCA	[136]
Beamforming design	Maximize the minimum pair-wise discriminant gain	AirComp	SVM, MLP	SCA	[137]
Device scheduling, quantization gain, resource allocation	Maximize the discriminant gain of all tasks	MEC	CNN	AO, greedy algorithm	[138]
Model selection, resource allocation	Minimize the energy consumption	MEC	SVM, MLP, CNN	AO	[139]

inference task with human motion recognition as an example. Since the instantaneous accuracy of inference is unknown and cannot be analyzed using a mathematical model, the authors use a similar discriminant gain as a substitute for this specific study. To maximize inference accuracy, the discriminant gain is maximized as the optimization objective to allocate system resources appropriately. To verify the validity of this index, trained SVM and MLP models are used for task inference. The results show that as the discriminant gain increases, the inference accuracy of both SVM and MLP also increases.

Summary: Deploying trained machine learning methods on edge devices or servers can quickly and efficiently lead to the final analysis of sensory data. However, before this deployment, the system needs to allocate resources using traditional optimization methods or the intelligent decisions described below.

3) RL for Intelligent Decision-Making: RL is an experience-driven autonomous learning behavior that learns optimal behavioral strategies mainly through interaction with the environment. In ISCC systems, the beamforming design and resource allocation problem involves adjusting design and allocation strategies in a timely manner based on the demands of system tasks. RL can be used to find these optimal strategies effectively.

Liu et al. [144] employed double DQN (DDQN) in DRL to obtain a computational node selection policy that minimizes the queuing delay of the system. Zhu et al. [142] employed the deep deterministic policy gradient (DDPG) method to derive policies for user selection, computational offloading rate, and UAV flight trajectory to minimize communication and computational latency. The scenario in [143] involves multiple UAVs and users, using the multiagent proximal policy optimization method to address the complex multiobjective optimization problem. The authors divide the problem into three policy optimizations: 1) offloading policy (offloading ratio and UAV association); 2) beamforming design policy (communication and sensing beamforming); and 3) UAV policy (mobility and computational resource allocation). Beta policy and attention mechanism are also applied in the training process to accelerate convergence. Yang et al. [145] used two

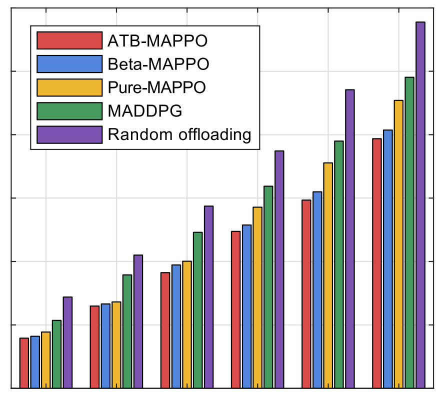

Fig. 13. Performance comparison versus different number of users [143].

methods based on the type of action space to collaboratively optimize the system policy. Specifically, this article optimizes the offloading policy and power allocation policy. Since the action space of the offloading decision is discrete and the action space of the power allocation decision is continuous, the DQN and twin delayed DDPG (TD3) methods are used to obtain the optimal policy according to the characteristics of each RL method.

Summary: In ISCC systems, RL is generally used in the intermediate strategy selection phase. Communication, sensing, and computation involve strategy optimization problems, such as beamforming design, computational offloading, power allocation, and UAV trajectory optimization. These complex nonconvex optimization problems can be solved using RL instead of traditional optimization methods. By selecting the appropriate RL method based on the properties of the optimization parameters during processing, effective solutions can be achieved. As shown in Fig. 13, the algorithm proposed in [143] achieves the best performance, resulting in the lowest weighted energy consumption for both UAVs and users. This research can be applied to future disaster relief scenarios. RL assists UAVs in optimizing flight trajectories while handling communication, sensing, and computing tasks, enabling precise and rapid search-and-rescue operations. The above articles are summarized in Table XI.

TABLE XI
SUMMARY OF LITERATURE ON AI-ASSISTED INTELLIGENT ISCC

Type of issue	Optimization objectives	AI method	Where AI is used	Technology involved	Application scenario	Reference
Sensing power assignment, transmit precoding and receive beamforming	Maximum minimum pairwise discriminant gain	PCA; SVM; MLP	Extracting a low-dimensional local feature vector; inference models; inference models	AirComp, edge inference	Human motion recognition task	[141]
Power assignment, communication time, and quantization bits	Maximum discriminant gain	PCA; SVM; MLP	Extracting a low-dimensional local feature vector; inference models; inference models	Edge inference	Human motion recognition task	[140]
Intelligent computation offloading and flight decisions	Minimize the total delay	DDPG	Computation offloading and flight decisions	MEC	UAV	[143]
Precoding matrix design, the association factor of users and computational resource allocation	Sensing beampattern, computation offloading energy consumption	Multi-agent proximal policy optimization	Precoding matrix design, the association factor of users and computational resource allocation	Digital twin, MEC	UAV	[144]
Joint computation offloading and resource allocation	Minimize the queuing latency	K-means, D-DQN	Computation offloading strategy	MEC, data fusion	V2X	[142]
Computation offloading and power allocation	Overall execution latency and overall conditional MI rate	DDQN; TD3	Computation offloading strategy; sensing and communication power allocation strategy	MEC	V2X	[145]

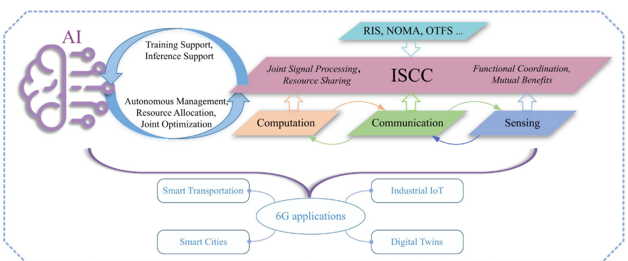

Fig. 14. ISCC and AI integration for advancing 6G.

V. CHALLENGES AND PROSPECTS

A. Challenges

1) How to Design Integration Metric: The metrics of concern for the three functions of communication, sensing, and computing are inherently inconsistent. Typically, each function's metrics are selected as optimization objectives or constraints in most articles. The design of integration should not only balance the individual indices of these functions but also create integrated parameters to evaluate the overall system performance. Additionally, theoretical studies should be conducted to validate the suitability of these integrated metric. One effective approach is to select evaluation metrics based on the specific application scenario. For example, in task-oriented edge inference scenarios, using discriminant gain as an evaluation metric has been proven effective in [137].

2) How to Deal With Complex Scenarios: Most current research focuses on simple scenarios, often considering sensing, communication, and computation at fixed locations. There is a lack of research on complex scenarios, such as those involving highly dynamic vehicle movements. In such scenarios, channels are more complex, making it difficult to capture environmental information. For sensing, it is crucial to capture environmental changes and obtain effective information in real time. For communication, ensuring the fast and effective transmission of sensory data in imperfect channels is vital. For computation, making fast and timely decisions based on environmental changes is essential. Addressing these challenges requires joint consideration of all three functions to provide optimal solutions. Consider more practical scenarios. For example, the study in [57] incorporates imperfect channels, providing insights for the real-world application of ISCC. In addition, real-world scenarios often involve a variety of device types, and the coordination among these heterogeneous devices as well as the processing of heterogeneous data represent important research directions. Furthermore, in 6G environments characterized by high-density, large-scale networks, reducing energy consumption overhead while maintaining performance is also a key focus of ISCC architectures. Some researchers have proposed device scheduling schemes and similar approaches to cut energy usage, which have proven to be viable solutions [138].

3) How to Design Hardware Devices: Much of the current research in ISCC is in the modeling and simulation phase, with few implementations of actual hardware devices. An integrated device must combine all three functions within a limited size and cost. The goal is to achieve integrated gains through integrated design, rather than merely aggregating hardware components. This requires considering the synergy between modules and balancing the needs of each function. Ultimately, ISCC research needs to be applied in real-world systems. The study in [139] validated actual hardware devices, proving the effectiveness of ISCC.

4) How to Protect Users' Privacy and Ensure Security: In an ISCC system, the cooperation between communication, sensing, and computation functions must be achieved.

However, there may be risks of data leakage during the exchange of information. For example, when transmitting sensing data to the server at the base station for inference, unauthorized users may eavesdrop, leading to the leakage of user information. Therefore, ensuring security while maintaining global cooperation and preventing data leakage is a critical issue. The addition of RIS or AI could potentially offer a solution to the problem [146]. RIS's reflective elements can be used to block unintended links, while AI can perform anomaly detection and predict potential attacks.

5) How Scalable Is ISCC: The scalability of ISCC technology is one of the key issues for its practical implementation. It is crucial to determine how ISCC can be deployed in existing networks and be adaptable to future 6G networks. Several studies have already explored this area. Qi et al. [84] investigated ISCC systems in B5G networks, while Xu et al. [130] combined promising technologies in 6G, providing insights for the application of ISCC in new 6G scenarios.

B. Prospects

1) Emerging Technology Applications: Emerging technologies can address several challenges faced by ISCC systems. For instance, the orthogonal time–frequency space (OTFS) approach is utilized to study high-speed dynamic vehicular networks, and applying this technology to ISCC systems is expected to alleviate the issues encountered in highly dynamic environments. Additionally, RIS technology is integrated into ISCC to mitigate poor channel states and help alleviate the interference problems associated with integration. In future 6G networks, an increasing number of intelligent devices will be deployed at the network edge, requiring efficient information processing under limited resources. This calls for research on ISCC systems tailored for edge AI. At the same time, edge AI can help edge devices intelligently manage resources and make action decisions. The joint research of ISCC and AI will contribute to the development of 6G, as shown in Fig. 14.

2) Multidevice and Multiserver Co-Design: The current ISCC architecture primarily involves intelligent devices perceiving data individually, with edge servers processing this data. In the future, the network will comprise an increasing number of intelligent devices, each equipped with communication, sensing, and computing functions. Base stations equipped with edge servers will also possess these capabilities. The design and research of intelligent network nodes will enhance the reliability and accuracy of terminals and base stations through unified coordination and management.

3) Smarter ISCC: Current AI-assisted ISCC technology employs AI techniques in specific areas, such as sensing data preprocessing and computational offloading. Future research can leverage AI methods to improve environmental understanding and adaptive resource allocation and scheduling based on environmental states. This will enable the automation and intelligent iteration of the network.

VI. Conclusion

ISCC and AI have garnered increasing attention as key research topics in 6G. This article begins by presenting the background and motivation for the research, highlighting the importance of ISCC research and the necessity of integrating AI. It also contrasts this work with other review literature. Following this, this article introduces basic ISCC concepts, explaining the idea of commensurate counting and its evaluation index. It then progresses to cover ISAC, ICSC, and ICAA, detailing the concepts, rationale, and research content to provide foundational technical support for ISCC research. This article then categorizes and discusses general ISCC research, analyzing specific related articles. Continuing the discussion on the synergy between ISCC and AI technology, this article explains how ISCC can be designed to accelerate AI model training and how AI can enable intelligent ISCC architectures. Finally, it summarizes the challenges faced by ISCC technology and explores future research directions.

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