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6G: From Theory to Practice—Article

Wireless Environmental Information Theory: A New Paradigm Toward 6G Online and Proactive Environment Intelligence Communication

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ABSTRACT

Channels are one of the five critical components of a communication system, and their ergodic capacity is based on all realizations of a statistical channel model. This statistical paradigm has successfully guided the design of mobile communication systems from first generation (1G) to fifth generation (5G). However, this approach relies on offline channel measurements in specific environments, and thus, the system passively adapts to new environments, resulting in deviation from the optimal performance. As sixth generation (6G) expands into ubiquitous environments and pursues higher capacity, numerous sensing and artificial intelligence (AI)-based methods have emerged to combat random channel fading. However, there remains an urgent need for a proactive and online system design paradigm. From a system perspective, we propose an environment intelligence communication (EIC) based on wireless environmental information theory (WEIT) for 6G. The proposed EIC architecture operates in three steps. First, wireless environmental information (WEI) is acquired using sensing techniques. Then, leveraging WEI and channel data, AI techniques are employed to predict channel fading, thereby mitigating channel uncertainty. Finally, the communication system autonomously determines the optimal air–interface transmission strategy based on real-time channel predictions, enabling intelligent interaction with the physical environment. To make this attractive paradigm shift from theory to practice, we establish WEIT for the first time by answering three key problems: How should WEI be defined? Can it be quantified? Does it hold the same properties as statistical communication information? Subsequently, EIC aided by WEI (EIC-WEI) is validated across multiple air–interface tasks, including channel state information prediction, beam prediction, and radio resource management. Simulation results demonstrate that the proposed EIC-WEI significantly outperforms the statistical paradigm in decreasing overhead and performance optimization. Finally, several open problems and challenges, including regarding its accuracy, complexity, and generalization, are discussed. This work explores a novel and promising way for integrating communication, sensing, and AI capability in 6G.

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1. Introduction

In 1948, Shannon published his seminal paper, "A mathematical theory of communication," in which he defined communication systems as comprising five components: information source, transmitter, receiver, destination, and channel. He initially described the channel as "the medium used to transmit the signal from transmitter to receiver. It may be a pair of wires, a coaxial cable, a band of radio frequencies, a beam of light, etc." [1]. It is evident that the aforementioned media are all physical elements. To consider certain general problems involving communication systems, he represented the various elements as mathematical entities—that is, random variables and statistical processes, idealized from their physical counterparts. Mobile communication uses "a band of radio frequencies" as the physical carrier, and its channel entity is stochastically modeled as Shannon's thought. Since the 1980s, mobile communication has undergone five generations of revolutionary evolution in services and techniques. Simultaneously, the radio channel, as the carrier entity of each generation of mobile communication, has undergone a dramatic expansion in the

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dimension and parameters of its statistical model, as illustrated in Fig. 1 [2–5]. Specifically, in first generation (1G), the channel was modeled as a time domain and one-dimensional random process, determined by a distribution of random variables, including key parameters such as the amplitude and phase of the multipath component (MPC). In the second generation (2G) era, the channel bandwidth increased, enabling the MPC to be resolved in one delay bin, and the classical tapped delay line (TDL) model emerged. This model involved two dimensions—that is, time and frequency, with delay as the added parameter. Around 1996, multiple-input multiple-output (MIMO) was developed, taking advantage of the spatial freedom of channels to increase system capacity. Then, the spatial channel model for third generation (3G) by the 3rd Generation Partnership Project (3GPP) and geometry-based stochastic model (GBSM) for fourth generation (4G) by the International Telecommunication Union (ITU) were standardized. These statistical models involved three dimensions (i.e., time, frequency, and horizontal angle), with the angles of arrival/departure at the azimuth plane as the added random parameters. Around the 2010s, the active antenna array captured the attention of researchers for its ability to flexibly realize three-dimensional (3D) beamforming, and a theoretical proof of 3D MIMO capacity increasing with the vertical MPC dispersion becoming larger was derived [6,7]. Then, the angles of arrival/departure at the vertical plane was introduced for the fifth generation (5G) channel model, and 3D-GBSM emerged as a model involving four dimensions—that is time, frequency, horizontal angle, and elevation angle [8,9].

This evolution of channel models from 1G to 5G illustrates the success of the statistical paradigm for mobile communication. However, past researchers have also realized that a purely statistical model cannot reflect different environmental influences, such as the building density, scatter types, and height of antennas. To overcome this, historically, an experimental method called the two-step method is widely used. First, measurements are implemented with a channel sounder, and the amount of data is collected in a typical mobile application environment. Second, the distribution of random parameters, such as delay, angle, and polarization, is fitted from channel impulse response (CIR) data. The parameters used to describe those distributions, including the mean and variance, are also given one by one for each environment. However, even though these two-step experiment-based statistical models are better than purely theoretical-based models and are mainstream in standardization, such as 3GPP TR 38.900/901 and ITU Radiocommunication Sector (ITU-R) M.2412 for 5G [10,11], they are still statistical models with limited types of test environments, such as urban macrocell (UMa), urban microcell (UMi), indoor hotspot (InH), and rural macrocell (RMa) [11]. Moreover, the data used for distribution fitting are collected offline. When those offline statistical models are used to design and test the performance of new techniques, systems passively adapt to the various new environments in practice, which often results in their deviation from the optimal performance. Furthermore, those statistical models cannot account for the real-time uncertainty of environmental influence, such as newly appeared buildings, vehicles, and bodies. The system performance will be degraded by those dynamic blockers, and the offline model will lead them to be blind to those variations. In all, the offline statistical model paradigm often requires significant amounts of both time and money for network optimization in real environments.

In June 2023, ITU-R defined the primary objectives and six typical application scenarios for sixth generation (6G). The new scenarios included integrated sensing and communication (ISAC), artificial intelligence (AI) and communication, and ubiquitous connectivity, in addition to the three expanded 5G scenarios [12–19]. With the further enhancement of data rates and capacities in 6G, traditional communication models face increasing challenges, particularly in ubiquitous environments. To combat the randomness of 6G channels, there is an urgent need for a new paradigm that adopts a more proactive and online approach. Fortunately, base stations and terminals in 6G are increasingly incorporating a diversity of devices, including industrial sensors, depth cameras, and millimeter-wave radar [20]. Earlier research has already considered the environment through sensing technologies. As an environment/map-based methodology (Fig. 1), the radio map (RM) became the focus of pioneering research by the Defense Advanced Research Projects Agency (DARPA) in the 1990s. In this

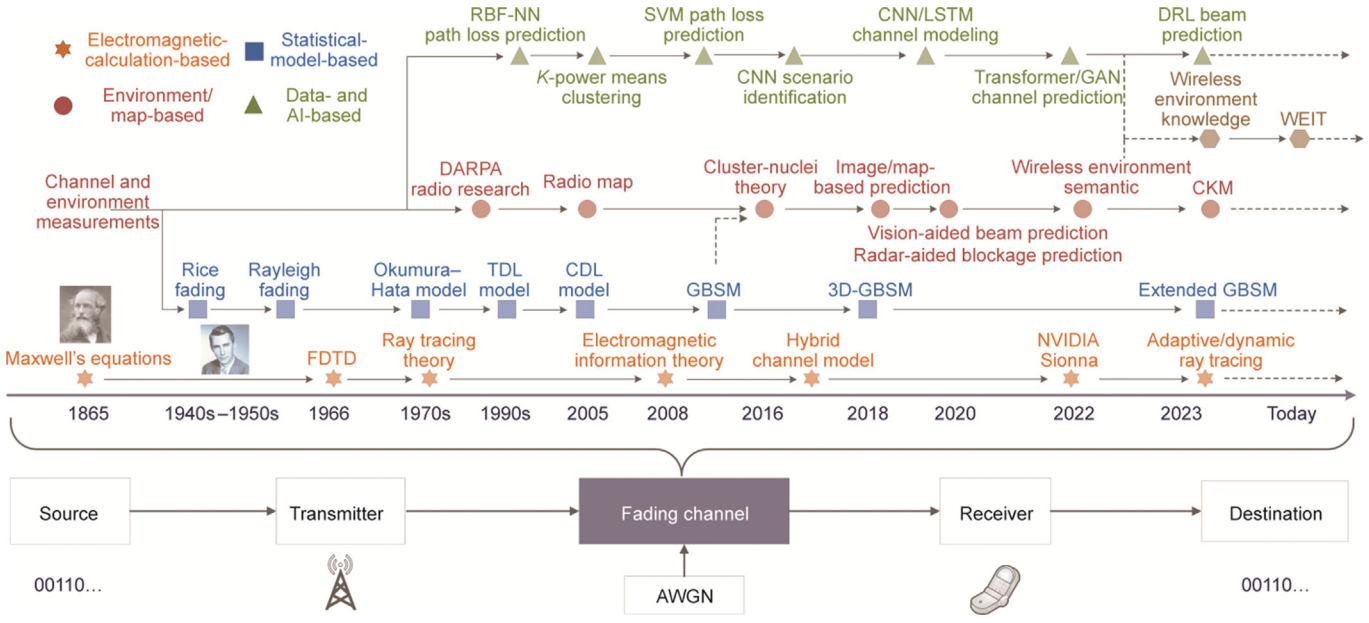

Fig. 1. Timeline of wireless channel research by different methodologies. AI: artificial intelligence; RBF: radial basis function; NN: neural network; CNN: convolutional neural network; SVM: support vector machines; LSTM: long short-term memory; GAN: generative adversarial network; DRL: deep reinforcement learning; WEIT: wireless environmental information theory; DARPA: Defense Advanced Research Projects Agency; CKM: channel knowledge map; TDL: tapped delay line; CDL: cluster delay line; GBSM: geometry-based stochastic model; FDTD: finite-difference time-domain; AWGN: additive white Gaussian noise.

method, the radio signal power is calculated based on grid map information systems with multiple sensor-equipped nodes, including vehicles, aircraft, and drones [21]. Depth camera images and computer vision (CV) techniques are also utilized to reconstruct real-time 3D environments, and then, stochastic clusters are matched with corresponding environment scatterers, forming semi-deterministic cluster-nuclei to improve the accuracy of the statistical channel model [22–25]. In addition, red–green–blue (RGB) images obtained by cameras are used to relate positions of scatter with mobility of terminal to achieve proactive beam selection [26]. Meanwhile, radar sensors can also be used to obtain information regarding the distance, velocity, and angle of moving objects, allowing the beam to avoid forward blockers [27]. In all, different sensing methods can be utilized to collect different kinds of environmental information to help the system "see" or "hear" the real-time varying environments. For generality, we define wireless environmental information (WEI) as referring to physical descriptions and properties (such as geometric size, mobility, and material types) scattered in the environment that, if taken into consideration, can help to eliminate channel uncertainty and affect MPC variation (such as phase, delay, and angle) for the wireless communication system. However, it should be asked: What kinds of information are involved? What properties does WEI have? Can we use entropy to quantize it? These urgent questions remain unanswered.

Meanwhile, with the rapid advancement and extensive spread of AI technologies, particularly machine learning (ML), it is expected that 6G will become more intelligent [19]. In particular, numerous research studies have introduced AI methods for combating channel uncertainty and randomness [28,29]. For example, a deep convolutional neural network (CNN)-based approach has been designed to predict path loss exponents and shadowing factors directly from two-dimensional (2D) satellite images [30]. An environment feature extraction module based on CNNs has been proposed to process panoramic environment images to predict accurate channel state information (CSI) with lower pilot overhead [31]. A channel knowledge map (CKM) has been proposed as a site-specific database, tagged with locations and channel-related information to facilitate CSI acquisition [32]. The aforementioned works have investigated the relationship between environmental information and channels via ML methods. However, to further improve system performance, specific transmission tasks should be considered. For example, in the task of beam prediction, environment semantics is abstracted to form an environment sensing, channel prediction, and task application loop [33].

Inspired by the progress thus far of integrating communication, sensing, and AI capability in 6G [34], in this paper, we first propose a new paradigm for 6G, which we refer to as environment intelligence communication (EIC). EIC involves three key steps: first, leveraging sensing techniques to acquire accurate and extensive environmental information; second, predicting channel variations based on WEI; and third, enabling the communication system to autonomously determine the optimal transmission strategy, achieving intelligent interaction. Through EIC, the 6G system is online and proactive to react to environmental uncertainty. To support EIC, the wireless environmental information theory (WEIT) is proposed, introducing the definition, classification, and properties of WEI, along with its relationship to environmental entropy, for the first time. The feasibility of WEI-assisted channel prediction is investigated, the EIC-WEI architecture is introduced in this paper, and then, its performance gains are validated across various tasks. Finally, several open problems and challenges, including regarding its accuracy, complexity, and generalization, are discussed.

2. Wireless environmental information theory

As mentioned earlier, the propagation environment and wireless channel are inextricably linked. We begin by reviewing research on the relationship between the environment and the channel, tracing the evolution of understanding regarding the significance of the environment. This leads us to introduce our key concept (i.e., WEI), and subsequently discuss the relationship between channel uncertainty and wireless environmental entropy, forming the WEIT.

2.1. Propagation environment and channel related work

As illustrated in Fig. 1, channel research is classified using different methodologies. Based on the interaction between environment and channel, these methodologies can be divided into four categories: electromagnetic-calculation-based, statistical-model-based, environment/map-based, and data- and AI-based.

Electromagnetic-calculation-based method: The electromagnetic calculation, originating from Maxwell in 1865, provides theoretically a perfect mathematical description of electromagnetic waves by constraining the boundary conditions of electric and magnetic fields, by which the propagation of electromagnetic waves can then be rigorously solved [35]. However, analytical solutions are limited to simple geometries with well-defined boundaries. The finite-difference time-domain (FDTD) method simplifies solving Maxwell's equations by discretization, enabling numerical solutions [36–38]. Ray tracing (RT), with roots in geometric optics, models electromagnetic wave propagation in a real-world environment by computing multipath effects such as direct paths, reflections, and scattering [39–42]. Electromagnetic information theory (EMIT) extends computational electromagnetics by integrating circuit and antenna effects to enhance communication degrees of freedom [43–47]. Recently, by integrating prior environmental information, RT has improved accuracy and reduced complexity, establishing itself as a widely used deterministic channel modeling method [48–50].

Statistical-model-based method: However, despite their high accuracy, electromagnetic-calculation-based channel research methods are consistently challenged by their high computational complexity. Statistical models, with their strong adaptability and lower computational demands, have therefore become the mainstream in standards. As summarized in the introduction, standardized channel models have evolved from one-dimensional models, such as the Hata model [51–54], to 2D broadband channel models, and eventually to 3D multi-parameter models such as the 3D-GBSM [11,55,56]. In 6G systems, to flexibly support new technologies such as ISAC, extremely large-scale MIMO (XL-MIMO), and reconfigurable intelligent surface (RIS), while maintaining backward compatibility with 5G models, the extended GBSM facilitates this smooth transition [57,58].

Environment/map-based method: Channel studies based on environment and maps have become a feasible solution, enabled by the advancements in depth camera, 3D point cloud light detection and ranging (LiDAR), Global Positioning System (GPS), and other sensing technologies. Leveraging extensive measurement data, the concept of the RM has been introduced to address the limitations of traditional static spectrum resource allocation in an effective manner [59,60]. Satellite imagery and map data can predict channel parameters such as shadowing factors [30,61]. Meanwhile, CKM is an evolving concept that integrates sensing capabilities to create detailed spatiotemporal maps containing channel characteristics, supporting channel behavior prediction and communication performance optimization [32,62–64].

Data- and AI-based method: AI demonstrates exceptional capability in uncovering hidden patterns from extensive channel data, driving significant advancements in channel research based on data and AI. Certain studies have employed CNNs for scenario identification and for assistance in channel modeling [65,66]. A joint time–frequency–space domain channel prediction method using transformer neural networks, through which the cross-domain strategy can accelerate the training process of the AI model and improve prediction accuracy, has been proposed [67]. To address dynamic beam selection, a deep reinforcement-learning-based method has been introduced to cope with changes in the wireless channel environment [68]. By integrating the reasoning capabilities of AI and wireless environments, wireless environment knowledge (WEK) establishes mapping relationships between wireless environments and channel characteristics [69–71].

Table 1 [11,21–23,26,27,30,32,33,35–82] presents a summary of the timeline, connections, and application differences of various research methodologies from environmental perspectives. It is evident that the research on channels is gradually shifting toward environment and intelligence. EIC represents the next step in the transition of channels from offline to online approaches. To better support EIC, the aforementioned research motivates the proposal of WEIT, which is the focus of this section.

2.2. Wireless environmental information

Before further discussions into WEIT, it is essential to understand how EIC contributes gains to the system. Most readers have likely experienced shopping for clothes. Similar to how finding a perfectly fitting garment can be difficult, acquiring fully accurate task-oriented channel characteristics in communication systems presents comparable challenges. This analogy is further illustrated in detail in Fig. 2. As different body shapes necessitate corresponding clothing sizes, various environments require distinct channel models. Comparable to garment sizes, including large, middle, and small sizes, the types of standardized communication environments are finite, such as UMi, UMa, and RMa [11]. This classification mode facilitates rapid access to clothes fit from the perspective of statistical sizes; however, people may not find clothes in the correct sizes for some individuals, such as those who are extremely tall or with a small figure. EIC resembles high-end customized tailoring, wherein detailed body measurements of an individual are obtained with measuring tapes to create the most fitting clothing. The multimodal sensing capabilities of the base station serve as the "measuring tape" for the communication system, capturing detailed geometry and distribution information for a specific environment to accurately obtain environmental information, whereas AI acts as the "tailor" to make the optimal decision to improve system performance. To develop and achieve environmental intelligence, it is a prerequisite to establish the fundamental theory for WEI.

Definition: The properties of the wireless environment determine the characteristics of the wireless channel. Electromagnetic waves interact with objects and scatterers in the physical environment, such as buildings, metallic vehicles, rough roads, and plants. Maxwell's equations, along with the boundary conditions, characterize the spatial strength distribution and variation of the electromagnetic wave via electromagnetic parameters of the environmental objects, including permittivity, permeability, and conductivity. Therefore, the physical properties of objects and scatterers in the propagation environment, which affect wireless channel characteristics, are defined as WEI. The diverse application scenarios of 6G, ranging from the ocean to space satellites, render the scope of WEI correspondingly broad, including variables such as water fluctuations, alterations in air humidity, and satellite trajectories.

Classification: As shown in Fig. 3, WEI can be divided into three categories: static, dynamic, and random information. Static

Table 1
Important milestones of channel research progress from environmental perspectives.

Methodology	Year(s)	Environment type	Online/offline application	Representative progress
Electromagnetic-calculation-based	1865	N/A	N/A	Maxwell's equations [35]
	1996	Deterministic	N/A	FDTD method [36–38]
	1960s	Deterministic	Offline	RT theory [39–42]
	2008	N/A	N/A	EMIT [43–47]
	2010s	Deterministic	Offline	Hybrid channel model [72–74]
	2022	Deterministic	Offline	NVIDIA Sionna [75]
	2024	Deterministic	Offline	Adaptive/dynamic RT [48–50]
Statistical-model-based	1944	Statistical	Offline	Rice fading [51]
	1968	Statistical	Offline	Rayleigh fading [52]
	1980	Statistical	Offline	Okumura–Hata model [53,54]
	1997	Statistical	Offline	TDL model [76,77]
	2005	Statistical	Offline	CDL model [55]
	2010s	Statistical	Offline	GBSM [11,56,78]
	2020s	Statistical	Offline	Extended GBSM [57,58]
Environment/map-based	1990s	Deterministic	Offline	DARPA radio research [21]
	2000s	Deterministic	Offline	RM [59,60]
	2016	Deterministic	Offline	Cluster-nuclei theory [22,23]
	2017	Deterministic	Offline	Image/map-based prediction [30,61]
	2020s	Deterministic	Offline	Vision/radar-aided prediction [26,27]
	2022	Deterministic	Online	Wireless environment semantic [33]
	2023	Deterministic	Online	CKM [32,62–64]
Data- and AI-based	1990s	Deterministic	Offline	RBF-NN path loss prediction [79]
	2005	Deterministic	Offline	*K*-power means clustering [80]
	2013	Deterministic	Offline	SVM path loss prediction [81]
	2017	Deterministic	Online	CNN scenario identification [65]
	2018	Deterministic	Online	CNN/LSTM channel modeling [66]
	2022	Deterministic	Online	Transformer/GAN channel prediction [67,82]
	2023	Deterministic	Online	DRL beam prediction [68]
Environment-intelligence-based	2023	Generalized	Online	WEK pool [69–71]
	This paper	Generalized	Online	WEIT

N/A: not applicable.

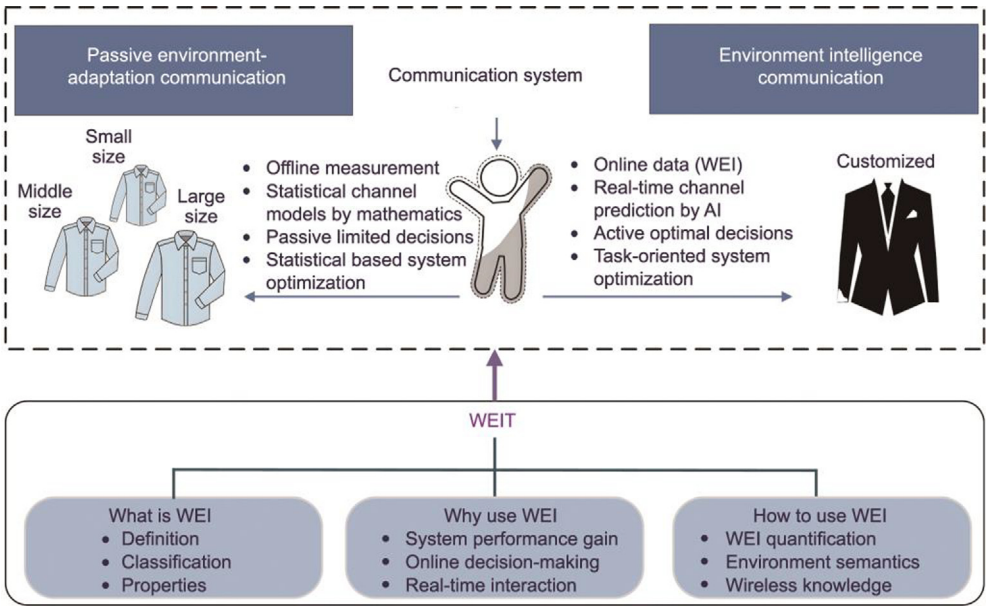

Fig. 2. WEIT: from passive environment-adaptation to EIC.

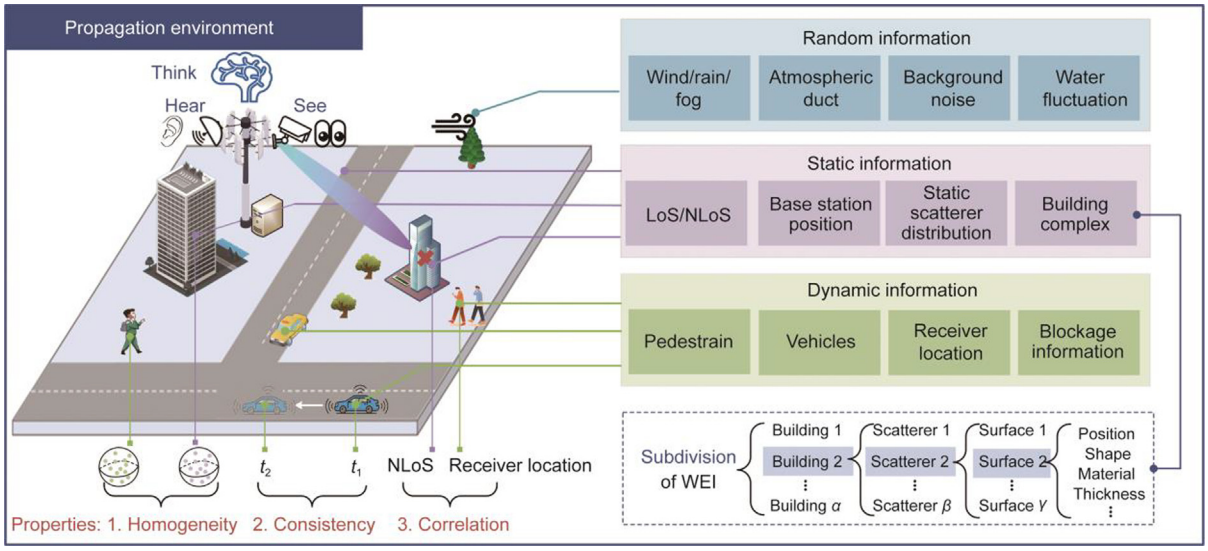

Fig. 3. WEI: definition, classification and properties. LoS: line-of-sight; NLoS: non-line-of-sight; t_1 and t_2: the start and end of time interval, respectively; α:αth building; β: βth scatterer; γ:γth surface.

information keeps stationary and maintains fixed shapes during the observation time scale; it includes objects such as buildings, vegetation, and streets, together with their height, outline, and distribution. Dynamic information exhibits temporal continuity and can be sensed and calculated; for example, vehicles, pedestrian, scatterer mobility, and other mobile information with a distinguishable time scale. In contrast, random information includes the birth and death of scatterers caused by wind or tree shaking, and the background noise generated by electromagnetic interference and molecular thermal motion in the environment, which exhibit strong unpredictability in the time domain.

Properties: WEI possesses properties such as homogeneity, consistency, and correlation. Homogeneity refers to the sameness in the attributes of the three types of WEI obtained by various sensing devices. For example, from the perspective of electromagnetic wave propagation, both static buildings and dynamic pedestrians can be modeled as scatterers, characterized by identical parameters including volume, shape, and material. Consistency refers to the stability and continuity of WEI across both spatial and temporal dimensions. For instance, during a stationary interval from t_1 to t_2 (where t_1 and t_2 are the start and end of time interval, respectively) the corresponding WEI parameters (e.g., position, velocity, and motion direction) of an object can be regarded as consistent. Correlation indicates the interdependence between multiple WEI. For example, blockage information depends on the positions of the base station, user, and scatterers, and changes as the user and dynamic scatterers move.

2.3. Wireless environmental entropy definition

Based on the preceding discussion, WEI helps to reduce channel variation uncertainty. Naturally, this prompts an inquiry: Does entropy associated with WEI exist? For communication systems, the environment can be assumed to be random. Wireless

environmental entropy serves to quantify the level of uncertainty in a stochastic wireless environment. In a given communication environment, the environmental entropy (S_e) should have an upper bound $S_e[\max]$ and a lower bound $S_e[\min]$. For the upper bound, the possible objects within a certain area (communication system service range) are finite, and the number of possible environments composed of these objects is also finite; thus, the environmental entropy should have a maximum value $S_e[\max]$. In contrast, the lower bound $S_e[\min]$ arises mostly from environmental measurement abilities and errors, resulting in uncertainty within the environment, similar to the implications of the Cramér–Rao bound [83,84]. However, how should environmental entropy be quantified for a specific environment? For example, in wireless communications, time-harmonic electromagnetic fields are the most commonly studied. In this context, it is sufficient to define the spatial boundary conditions—specifically, the spatial distributions of permittivity $\epsilon(r)$ and permeability $\mu(r)$, where r is the spatial sampling point. We discretize $\epsilon(r)$ and $\mu(r)$ with a prescribed spatial resolution. Formally, given a set of spatial sampling points $R = \{r_1, r_2, \ldots, r_n\}$ where n denotes the number of sampling points, we define the discrete stochastic environment as $\boldsymbol{S} = \{\epsilon(R), \mu(R)\}$, where $\epsilon(R) = \{\epsilon(r_1), \epsilon(r_2), \ldots, \epsilon(r_n)\}, \mu(R) = \{\mu(r_1), \mu(r_2), \ldots, \mu(r_n)\}$. This formulation represents $\boldsymbol{S}$ as a $2n$-dimensional random vector. Consequently, the wireless environmental entropy can be characterized through the joint entropy $H(\cdot)$ of this random vector: $H(\boldsymbol{S}) = H(\epsilon(r_1), \epsilon(r_2), \ldots, \epsilon(r_n), \mu(r_1), \mu(r_2), \ldots, \mu(r_n))$. Any WEI ($\xi$) can be characterized by its dimension d and quantity θ, expressed as $\xi(\theta) = d \cdot \theta$. From the perspective of dimension, spatial position can be quantified as a 3D vector. From the perspective of quantity, the precision of the position information is related to its measurement accuracy. A high-precision WEI $\xi_2(\theta)$ contains more information than is in a low-precision WEI $\xi_1(\theta)$. Thus, as the mean squared error (MSE) for a measurement decreases, the amount of WEI increases. Fig. 3 further demonstrates the detailed subdivision method for WEI. Herein, a building complex is considered as an example. The complex contains A buildings, among which the αth building contains B scatterers, and the βth scatterer is composed of Γ surfaces, where A is the total number of buildings, B is the total number of scatterers, and Γ is the total number of surfaces. The information related to electromagnetic wave propagation on each surface can be divided into i categories, such as position, shape, material, and thickness. The total amount of WEI that this building complex can provide is $A \times B \times \Gamma \times \sum_i \xi_i(\theta)$.

Evaluating environmental entropy from the perspective of system capacity is crucial for communication systems. Fig. 4 demonstrates the sources of system capacity improvements realized through EIC compared with traditional communication. The system capacity is directly related to the quality of the channel and allocated time–frequency resources. With the same time–frequency allocation, better channel quality results in higher system capacity; Similarly, with fixed channel quality, allocating more time–frequency resources lead to greater capacity. Traditional communication systems rely on statistical channel models with statistical averages of selected typical environments, which makes it difficult to approach the instantaneous optimal upper limit of performance. It requires certain time–frequency resources (e.g., pilot signals) to acquire CSI. As the antenna scale increases, the pilot overhead of the system also grows. Therefore, pilot-based traditional systems need to strike a balance between pilot resources and communication resources. This establishes a balance between time–frequency resources and channel quality, thereby constraining the system capacity. By contrast, EIC employs dedicated sensing devices and AI to obtain accurate channel information. Because the sensing process uses separate, non communication frequency bands and time slots, the system can devote virtually all its allocated time–frequency resources to data transmission, thereby achieving higher system capacity.

As previously stated, in communication systems, the relevant information of interest is related to electromagnetic wave propagation. The precision and property of information are both critical considerations. For example, compared with the mass of objects, the dielectric constant is a greater focus of concern for the system. Therefore, it is necessary to restrict the maximum types of WEIs that a system can obtain, while also addressing accuracy problems and challenges. WEI serves as the bridge between the propagation environment and the channel, and a decrease in environmental entropy indicates an increase in the channel determinacy. A mapping relationship $\mathscr{F}(\cdot)$ is employed to process the obtained WEI into various channel parameters. Different WEI is transformed into specific channel parameters, such as delay, Doppler shift, and power, via the mapping relationship $\mathscr{F}(\xi_1, \xi_2, \ldots, \xi_i)$.

3. EIC aided by WEI

To overcome the limitations of the statistical paradigm and enable a communication system that interacts in real time and utilizes WEI online, in this section, we propose a WEI-based EIC framework. The motivation for introducing intelligence into the communication system is elaborated herein in detail, and the use of WEI is graded.

3.1. Three cornerstones for EIC

Compared with 5G, 6G wireless channels will continue to expand in terms of frequency, application scenarios, and support technologies. This requires precise capture of new features and characteristics of the channel, and low complexity integration into the theoretical framework of 6G. Channel prediction based on the online acquired WEI is a relatively low-cost method for channel acquisition. Therefore, the following three techniques will play an important role in extracting WEI and predicting channel changes.

Multimodal environment sensing: ISAC technology can enable smarter and more efficient environmental sensing and WEI acquisition. To accomplish this, base stations are progressively incorporating various sensing devices such as industrial sensors, depth cameras, LiDARs, and millimeter-wave radar. These devices can collect multimodal sensing data from different angles, locations, and scales, thereby providing a comprehensive perception of the environment. For example, millimeter-wave radar can provide precise information on the position and velocity of objects, LiDAR can offer high-precision spatial data, and color cameras can capture material information about objects. These sensing data can be efficiently fused, enabling accurate capture of full-dimensional WEI for both moving objects and static scatterers, thus providing a data foundation for channel fading prediction.

AI-enabled online channel prediction: Traditional channel fading derived from empirical and statistical models typically relies on a limited set of typical environments, making it insufficient to fully capture the complexity of wireless channel variations. With the rise of AI technologies, particularly advancements in ML and deep learning, AI has become a crucial tool for tackling this problem. By fully utilizing WEI that encompasses comprehensive environmental states, AI models become better equipped to understand and predict the dynamic changes in wireless channels. With their powerful feature extraction and nonlinear mapping capabilities, AI models can accurately uncover knowledge from vast amounts of WEI, learning and identifying potential patterns in channel fading, thereby providing valuable insights for applications such as pilot cost reduction, beam management, and resource optimization.

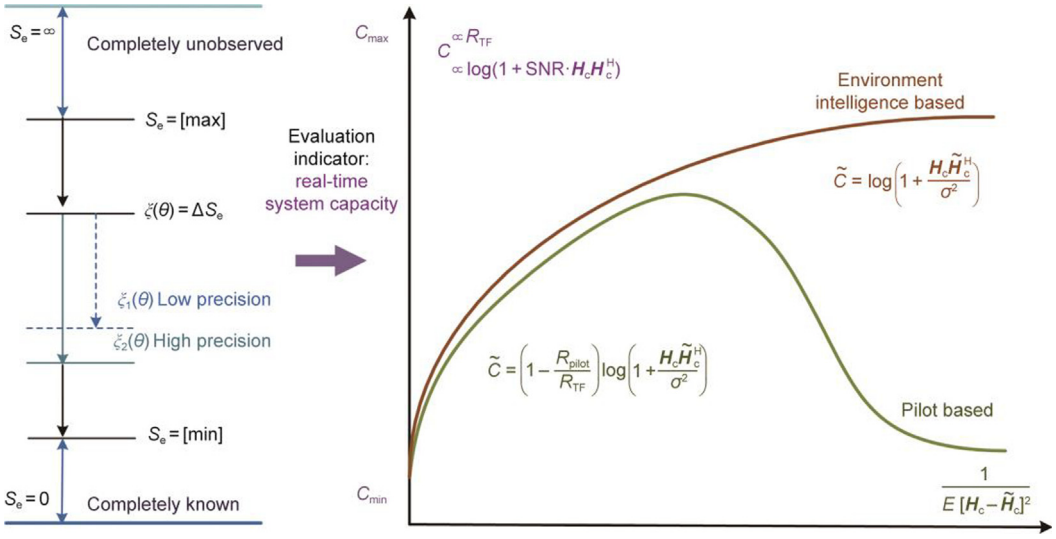

Fig. 4. Relationship between WEI and environmental entropy. C: channel capacity; $C_{\max}$: upper limit of channel capacity; $C_{\min}$: lower limit of channel capacity; $\tilde{C}$: actual channel capacity; R_{TF}: time–frequency resources; R_{pilot}: pilot resource; $\boldsymbol{H}_c$: channel matrix; $\tilde{\boldsymbol{H}}_c$: actual channel matrix; σ: noise variance; $E[\cdot]$: expectation; SNR: signal-to-noise ratio.

WEK construction: With the improvement in measurement device resolution and the increasing number of sensing devices, wireless channel data will inevitably exhibit significant big data trends across various environments. A large volume of channel data forms a foundation for uncovering hidden patterns; however, this increases the computational complexity of channel fading prediction, limiting the real-time performance of inference. To reduce data volume and extract channel-relevant information, we propose WEK as a representation of the mapping relationship between the environment and the channel [82]. This abstracts the channel propagation process from both the environment and the channel, enabling intelligent understanding of the underlying propagation laws through theoretical derivations, mathematical formulations, or semantic interpretations.

3.2. Different levels to acquire CSI from system perspective

The acquisition and processing of WEI can be categorized into four levels, progressively reflecting the evolution from manual operation to fully automated intelligent sensing:

Level 1: At this stage, the acquisition of WEI relies entirely on manual operations. Environmental measurements are conducted manually, and the collected data are used to reconstruct a complete 3D environment model by hand. This offline WEI acquisition approach is inefficient and incapable of meeting the demands of large-scale dynamic environments.

Level 2: Although the collection of environmental data still depends on manual operation, the data processing methods have been optimized. After data collection, key features are extracted either manually or through automated techniques such as AI algorithms, enabling low-dimensional feature extraction and data organization. For example, a complex 3D environmental model is simplified into a parameter set consisting of specific features such as the height of base station, scene size, and number of buildings.

Level 3: At this level, the data collection process becomes automated. Various sensing devices deployed in the environment automatically collects WEI. AI algorithms are then employed to automatically extract the environmental features necessary for channel prediction. This stage eliminates the limitations of manual data collection, significantly improving the efficiency of data acquisition and enabling adaptation to more complex environmental changes. However, the reliance on neural-network-based feature extraction introduces a limitation in the interpretability of WEI.

Level 4: On the foundation of fully automated multimodal sensing and data fusion, the environment-specific features and channel characteristic parameters are explicitly related using WEK. This enables interpretable extraction of core features required for subsequent tasks. This stage not only achieves real-time WEI acquisition but also allows for concise and accurate representation of channel characteristics, combining efficiency with interpretability.

Since the advent of wireless communications, extensive research is being conducted on propagation environments. WEI is now used in various domains, including channel modeling, channel estimation, and channel prediction. The use of WEI is gradually transitioning from offline to online and from vague to precise. In both deterministic and statistical models, the utilization of WEI in channel modeling remains relatively basic. Channel estimation schemes currently rely on pilots to capture channel variations, requiring time–frequency resource overhead, which encroaches on communication resources. Early applications of AI for channel prediction use environmental information primarily offline, employing statistical learning on historical channel data to predict future channel states. By comparison, traditional signal processing focuses more on processing past instantaneous information rather than forecasting future channel variations. With the theoretical support of WEIT, environment intelligence now enables the real-time, online utilization of WEI, ensuring that communication resources are preserved while achieving accurate channel fading predictions. Although collecting and processing WEI introduces additional hardware and computational overhead, the rapid development of edge computing infrastructure, high-performance computing technologies, and high-resolution multimodal sensors are progressively reducing these costs. Table 2 provides a conceptual comparison of WEI between different channel concepts.

3.3. Architecture for proposed EIC-WEI

EIC is a closed-loop process. It begins with leveraging sensing methods to obtain accurate and comprehensive WEI based on the task requirements of the communication system. Next, WEI is used to predict the various channel fading, and finally, the

Table 2
Characteristics of different channel acquisition methodologies from system perspective.

Channel acquisition	Method	Real-time	WEI utilization	WEI acquisition	Complexity/cost	Tasks
Channel modeling	Statistical model	Offline	Level 2	Channel measurement	Low	System deployment
Channel modeling	Deterministic model	Offline	Level 1	Environmental measurement	High	System deployment
Channel estimation	Pilot/pre-training	Online	Level 2	Pilot	High	Obtain current channel parameters
Channel prediction	Neural network	Online	Level 3	Historical CSI	Acceptable	Predicting channel parameters
Channel prediction	Signal processing	Online	N/A	Current signal	High	Predicting channel parameters
Environment intelligence	WEK + AI	Online	Level 4	Sensing	High (building) and low (usage)	Task-oriented intelligent interaction

communication system autonomously determines the optimal transmission strategy, enabling intelligent interaction.

Step 1. Multimodal sensing and environment reconstruction: By intelligently integrating multimodal sensing data, the system automatically analyzes information collected from various sensing devices to reconstruct a high-precision 3D model of the entire scene. In this process, devices such as cameras and LiDAR act similar to human eyes, accurately capturing the structure of the surrounding environment, whereas radar acts as human ears, acquiring the velocity and position of scatterers by "listening" to the echo signals. This enables the reconstructed environment model to obtain all critical details of the propagation environment, providing comprehensive environmental information for the communication system.

Step 2. Knowledge mapping: For a specific communication task, the complete 3D model often contains redundant and complex information. Therefore, it needs to be processed based on the task requirements to extract usable WEI. These requirements can originate from various layers of the network, including the physical layer, resource layer, and others. The WEI extraction methods involve noise reduction, removal of irrelevant data, and ultimately mapping the information into a form suitable for the prediction layer. More details are provided in the next subsection.

Step 3. AI-based channel fading prediction: Leveraging trained neural networks, the processed WEI is utilized to selectively predict channel parameters based on the communication task requirement, thereby reducing overhead. At this stage, WEI is employed in an online manner, and the final prediction results directly influence system decisions.

Step 4. Proactive decision: User actions often follow multiple potential paths, requiring the communication system to make proactive decisions tailored to each environment. As shown in Fig. 5, a vehicle approaching an intersection may choose to turn left, go straight, or turn right. Here, similar to the human brain, AI-enabled EIC can make fast and optimal strategy decisions based on multiple possible channel predictions of user moving status, thereby improving the system performance intelligently.

Step 5. Optimal transmission strategy: Once the actual choice of the user is made, the communication system applies the corresponding optimal strategy from the previous step. The process then proceeds to the next round of task requirements.

3.4. WEI flow: Unlocking the EIC

In the closed-loop process of environment intelligence, it is very important to recognize and utilize WEI as the bridge between the environment and the channel. Now, focusing on Fig. 6, we provide a detailed explanation of each module in the WEI flow processing.

(1) **Raw-data collection module:** The raw environmental data can be divided into two categories: visual sensitive data, such as volume; and electromagnetic sensitive data, such as scattering coefficients, which cannot be fully captured by a single device. For instance, using a camera is a conventional approach for collecting raw environmental data. Exploiting CV technologies, such as object detection, object tracking, and semantic segmentation, one can identify and extract environmental objects from images. Meanwhile, radar can determine the position of objects through echoes. Through the use of multimodal sensing devices, we can acquire a vast amount of raw wireless environmental data in various forms, typically measured in the millions.

(2) **WEI preprocessing module:** The raw wireless environmental data contain a massive amount of multimodal data along with significant ambient noise, necessitating processes such as denoising, integration, and classification to transform the data to WEI. The processed WEI is then divided into three categories: static WEI, dynamic WEI, and random WEI. Subsequently, each category of WEI is processed using distinct workflows tailored to its characteristics.

(3) **Environmental feature analysis module:** The processed WEI is analyzed for specific features according to channel characteristic requirements, including but not limited to the correlation between transmitting–receiving distance and path loss/delay characteristics, and as the velocity and Doppler shift effects. ML and data-mining technologies can be used to achieve efficient feature extraction and reduce data dimension. In this process, three types of WEIs are processed separately; however, the extracted features may be similar. For example, buildings can be simplified to position, size, and material, whereas dynamic vehicles can extract features such as position, material, and speed. This module significantly reduces the data dimension while providing structured input for subsequent processes.

(4) **WEK module:** WEK is the key to rapidly and accurately obtaining channel characteristics. It is a more complex and diverse relational graph with intricate connections. Owing to its multilevel correlations, it exhibits generalizability across various scenarios and tasks. This enables AI algorithms to understand and learn the underlying mapping rules of channel behavior, facilitating accurate predictions of channel fading states. These predictions can be utilized to optimize transmission techniques, significantly enhancing system performance [82].

(5) **Channel characteristic module:** In this module, the processed channel parameters are mapped to different channel characteristics, including both large-scale and small-scale characteristics. Different channel characteristics are mapped separately to improve system efficiency. The channel characteristic module is closely connected to the preceding feature analysis stage. To ensure system efficiency, feedback information should be provided to the environmental feature analysis module, enabling targeted predictions and computations. The feedback information should also be translated into simple control commands to fulfill real-time requirements.

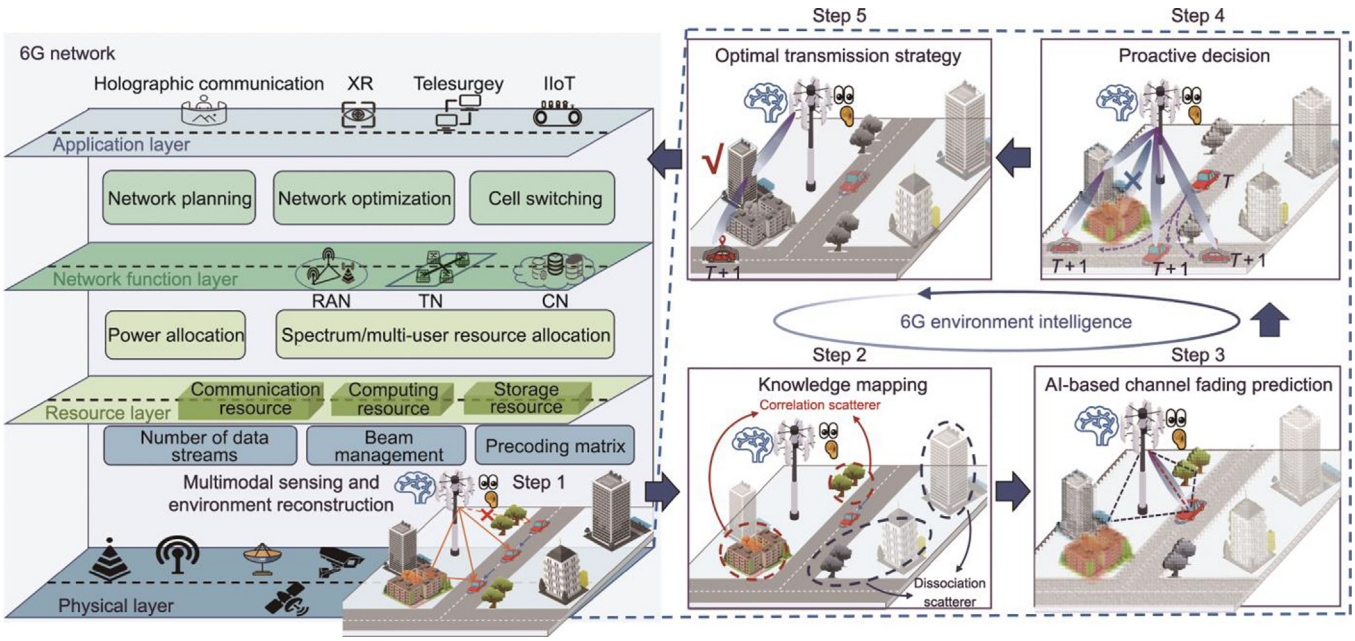

Fig. 5. EIC for 6G system. XR: extended reality; IIoT: industrial Internet of Things; RAN: radio access network; TN: transport network; CN: core network; *T*: certain time.

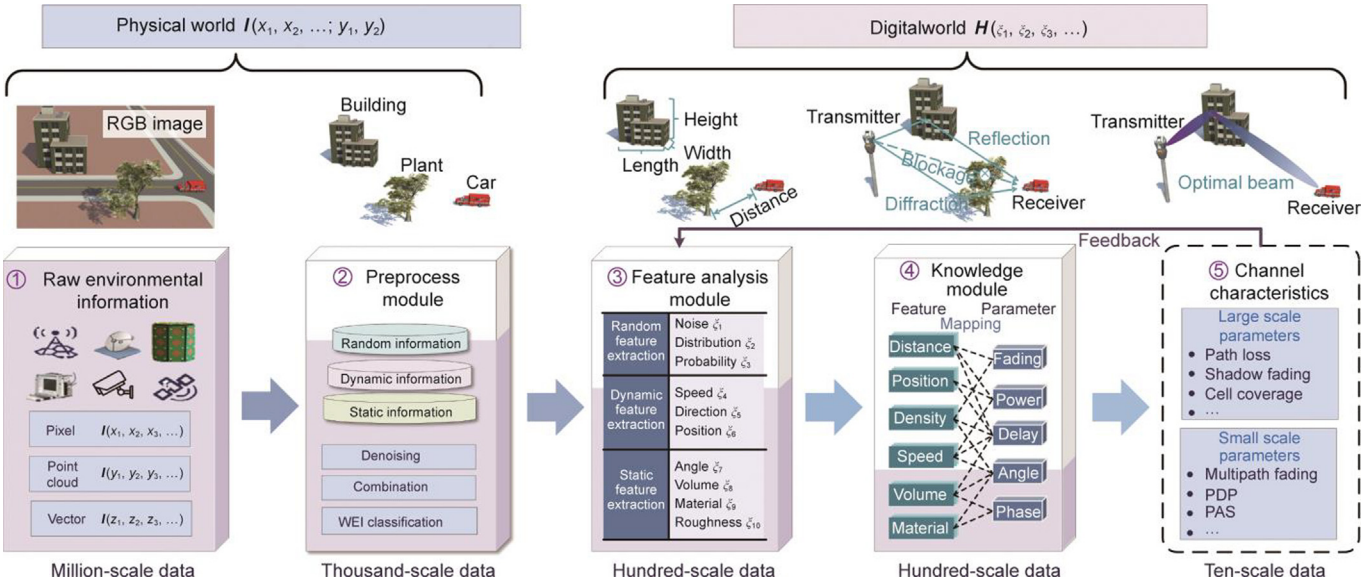

Fig. 6. WEI five-step flow for EIC: from raw data to WEK. x_1, x_2, and x_3: generic representations of pixel information; y_1, y_2, and y_3: generic representations of point cloud information; z_1, z_2, and z_3: generic representations of vector information; $\boldsymbol{I}(\cdot)$: raw environmental information set; $\boldsymbol{H}(\cdot)$: WEI set; PDP: power delay profile; PAS: power azimuth spectrum.

4. Task-oriented EIC-WEI validation from theory to practice

In this section, to evaluate the performance of environment-enhanced channel prediction, we discuss the gains that the EIC-WEI architecture brings to the communication system based on four tasks: cell coverage, CSI prediction, beam selection within the same test environment, and resource management in a new test environment, to validate the generalization. The simulation test environment is shown in Fig. 7, where the location of the transmitter is marked with an asterisk at a height of 19 m, and single-antenna users are evenly distributed across four lanes. The constructed outdoor urban environment is built using the autonomous driving simulation software CARLA (Computer Vision Center and Intel Labs, Spain and the United States) [85] with four building groups, and different types of vehicles are randomly placed on one side of the road to ensure that the environment has sufficient diversity. Given that the loss of surface detail has a limited effect on the channel, the entire test environment is imported into Blender software (Blender Foundation, the Netherlands) for simplification, where buildings and vehicles are replaced with simple cubes. The simplified model of the environment is imported into Wireless Insite for RT simulation. The test environment is a square with a side length of 200 m. Detailed parameter settings are listed in Table 3. WEI includes panoramic image (segmented into four directions) of the receiver and coordinates of buildings within the environment. All datasets are generated by the Beijing

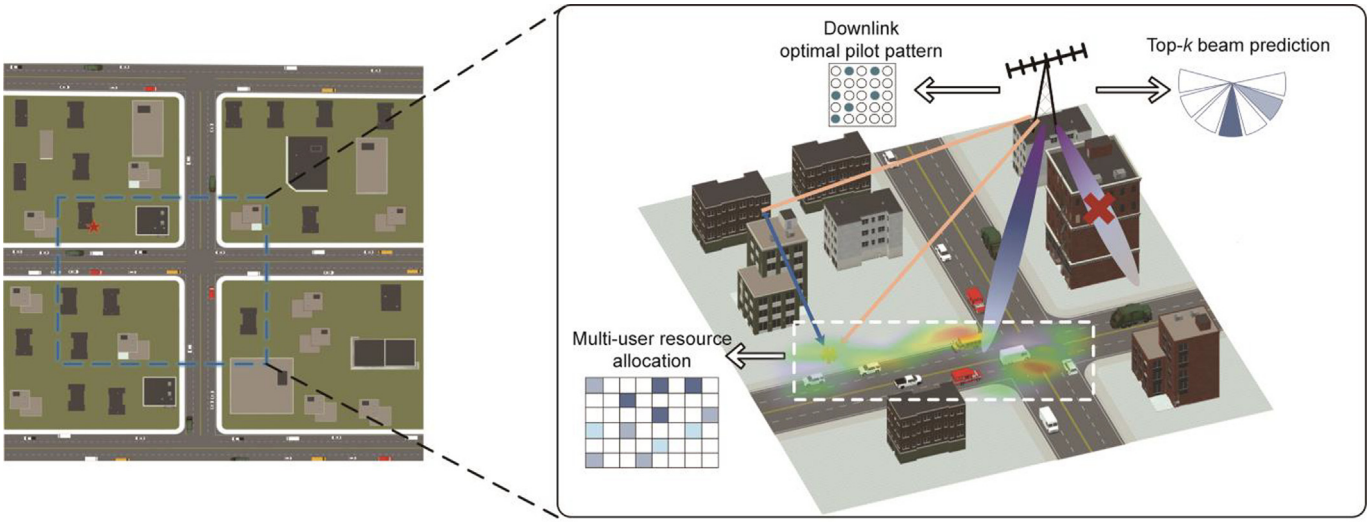

Fig. 7. 2D perspective of simulation test environment A and specific tasks. Top-*k*: the best *k* beams.

Table 3
Simulation parameter settings.

Parameter	Setting
Modulation	Orthogonal frequency division multiplexing (OFDM)
Middle frequency (MHz)	6775
Bandwidth (MHz)	8.28
Subcarrier (kHz)	120
OFDM symbol number	3
Transmitter antenna number	128
Receiver antenna number	1
Transmitter location (m)	[−57.4, 27, 19]
Receiver set	Height: 2 m, gap: 0.25 m
Panoramic image	600 × 200 pixels

University of Posts and Telecommunications and China Mobile Communications Group-DataAI-6G Dataset (BUPTCMCC-DataAI-6G Dataset) [86,87].

Task 1: Cell coverage. The receiving area verifying cell coverage is illustrated in Fig. 8. Within the selected area, there is a tall building to the right of transmitter, which creates significant blockage. Fig. 8 shows the results of different channel acquisition methods for predicting cell coverage of channels at 6.775 GHz. The statistical channel model uses different empirical formulas in the line-of-sight (LoS) and non-line-of-sight (NLoS) regions, and the prediction results have clear regional divisions. However, the simplistic relationship between channel fading and propagation distance results in severe distortion [11]. Channel prediction based solely on simple distance features has significant shortcomings in determining direct areas. By contrast, the prediction results produced by the proposed EIC-WEI approach are significantly closer to the true values, demonstrating good fitting. The introduction of multimodal environmental information makes it possible to extract a more comprehensive set of propagation contribution features, which allows the AI to better learn the complex propagation patterns. Consequently, our approach outperforms both traditional statistical models and methods based on simple features.

Task 2: Large/small-scale parameter channel prediction. Fig. 9 illustrates the cumulative distribution functions (CDFs) of the aforementioned methods for predicting the path loss of the channel. The prediction results of the statistical channel model show clear and evident segmentation because of the use of different empirical formulas for the LoS and NLoS regions; channel prediction based on simple features more closely aligns with the trend of the true value compared with that obtained with the statistical channel model. However, there remains a noticeable deviation from the true value. Compared with the first two methods, EIC-WEI produces results that are closer to the true values, with the vast majority of its results within the 95% confidence interval.

Fig. 10 illustrates the performance of the proposed method in capturing small-scale channel characteristics. We use the normalized MSE (NMSE) as an evaluation indicator and employ 1/8 of the resources for pilot signals. The channel modeling method based on TR 38.901 [11] incurs no additional overhead. However, owing to its inherent decoupling from the actual environment, its NMSE is significantly worse compared with those of several other methods. This limitation indicates that the channel model in its current form is not suitable for real-time communication tasks. The EIC-WEI architecture uses a panoramic image around the receiver as input for WEI. Compared with those of the prediction results without WEI, after the convergence of the network model training, the NMSE decreases by approximately 59.8%, highlighting the potential of this architecture for predicting small-scale parameters.

Task 3: Optimal beam selection. In addition to predicting channel parameters, WEI can also optimize channel beam prediction. In this task, beam codebook selection is performed at transmitter, which is equipped with 32 codebook options, aiming to maximize the received power. The prediction without WEI relies on past CSI, whereas the prediction with WEI utilizes panoramic images and CSI. Significant results can be observed from Fig. 11: the prediction accuracies of the top 5 beams with the highest power improve by 23%, whereas the accuracies of the top 3 beams increase by 29%. Additionally, the inclusion of WEI leads to faster and more stable convergence. This result demonstrates the potential of the EIC-WEI.

Task 4: Optimization of air interface resources. To optimize multi-user service in a typical vehicle-to-infrastructure (V2I) test environment, we simulate a resource allocation problem based on fairness. Ten terminal users are randomly selected as the served users on the main road, marked by the dashed box. Through the sensing capabilities of the base station, the system can autonomously track the movement of user locations. Given the significant differences in the communication environments across various user positions, our objective is to ensure the best possible service quality for each user. To achieve this, the objective of the resource fairness optimization is to maximize the minimum throughput of users, which can be formulated as $\max_{\boldsymbol{X}_u, u=1,2,\ldots,J} \mathrm{Tpt}_{\min}$. Here,

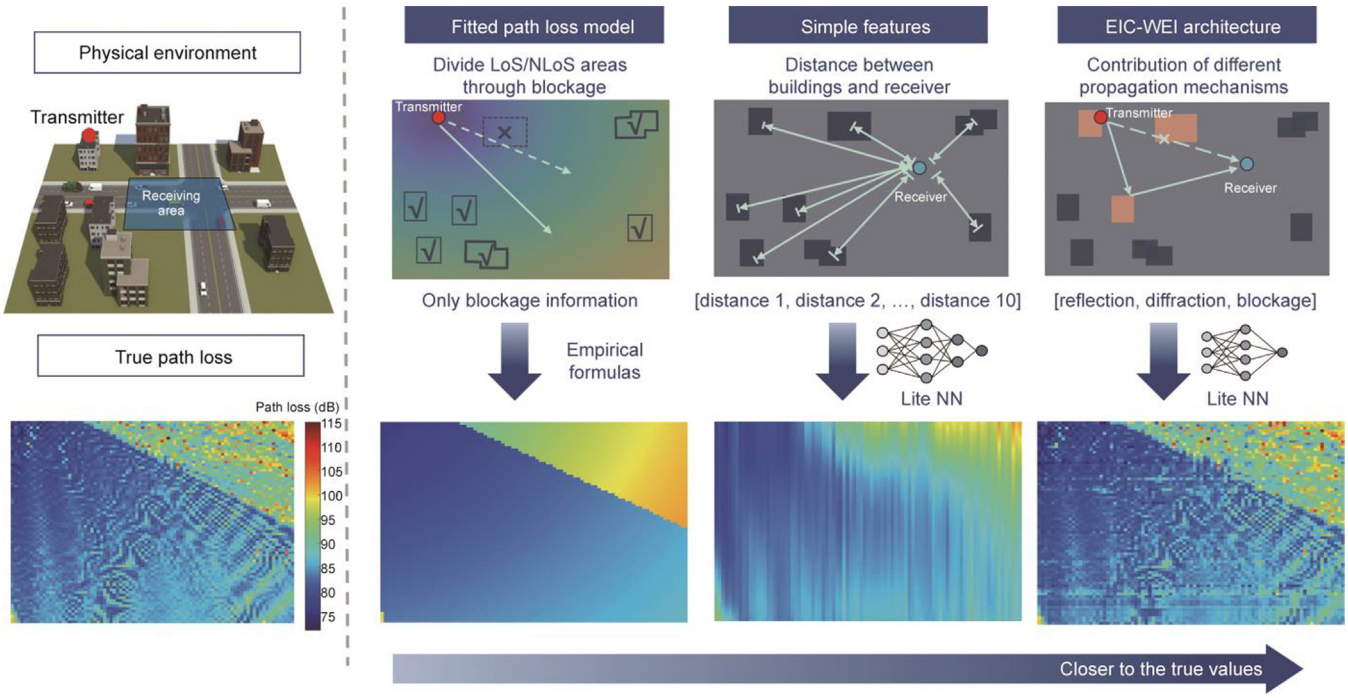

Fig. 8. Cell coverage results based on true channel statistical channel model, simple features, and EIC-WEI.

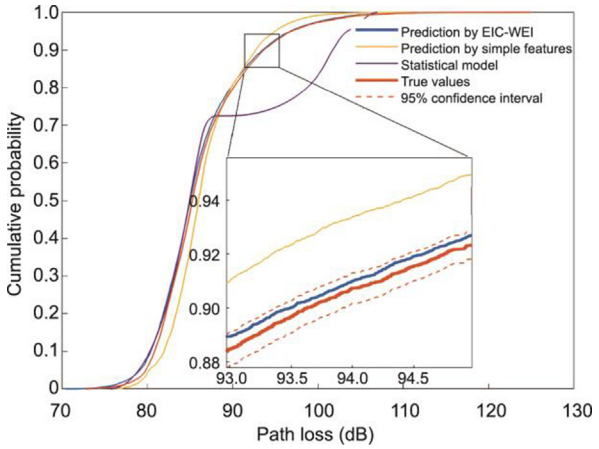

Fig. 9. CDF plots of proposed WEI-based prediction and the contrast methods.

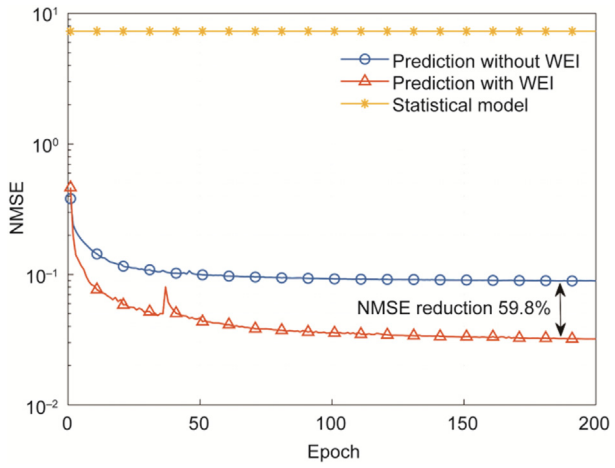

Fig. 10. Normalized MSEs (NMSEs) of proposed WEI-based prediction and GBSM methods for the channel.

$\mathrm{Tpt}_{\min} = \min_{u=1,2,\ldots,J}\{\mathrm{Tpt}_u\}$ and $\mathrm{Tpt}_u = \sum_{p=1}^{P}\sum_{q=1}^{Q} D_{u,p,q} \cdot \boldsymbol{X}_u[p,q]$, where $\mathrm{Tpt}_{\min}$ and Tpt_u denotes the sum of minimum throughput and throughput of user u, respectively; J is the total number of users; P and Q denotes the total number of time slot and frequency slot resource blocks, respectively. $D_{u,p,q}$ denotes the rate of data transmission by user u in the pth time domain and qth frequency domain resource block, and $\boldsymbol{X}_u \in \{0,1\}^{P\times Q}$ denotes the resource allocation matrix for user u, with dimensions $P \times Q$, where each element takes values from the set $\{0,1\}$. The constraint is satisfied for all $\boldsymbol{X}_u$ such that $\sum_{u=1}^{J}\boldsymbol{X}_u = \mathbf{1}_{P\times Q}$, where $\mathbf{1}_{P\times Q}$ represents a matrix of dimensions $P \times Q$ with all elements equal to 1.

To verify the generalization of the proposed method, we use the same model as that in task 2 to perform predictions in test environment B, as shown in Fig. 12. The goal of the optimization is to allocate resources more evenly among the ten users within the blue box, with each antenna transmitting at a power of –8 dBm. Before WEI is incorporated for resource allocation, user 1 receives significantly more resources compared with user 2. After WEI is incorporated, the time–frequency resource allocation between users 1 and 2 becomes more balanced, as shown in Fig. 13. Fig. 14 presents the throughputs of the users. Before WEI is incorporated, the throughput gap between the users with the lowest and highest throughputs is 2.804 gigabits per second (Gbps). After resource allocation using WEI, this gap reduces to 0.977 Gbps. The variance of throughput among the ten users is 0.10 Gbps, and the total system throughput is 72.04 Gbps. By contrast, without WEI, the variance of throughput among the ten users is 1.18 Gbps for a total system throughput of 72.21 Gbps. Fairness optimization among multiple users is achieved without sacrificing total throughput.

5. Main challenges and future work

As shown in Fig. 15, we have developed a real-time interaction platform enabled by environment sensing as a prototype system

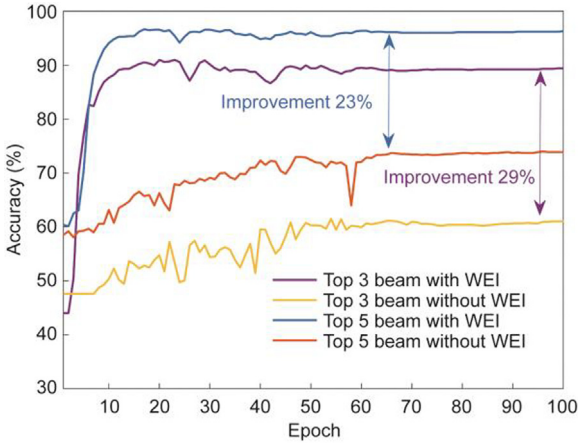

Fig. 11. Optimal beam prediction based on WEI.

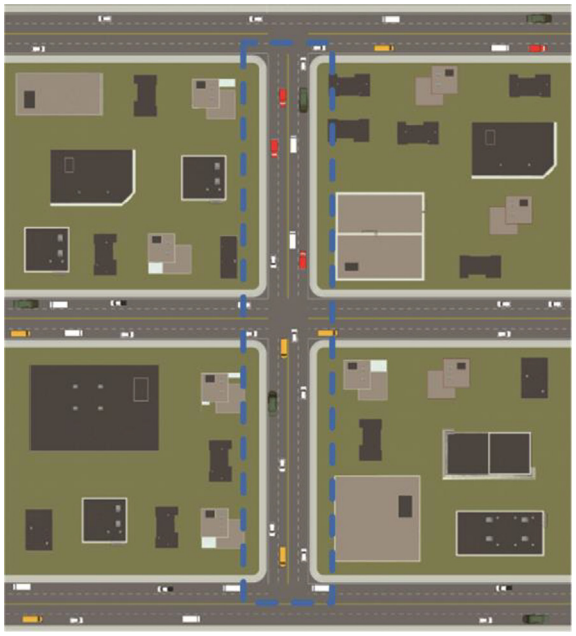

Fig. 12. Simulation test environment B: generalization verification.

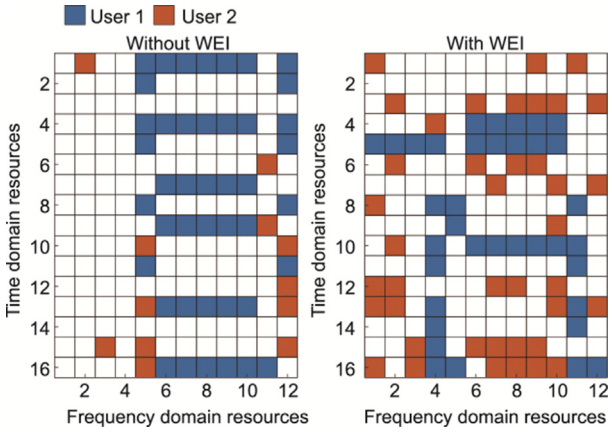

Fig. 13. Time–frequency resource block allocation for two users based on WEI.

for EIC. Specifically, this system leverages collected point cloud data to automatically extract scatterer features and perform multimodal fusion. Subsequently, it reconstructs environmental objects

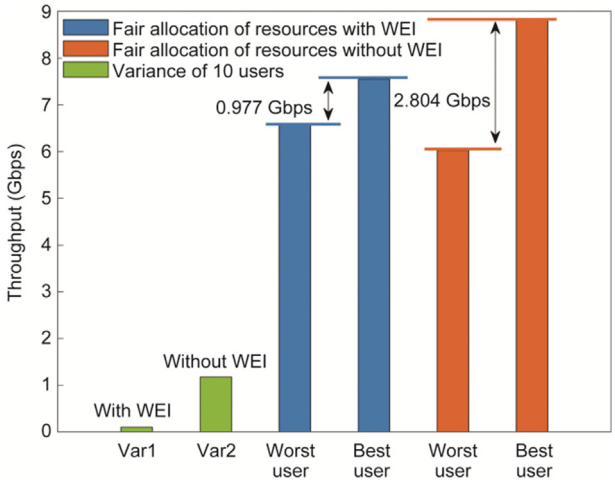

Fig. 14. Throughput variance for ten users and throughput difference between the best and worst users. Var1: variance of ten users with WEI; var2: variance of ten users without WEI.

in real time and predicts propagation paths, deriving channel parameters based on propagation paths. This system demonstrates the feasibility of integrating sensing and AI for channel prediction. However, to achieve a fully intelligent and comprehensive EIC-WEI suitable for 6G, several challenges and open problems require further investigation.

Accuracy of WEI acquisition to ensure system performance: High-fidelity environmental reconstruction remains a challenge in WEI collection. Accurate data collection is crucial for subsequent processing, yet current methods often struggle with precision. Moreover, sensing devices are evolving toward multimodal deployments and will provide a variety of WEI streams. Future EIC systems should support these multimodal WEI fusions at three levels: data level alignment and integration, feature level representation fusion, and decision level output aggregation. Regardless, quantitatively describing the various types of collected WEI remains a challenging work.

Low-complexity environment interaction to support real-time tasks: Real-time interaction is a key requirement of EIC-WEI, with its core lying in the rapid sensing, processing, and response to the dynamic wireless environment. However, implementing real-time WEI acquisition, WEI processing, channel fading prediction, and decision-making within the base station is a complex and challenging task. The interaction between the system and the environment should be achieved with minimal resource overhead and the lowest possible complexity to fulfill the demands of the 6G network for low latency and high efficiency. For example, model compression techniques such as pruning, quantization, and knowledge distillation can be applied, and edge computing can be leveraged to reduce data round trip latency.

Environmental generalization to achieve ubiquitous intelligence: Existing channel prediction networks face significant generalization challenges, requiring not only adaptability to diverse communication tasks but also robust performance across different environments. To address these challenges, the construction of WEK can offer a feasible solution. WEK has strong representational power, enabling the establishment of many-to-many mappings that link multiple environmental features with various channel parameters, thereby capturing the comprehensive impact of the environment on the channel. This mapping framework provides a unified description of channel characteristics, which can be adapted to different environments,

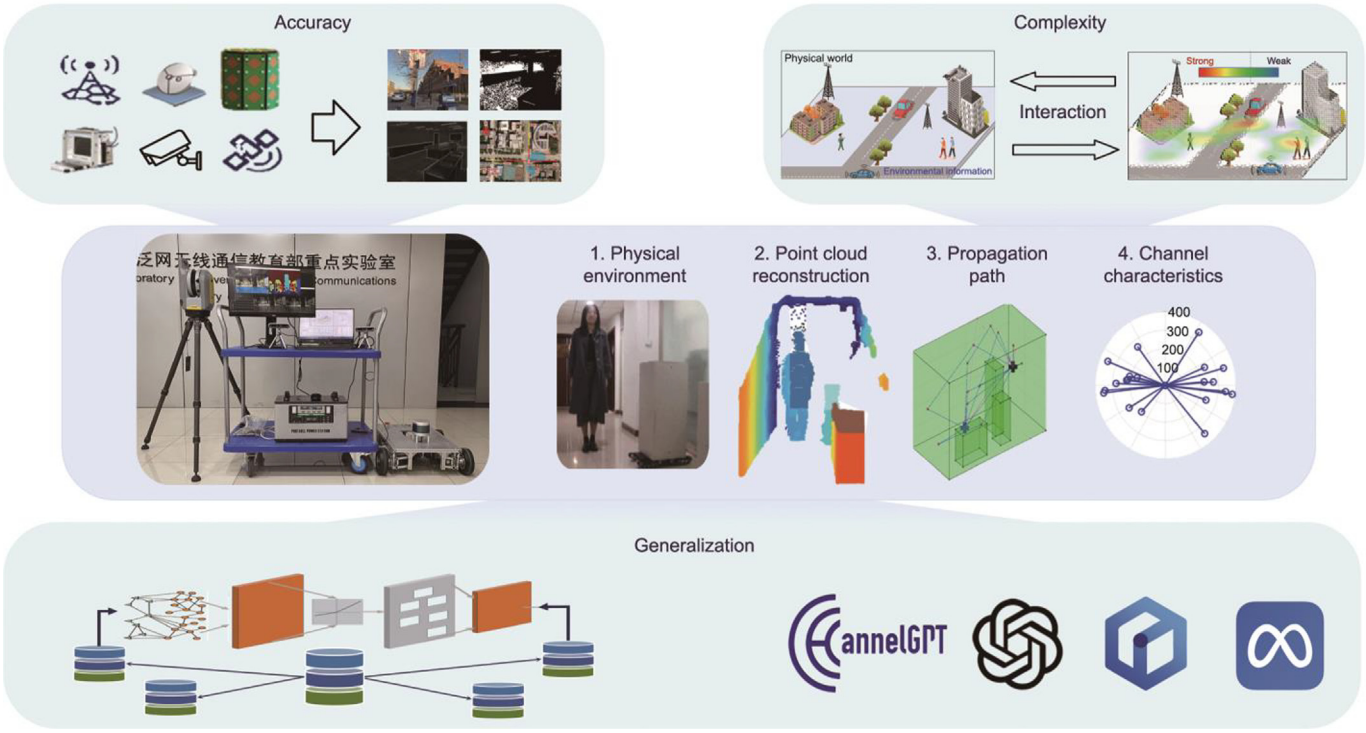

Fig. 15. Main challenges and prospects for future EIC systems: accuracy, complexity, and generalization.

thus overcoming the limitations of task- and environment-specific models. Moreover, channel large models demonstrate exceptional modeling capabilities, multitask learning potential, and superior generalization performance [88]. These models adopt a multitask learning framework to integrate channel knowledge across different communication tasks, enhancing their adaptability to new tasks. Additionally, by applying federated learning to aggregate diversified training data from base stations in different environments, the fundamental model can learn variations in channel characteristics across diverse scenarios, ensuring reliable generalization in diverse propagation environments. However, integrating specific knowledge into large models requires further exploration.

6. Conclusions

Wireless channels play an increasingly important role in communication systems. In this paper, we propose a novel EIC paradigm for 6G networks. The fundamental distinction between EIC and prior AI/sensing-integrated methods lies in the system-level perspective. To facilitate further research, we first introduce WEIT, systematically defining, classifying, and discussing the properties of WEI, and then derive the wireless environmental entropy from the perspective of system capacity. Next, we propose the EIC-WEI architecture, which consists of environment sensing and reconstruction, WEI processing and extraction, AI-based channel prediction, and optimal transmission strategy decision, to implement online intelligent interaction with the physical environment. To further expose the function of WEI within the EIC, a detailed step-by-step processing flow from raw environment data to wireless knowledge is illustrated. Finally, successive numerical results are presented to validate the feasibility of our work based on several different-level tasks for a specific test environment. Finally, several potential future research directions and promising application environments are discussed.

CRediT authorship contribution statement

Jianhua Zhang: Supervision, Methodology, Formal analysis, Writing – review & editing, Resources, Funding acquisition, Conceptualization. **Li Yu:** Writing – review & editing, Supervision, Investigation, Conceptualization, Validation, Project administration, Funding acquisition. **Shaoyi Liu:** Writing – original draft, Validation, Investigation, Writing – review & editing, Visualization, Project administration, Conceptualization. **Yichen Cai:** Writing – review & editing, Validation, Visualization. **Yuxiang Zhang:** Supervision, Writing – review & editing, Conceptualization. **Hongbo Xing:** Conceptualization, Writing – review & editing. **Tao Jiang:** Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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