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Research Article

Meta Fiberverse: Towards Symbiotic Edge Intelligence with Fabric Computing and LLMs

Yue Wang, Jia Liu, Lejun Ai, Xiao-Kun Wu, Wenjing Xiao, Salman A. AlQahtani, Min Chen*, and Guangming Tao

Abstract: With the development of ubiquitous computing and multimodal sensing, intelligent terminals are evolving towards a "human–machine symbiosis" paradigm, increasing demands for intelligent, autonomous, and self-adaptive terminal systems. However, existing systems still face fundamental challenges in real-world deployments: (1) Trade-off between user comfort, data fidelity, and privacy; (2) absence of context-aware scheduling mechanisms; and (3) limited capabilities in semantic generalization. To address these challenges, we propose Meta Fiberverse, a fabric-based computational platform designed for human–machine–environment symbiosis. The system integrates high-density fabric sensing, high-fidelity scheduling mechanisms, and plugin-enhanced semantic coordination framework powered by Large Language Models (LLMs). Experimental results demonstrate the system's performance in communication latency and task accuracy, offering a feasible path and technical reference for next-generation human-centered intelligent terminals with human–machine symbiosis, resource self-consistency, and semantic autonomy.

Key words: fabric computing; edge intelligence; Large Language Models (LLMs)

1 Introduction

With the rapid advancement of ubiquitous computing and multimodal sensing techniques, intelligent terminals at the edge are transitioning from traditional passive sensors to autonomous agents, with capabilities of semantic understanding and collaborative task execution[1, 2]. In human-centered application scenarios, such as healthcare, smart homes, and wearable computing, user expectations are also shifting from data acquisition to a higher-level capabilities,

• Yue Wang and Lejun Ai are with School of Computer Science and Engineering, South China University of Technology, Guangzhou 510006, China. E-mail: csyuewang@mail.scut.edu.cn; cs_ailejun@mail.scut.edu.cn.
• Jia Liu is with School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan 430074, China. E-mail: jialiu0330@hust.edu.cn.
• Xiao-Kun Wu is with School of Journalism and Communication, Renmin University of China, Beijing 100872, China. E-mail: wuxiaokun@ruc.edu.cn.
• Wenjing Xiao is with School of Computer and Electronics and Information and Guangxi Key Laboratory of Multimedia Communications and Network Technology, Guangxi University, Nanning 530004, China. E-mail: wenjingx@gxu.edu.cn.
• Salman A. AlQahtani is with Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 12372, Saudi Arabia. E-mail: salmanq@ksu.edu.sa.
• Min Chen is with School of Computer Science and Engineering, South China University of Technology, Guangzhou 510006, China, and also with Pazhou Laboratory, Guangzhou 510335, China. E-mail: minchen@ieee.org.
• Guangming Tao is with School of Optical and Electronic Information and Wuhan National Laboratory for Optoelectronics, Huazhong University of Science and Technology, Wuhan 430074, China. E-mail: tao@hust.edu.cn.
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including semantic interpretation, contextual reasoning, and adaptive task coordination. This evolution signals a shift towards a "human–machine symbiosis" paradigm, where intelligent terminal devices are not only embedded in physical spaces, but also deeply integrated into user contexts, enabling closed-loop autonomy across the chain of sensing, communication, and computation[3].

Despite recent progress in related technologies, intelligent systems built upon current consumer electronics and edge computing architectures still face three fundamental challenges in practical deployment. First, there exists a structural contradiction among user comfort, data fidelity, and privacy protection. Though vision-based sensing enables high-resolution and contactless monitoring, it oftens compromises user privacy[4]. Conversely, conventional wearable devices offer improved data integrity and privacy, but they still suffer from rigid form factors and user discomfort after long-term wearing, limiting their abilities to coexists with users. Second, existing systems lack context-aware mechanisms for sensing and resource scheduing. In dynamic human-centered environments, fixed sampling strategies and static computation pipelines often fail to handle fluctuations, resulting in additional response latency and transmission costs, undermining system coherence. Third, mainstream models offering analyses are still tailored for task-specific inference, lacking semantic generalization. In complex physical scenarios involving high-dimensional, multimodal tasks, static fusion schemes are insufficent to support system interpretability, restricting the development of semantically autonomous systems.

In the era of edge intelligence, studies are exploring paradigms of application layer[5]. Early approaches often rely on static multimodal fusion architectures and lightweight deep learning models. Early and late fusion schemes integrate sensor inputs at fixed stages, and compressed models are deployed to meet latency and energy constraints. Although effective for specific tasks, these methods lack adaptation to dynamic contexts, making them unsuitable for complex, evolving environments. More recently, Large Language Models (LLMs) have been introduced into sensor-rich applications, and some studies incorporate LLMs to interpret structured sensor data or to issue control commands in smart environments[6]. Furthermore, pretrained LLMs lack modularity and are difficult to adapt or optimize in edge deployments[7]. These limitations highlight the absence of a flexible and extensible system architecture capable of bridging physical perception with high-level reasoning in a dynamic, multimodal, and resource-constrained edge setting.

To bridge the technical gaps and address these challenges, we propose Meta Fiberverse, a fabric-based intelligent terminal platform designed for human–machine–environment symbiosis. Our system integrates three key components. At its foundation, the system leverages high-density fabric sensing, a novel modality specifically to resolve the fundamental conflict among user comfort, data fidelity, and privacy by enabling unobtrusive, non-visual data acquisition. Building upon the data layer, we introduce a context-driven adaptive scheduling mechanism by dynamically allocating sensing and communication resources. Finally, to achieve high-level semantic generalization, the architecture is crowned with a plugin-enhanced semantic coordination framework, which empowers LLMs to perform complex reasoning and multi-task coordination. This integrated design ensures coexistence in sensing, resource self-consistency in communication, and semantic autonomy in computation, thereby towards a symbiotic intelligent system.

The contributions of this paper are as follows.

- We propose Meta Fiberverse, a novel architecture leveraging fabric computing and LLMs. This platform constructs an intelligent terminal platform with human–machine symbiotic properties, achieving coordinated optimization of comfort, fidelity, and semantic awareness.
- We design a context-adaptive mechanism including sampling, scheduling, and task inference, and employ Reinforcement Learning (RL) to optimize transmission efficiency and computational pathways, achieving reduced communication latency without compromising task accuracy.
- We develop a plugin-enhanced semantic coordination framework, enabling dynamic interaction between multimodal signals and LLMs, equipping the system with semantic generalization and multi-task coordination capabilities to support efficient natural language-driven task execution at the edge.

The remainder of this paper is organized as follows. Section 2 reviews related work on multimodal sensing, LLMs, and edge intelligence. Section 3 introduces the overall system architecture of Meta Fiberverse, detailing its sensing, communication, and semantic coordination modules. In Section 4, we define the problem formulation of the context-adaptive scheduling mechanism. Section 5 outlines the experimental setup. The experimental results and comparative analysis are reported in Section 6. Section 7 discusses open challenges and future research directions. Finally, Section 8 concludes the paper.

2 Related Work

Meta Fiberverse introduces a novel system integrating multimodal textile-based sensing, plugin-augmented LLMs, and context-aware adaptive sampling. In this section, we review prior works most closely related to these areas, from the perspective of computer science. We focus on three key lines of related research: Multimodal wearable and ambient sensing systems, task-oriented language model systems in ubiquitous environments, and adaptive perception and scheduling strategies for efficient edge intelligence.

2.1 Wearable and ambient sensing system

Recent advances in wearable sensing have significantly expanded the capacity of edge devices to perceive human physiological and behavioral states. Non-textile wearables, such as wristbands, smartwatches, and patches, have demonstrated reliable performance in tracking heart rate, motion, temperature, and blood oxygen levels using Inertial Measurement Units (IMUs)[8], photoplethysmography (PPG)[9], and skin temperature sensors[10]. Despite their utility, such devices suffer from rigid mechanical structures, limited battery life, and sparse coverage areas, posing ergonomic and scalability limitations[2].

To overcome these constraints, fabric-based wearable systems have emerged as a promising alternative. Textile-integrated electronics enable unobtrusive, body-conforming, and wide-area sensing, making them ideal for continuous physiological monitoring in daily environments[11]. Multifunctional e-textiles now integrate pressure mapping, electrocardiogram (ECG) acquisition, and respiration tracking directly into garments, bed surfaces, or furniture upholstery[12–14]. These systems utilize conductive yarns, fiber-based sensors, and knitted or embroidered circuits, offering enhanced comfort and greater coverage compared to rigid counterparts[15, 16].

Ambient sensing systems embedded in physical spaces, such as vision-based cameras and monitors, Wireless Fidelity (Wi-Fi) sensing systems, pressure-sensitive arrays, provide contextual information about user presence, posture, and interaction[17, 18]. These ambient modalities complement wearables by enabling non-contact, space-aware inference[19]. Recent advances in algorithm-level further enhance ambient sensing in various applications, such as human pose estimation[20]. The fusion of wearable and ambient sensing has shown promise in enhancing task recognition and behavioral monitoring, especially in healthcare and smart home scenarios[4, 21].

2.2 Task-oriented LLMs in ubiquitous environments

LLMs have recently emerged as a potential semantic interface layer for Internet of Things (IoTs) systems. Several studies have explored the use of LLMs to control devices, generate summaries, or detect anomalies from sensor data[6, 22]. While these models show impressive zero-shot capabilities, their integration with multimodal data and real-time IoTs streams remains limited.

To extend LLM capabilities, Retrieval-Augmented Generation (RAG) architectures[23] have been introduced, enabling external knowledge access. Tool-augmented LLMs such as Toolformer[24] and HuggingGPT[25] further enable models to invoke APIs or delegate subtasks, acting as orchestrators across heterogeneous services. In the meanwhile, LLM fine-tuning also serves an effective approach for domain-level deployment in embodied systems[7, 26].

Despite these innovations, current deployments heavily rely on cloud inference due to the resource demands of LLMs. Recent efforts such as PerLLM[27] and edge-optimized quantization strategies[28] explore lightweight deployment. Some emerging frameworks have started to explore autonomous agent towards in-situ intelligence using LLMs[29].

2.3 Adaptive scheduling for edge intelligence

Adaptive sensing strategies aim to reduce resource usage while maintaining sensing quality. Event-driven or context-aware sampling has been shown to significantly reduce data redundancy and energy consumption[30, 31]. RL approaches have also been explored for optimizing multi-sensor sampling policies[31].

On the processing side, early-exit networks[32], edge-cloud collaboration mechanisms[27], and resource-aware inference schedulers[33] further improve efficiency, though most do not incorporate sensor-level feedback. Scheduling decisions are often based on system metrics (e.g., CPU load), without semantic awareness of user intent or data context. Some studies proposed virtualization and service slicing for dynamic environments[3, 5], which provide one of the possible solutions for dynamic scheduling.

3 Meta Fiberverse Architecture

As shown in Fig. 1, Meta Fiberverse is a fabric-computing-driven platform architected for human-centric autonomous systems. It features a hierarchical, distributed architecture comprising three core layers: (1) A multimodal fabric sensing layer for high-fidelity acquisition of physiological and environmental states; (2) an edge scheduling layer that dynamically regulates sampling and transmission behaviors; and (3) a plugin-enhanced application layer that interfaces with LLMs for semantic-level reasoning and multimodal interaction. By centering on the concept of fabric-state intelligence, the system unifies perception, communication, and computation within a coherent design paradigm—bridging traditional boundaries between sensing hardware, edge autonomy, and LLM-driven task execution.

3.1 Sensing layer

The sensing layer constitutes the physical realization of our framework's foundational component. As shown in Fig. 2, we design and integrate a cohesive testbed that combines diverse wearable and ambient fabric sensing modalities. This implemented layer serves as the physical interface between the user and the Meta Fiberverse system, enabling comprehensive, contact-aware monitoring.

- **Wearable sensing:** Wearable modules integrate textile-based sensors into stretchable garments, enabling conformal acquisition of vital signals such as electrocardiogram (ECG), PPG, body temperature, and motion. In our testbed, a dry-contact tri-lead ECG array provides gel-free, long-term cardiac monitoring, while PPG-based optical modules support cuffless blood pressure and blood oxygen estimation, all of which are embedded within fabrics for unobtrusive use.
- **Ambient sensing:** Complementing the wearable components, ambient sensing is realized through a smart fabric bed platform equipped with a high-density grid of resistive pressure sensors and Negative Temperature Coefficient (NTC) thermistors. These sensors capture body-contact pressure, posture, respiratory cycles, and local temperature without direct skin contact. Through fabric-level integration and multi-channel sensing array acquisition, the system supports high spatial resolution and temporal fidelity.

3.2 Scheduling layer

Situated between sensing and application, the edge intelligence layer governs sampling behavior and communication strategies in a context-aware manner. A fabric agent, embodied on a MicroController Unit (MCU), dynamically adjusts the sampling rate and sampling density of each sensing modality according to

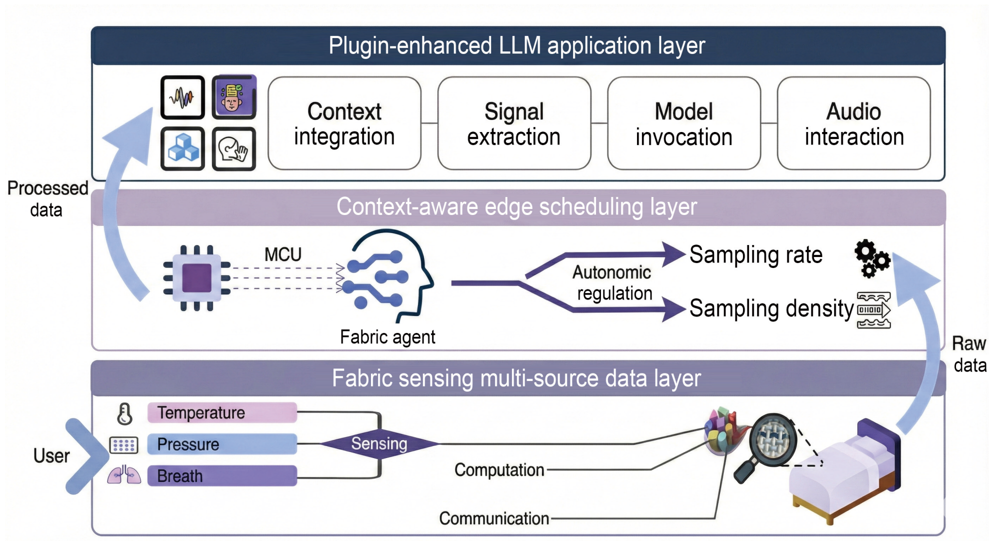

Fig. 1 Meta fiberverse architecture. It is organized into three primary layers: Fabric-based multimodal sensing layer, edge-side adaptive scheduling layer, and plugin-enhanced LLM application layer.

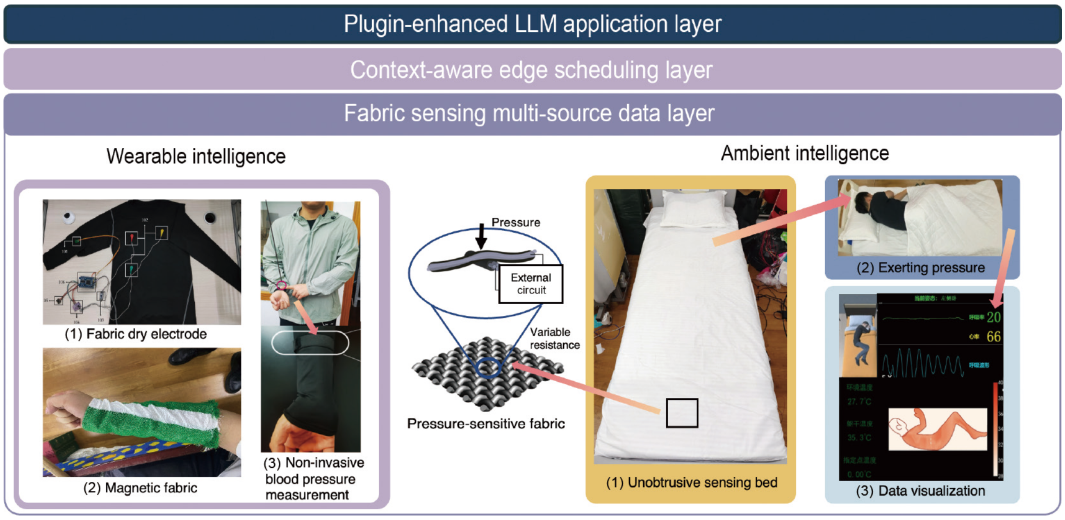

Fig. 2 Fabric-based multimodal sensing layer as hardware component of Meta Fiberverse. The left panel illustrates wearable sensing: (1) A textile-based dry electrode system for three-lead ECG acquisition, integrated into garments using flexible conductive fabrics; (2) a magnetic-fabric interface for motion detection on a rowing platform, enabled by embedded textile coils interacting with attached magnets; and (3) a cuffless blood pressure monitoring technique based on PPG and embedded optical sensors. The right panel showcases ambient sensing: (1) A smart bed with embedded pressure-sensitive textile grid for (2) high-resolution body contact detection; and (3) data collection for respiration, temperature, and ECG, supporting contactless physiological monitoring.

upstream requirements and local resource constraints. By autonomously regulating sensing fidelity and transmission priority, this layer minimizes redundant data while preserving semantic saliency, forming a closed-loop bridge between raw physical signals and high-level computational demands.

3.3 Application layer

At the top layer of Fig. 1, we deploy a plugin-augmented LLM interface to facilitate multimodal inference, decision-making, and interaction. As shown in Fig. 3, each plugin module transforms domain-specific sensor inputs into semantically enriched prompts, allowing the LLM to integrate multimodal information within a unified reasoning framework. Perception-oriented plugins extract embeddings from pressure distributions and physiological signals, while auxiliary modules encode audio data and personalized user context. Through prompt fusion and sequence alignment, the LLM performs holistic analysis and generates task-oriented responses in natural language, enabling scalable interaction scenarios such as health monitoring, behavior interpretation, and anomaly alerting.

4 Context-Aware Scheduling Formulation

We consider a task-aware scheduling system that dynamically configures sensing and transmission strategies over multimodal sensor streams. The goal is to minimize end-to-end delay for task-relevant modalities while ensuring efficient resource utilization under bandwidth and compute constraints.

Let $\mathcal{T}$ denote the set of semantic tasks (e.g., posture recognition, health monitoring, and multimodal question answering). Each user $n \in \mathcal{N} = \{1, 2, \ldots, N\}$ is assigned a task $\tau_n \in \mathcal{T}$, which is semantically associated with a subset of modalities in Eq. (1),

$$\mathcal{M}_{\mathrm{rel}}(\tau) \subseteq \mathcal{M} = \{1, 2, \ldots, M\} \tag{1}$$

We define a binary mask to capture user-task-driven modality preferences, $\omega_{n,m}$ refers to binary mask of user n and modality m, and is set to one if task of user n has preference with modality m, as shown in Eq. (2),

$$\omega_{n,m} = \begin{cases} 1, & \text{if } m \in \mathcal{M}_{\mathrm{rel}}(\tau_n) \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

This binary mask determines which modalities are prioritized for high-fidelity transmission and computation.

For each user–modality pair (n, m), the system jointly selects three types of decision variables as follows:

- A sampling resolution, $q_{n,m} \in \mathcal{Q}$, where $\mathcal{Q}$ is a discrete set of upstream encoder models.
- A signal processing strategy, $\phi_{n,m} \in \Phi$, where

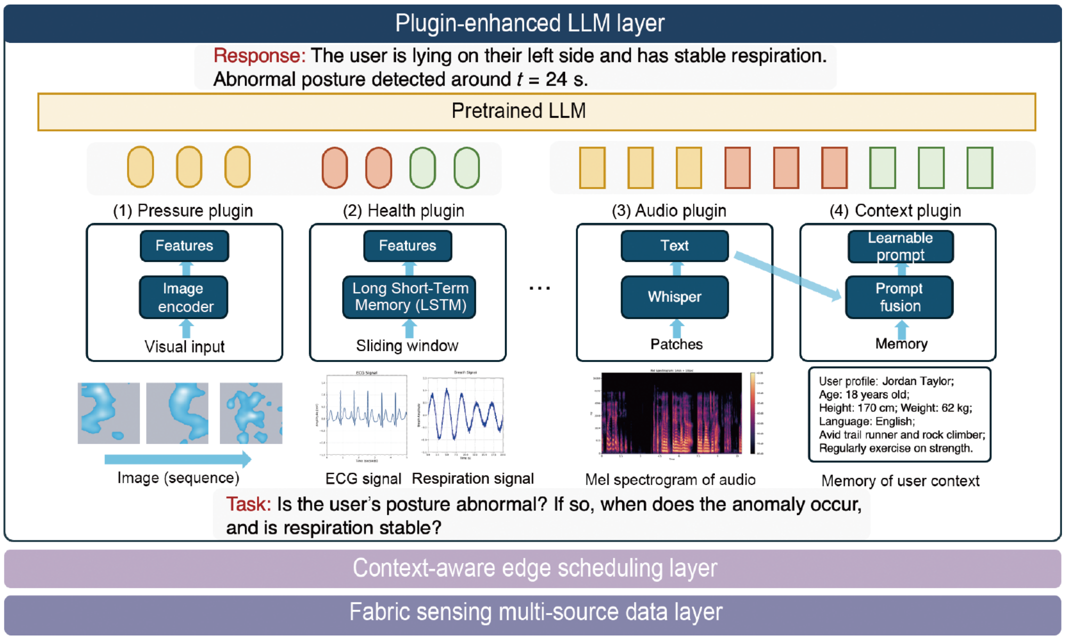

Fig. 3 Plugin-enhanced LLM application layer. To enable multimodal reasoning with LLMs, we introduce multiple plugin modules that convert heterogeneous inputs into unified prompt tokens. For example, plugins (1) and (2) extract semantic embeddings from pressure and physiological signals, serving as perception-oriented modules, and plugins (3) and (4) handle audio input and user-specific context, functioning as learnable prompts for conditioning the LLM. Plugin-enhanced LLM supports unified, context-aware reasoning across modalities.

$\Phi = 0, 1, 2$ corresponds to raw, preprocessed, and compressed signals, respectively.

- An allocated communication bandwidth B_n and computation resource R_m.

We define the per-user task-aware latency in Eq. (3),

$$D_n = \sum_{m=1}^{M} \omega_{n,m} \cdot \left[\frac{C_m(\phi_{n,m}, q_{n,m})}{R_m} + \frac{S_m(\phi_{n,m}, q_{n,m})}{B_n} \right] \tag{3}$$

where $C_m(\cdot)$ denotes compute load and $S_m(\cdot)$ denotes the effective signal size after sampling and preprocessing. R_m is the processing bandwidth allocated for modality m, and B_n is the transmission bandwidth allocated for user n.

Additionally, we consider an empirical accuracy function $A_{n,m}$ to estimate the trends of accuracy in terms of different settings in Eq. (4),

$$A_{n,m} = \alpha_n \cdot \left(\beta_n + (1-\beta_n)\left(1 - \frac{q_{n,m}}{q_{\max}}\right)^{\sigma_n} \right) \times \gamma^{\mathbf{1}_{\{\phi_{n,m}=0\}}} \tag{4}$$

where α_n represents the empirical average accuracy of τ_n, β_n is the base proportion of accuracy of τ_n, σ_n is the sensitivity of accuracy of τ_n, γ is the discount factor if data compression is adopted, $\mathbf{1}_{[\cdot]}$ is the indicator function, it equals 1 when the enclosed condition is satisfied, and 0 otherwise, and $q_{\max}$ represents the maximum sampling resolution in $\mathcal{Q}$.

Therefore, empirical accuracy of each τ_n can be aggregated in Eq. (5),

$$A_n = \frac{1}{|\mathcal{M}_{\text{rel}}(\tau_n)|} \sum_{m \in \mathcal{M}_{\text{rel}}(\tau_n)} A_{n,m}(q_{n,m}, \phi_{n,m}) \tag{5}$$

Rather than optimizing task-specific post-hoc accuracy, we adopt a latency-centric optimization paradigm. Let $\Theta = \{q_{n,m}, \phi_{n,m}, B_n, R_m \mid n \in \mathcal{N}, m \in \mathcal{M}\}$ denote the system configuration strategy. We assume the edge system has a total communication bandwidth limit $B_{\max}$ and a total computational capacity $R_{\max}$. We formulate this as a constrained minimization problem in Formulas (6)–(10),

$$\min_{\Theta} \left(\sum_{n=1}^{N} D_n(\Theta), \quad \sum_{n=1}^{N} (1 - A_n(\Theta)) \right) \tag{6}$$

$$\text{s.t.,} \quad \sum_{n=1}^{N} B_n \leqslant B_{\max} \tag{7}$$

$$\sum_{m=1}^{M} R_m \leqslant R_{\max} \tag{8}$$

$$q_{n,m} \in \mathcal{Q}, \ \phi_{n,m} \in \Phi \tag{9}$$

$$B_n \geqslant 0, \ R_m \geqslant 0 \tag{10}$$

where Formulas (7) and (8) represent the global constraints on bandwidth and computing resources, respectively. This formulation enables adaptive resource scheduling across users and modalities, while ensuring task-critical information flows are prioritized and latency minimized. Empirical validation in later sections will demonstrate that the proposed strategy achieves this delay minimization without significantly compromising downstream task performance.

5 Experimental Setup

5.1 Sensing layer

5.1.1 Ambient intelligence

The ambient intelligence layer of Meta Fiberverse is constructed upon a high-density, fabric-embedded sensor infrastructure designed for passive and spatially distributed environment sensing. Unlike wearable intelligence, which emphasizes on-body signal capture, ambient intelligence focuses on context-aware observation through surface-integrated sensing. The core substrate is a $2\,\mathrm{m} \times 1\,\mathrm{m}$ fabric sensor array incorporating flexible conductive fibers and thin-film elements, enabling the detection of pressure, strain, temperature, and micro-motion events across a continuous spatial field.

At the hardware level, three distinct classes of sensing fibers are deployed: temperature sensing fibers, conventional pressure sensing fibers, and micro-motion pressure sensing fibers. These fibers translate thermomechanical signals into voltage variations, which are sampled by an ATMEGA328P-AU microcontroller with a 20 MHz clock and 1-cycle-per-instruction execution. The system supports up to 16 analog channels, each sampled at 10-bit resolution and 32 Hz, leading to a total throughput of 4 kB/s across all channels. Data acquisition is managed on an Arduino-based platform and temporarily stored in a local 4 MB buffer.

For wireless data offloading, an ESP-12F communication module is used, supporting Wi-Fi 4 (IEEE 802.11n) with User Datagram Protocol (UDP) protocol. Each UDP packet is constrained by an effective payload ceiling of 1024 Bytes, with a theoretical maximum transfer rate of 450 Mbit/s and adaptive bandwidth operation from 10 Mbit/s to 100 Mbit/s. The UDP-based transmission scheme ensures low-latency delivery suitable for high-throughput sensing, while maintaining flexibility for heterogeneous deployments.

5.1.2 Wearable intelligence

The wearable intelligence layer of Meta Fiberverse is built upon a new generation of fabric-integrated sensing fabrics, exemplified by smart textiles capable of continuous physiological monitoring. At its core lies a washable, textile-based electronic system—referred to as the smart fabric node—which embeds multiple biomedical sensors into wearable fabrics using dry electrode techniques. This design achieves real-time acquisition of vital signs, such as ECG, heart rate, blood oxygen saturation (SpO_2), body temperature, and blood pressure, while maintaining wearability and comfort even under long-duration deployments.

Unlike traditional wearable devices that suffer from rigid form factors and motion-induced signal degradation, the proposed fabric sensor integrates conductive textiles and soft microelectronic components into a distributed, skin-conformal system. Notably, the ECG module employs a tri-electrode dry-contact configuration (Right Arm (RA), Left Arm (LA), and Left Leg (LL)), based on a custom-developed conductive sponge electrode, enabling gel-free, low-noise signal acquisition suitable for long-term use. The ECG signals are processed in situ using the AD8232 analog front-end, allowing for signal conditioning before wireless offloading.

Blood oxygen and heart rate measurements are realized through an embedded MAX30102 module, which implements dual-wavelength PPG. Its positioning on the lateral forearm ensures stable contact while supporting dynamic posture adaptation. Meanwhile, cuffless blood pressure monitoring is achieved via a photoplethysmography-derivative method using HR6707 and HR6816 chipsets, with algorithmic estimation performed on a dedicated SFB9712 MCU. This non-invasive and passive technique facilitates continuous systolic and diastolic trend estimation with minimal intrusion.

To support high-fidelity signal delivery, the smart fabric incorporates a Bluetooth Low Energy (BLE) 4.0 module (DX-BT05A) optimized for ultra-low power transmission. Physiological data are streamed in real-time to a proximal edge device or mobile terminal, forming the gateway into the broader Meta Fiberverse system. Locally, a mobile application offers real-time visualization, anomaly alerts, and cloud synchronization. When integrated with the plugin orchestration mechanism of the central LLM, this enables autonomous multi-modal health state inference and human-aware context enrichment.

5.2 Scheduling layer

To assess the performance of the edge scheduling layer in Meta Fiberverse, we formulate the adaptive resource scheduling task as a Markov Decision Process (MDP), consisting of three components: the state space, the action space, and the reward function. The optimization objective is solved using the Proximal Policy Optimization (PPO) algorithm from deep RL.

5.2.1 State space

The state space is designed to capture the essential communication and application-level context required for decision-making. At each time step t, the state s_t is in Eq. (11),

$$s_t = \left[\boldsymbol{D}_t^{\text{proc}}, \boldsymbol{D}_t^{\text{tran}}, \boldsymbol{D}_t, \boldsymbol{\alpha}_t\right] \tag{11}$$

where $\boldsymbol{D}_t^{\text{proc}} = (D_{1,t}^{\text{proc}}, D_{2,t}^{\text{proc}}, \ldots, D_{N,t}^{\text{proc}})$ denotes the vector of processing delays for all users, $\boldsymbol{D}_t^{\text{tran}} = (D_{1,t}^{\text{tran}}, D_{2,t}^{\text{tran}}, \ldots, D_{N,t}^{\text{tran}})$ denotes the vector of transmission delays, and $\boldsymbol{D}_t = \boldsymbol{D}_t^{\text{proc}} + \boldsymbol{D}_t^{\text{tran}}$ represents the total end-to-end delay for each user. Additionally, $\boldsymbol{\alpha}_t = (\alpha_{1,t}, \alpha_{2,t}, \ldots, \alpha_{N,t})$ encodes the empirical task accuracy associated with each user at time step t.

5.2.2 Action space

We adopt a multidiscrete action space formulation to represent the decision variables. The agent selects actions from a combination of transmission and computation control parameters, as show in Eq. (12),

$$a_t = (\phi_{n,m}, q_{n,m}, B_n, R_m) \tag{12}$$

5.2.3 Reward

At time step t, r_t is a weighted composite score that balances communication delay and task accuracy, as shown in Eq. (13),

$$r_t = \lambda \cdot E_n\left(\frac{1}{1+D_{n,t}}\right) + (1-\lambda) \cdot E_n\left(\frac{\alpha_{n,t}}{\alpha_{n,t}^{\max}}\right) \tag{13}$$

where $D_{n,t}$ is the total delay for user n at time step t, $\alpha_{n,t}^{\max}$ represents the maximum theoretical accuracy for task τ_n (used for normalization), and $\lambda \in [0, 1]$ is a tunable parameter controlling the trade-off between latency and accuracy. The first term rewards lower communication delays, while the second term normalizes the empirical task accuracy across users to ensure fair evaluation in multi-task settings.

5.3 Application layer

The core of our application layer is a principled framework for multimodal context inference to holistically reason over heterogeneous and multimodal data streams from our fabric sensing platform. All experiments involving the LLM backbone are conducted on a server equipped with NVIDIA A800 80 GB GPUs and computationally intensive tasks, such as LLM inference, are offloaded from the resource-constrained sensing devices. For LLM backbone and multimodal plugin architecture, we use LLaVA-7B as our system's backbone and a strong and reproducible baseline, for its open-source implementation and capabilities in joint vision–language understanding.

For native visual modality, the raw pressure matrix $P \in \mathbb{R}^{H_{\text{P}} \times W_{\text{P}}}$ is the primary visual signal, where H_{P} and W_{P} denote the height and width of the pressure sensor array, respectively. It is first rendered as an image and then upsampled to interface with the Contrastive Language Image Pre-training (CLIP) ViT-L/14 vision encoder. With patch-based visual features $F_{\text{V}} \in \mathbb{R}^{N_{\text{V}} \times D_{\text{V}}}$, where N_{V} is the number of visual patches and D_{V} is the feature dimension, a linear projection layer g_{V} serves as adapter, mapping into visual embeddings $Q_V = g_{\text{V}}(F_{\text{V}}) \in \mathbb{R}^{N_{\text{V}} \times K}$, in which K is the word embedding dimension of LLM.

To handle non-native sequential data, we employ fixed, domain-specific feature extractors as plugins. Time-series physiological signals are processed by a pretrained LSTM encoder ϵ_{H} to produce feature vector $F_{\text{H}} \in \mathbb{R}^{D_{\text{H}}}$, where D_{H} represents the hidden size of the LSTM encoder. F_{H} is also projected via adapter g_{H} to embedding token $Q_{\text{H}} = g_{\text{H}}(F_{\text{H}}) \in \mathbb{R}^{1 \times K}$. Similarly, the audio plugin utilizes the pretrained Whisper model as speech-to-text engine, and produce vector of text embeddings $Q_{\text{A}} \in \mathbb{R}^{L_{\text{A}} \times K}$, where L_{A} denotes the sequence length of the transcribed audio tokens.

To ensure personalized outputs, context plugin is utilized. That is, static user profile information is injected via a set of learnable prompt embeddings, $Q_{\text{C}} \in \mathbb{R}^{N_{\text{C}}} \times K$, where N_{C} is the number of context prompt tokens. This technique provides user-specific context for the generative process of the LLM.

The user's textual query is embedded into $Q_t \in \mathbb{R}^{L_t \times K}$, where L_{t} is the length of the query tokens. The final input sequence into LLM is a ordered concatenation of all modality-derived embeddings, shown in Eq. (14),

$$Q = \text{concat}\,[Q_{\text{t}}, Q_{\text{V}}, Q_{\text{H}}, Q_{\text{A}}, Q_{\text{C}}] \tag{14}$$

To train and evaluate the system, we collect a dataset using a smart fabric bed equipped with a high-resolution pressure sensor array. The dataset comprises a total of 36 000 labeled pressure frames from multiple participants across three primary postures: Supine, left lateral, and right lateral. Recognizing that the scale of the collected data is limited by practical constraints, which could hinder model generalization, we employ a data augmentation strategy. We utiliz Deep Convolutional Generative Adversarial Network (DCGAN) to synthesize new, realistic pressure maps, thereby enriching the dataset's diversity. As illustrated in Fig. 4, this approach is highly effective, leading to a significant improvement in task accuracy and demonstrating that data augmentation is a necessary strategy in this context.

6 Result

6.1 Comparative and ablation analysis

To validate the contribution of the key components of Meta Fiberverse, we conduct several ablation analyses for both the application and scheduling layers. First, for the plugin-enhanced LLM application layer, we perform two distinct ablation studies. The initial study, shown in Fig. 5, validates the fundamental benefit of multimodal data fusion at the input level. The bar chart depicts the posture recognition accuracy across different sensing configurations and training epochs. The results show that using pressure sensing alone establishes a robust baseline, achieving an accuracy exceeding 83% after three epochs. The integration of additional physiological modalities, such as respiration or ECG signals, consistently leads to notable accuracy improvements over this single-modality setup. While multi-modal configurations sometimes require a longer convergence period, they eventually outperform their single-modality counterparts, quantitatively validating the effectiveness of data fusion in enhancing task accuracy. Building on this, the second study, shown in Fig. 6, directly ablates the plugin modules to demonstrate their individual contributions to high-level semantic tasks. Using the pressure plugin as the system baseline, we evaluated performance on various Question–Answer (QA) tasks. The results clearly show that for task-specific queries, only the relevant plugins yield substantial gains; for example, respiration-QA relies on real-time physiological data from the Health plugin, while health-risk-QA is driven primarily by the user's contextual information. Conversely, unrelated plugins provide little benefit, substantiating the merit of our on-demand, modular design. Importantly, enabling multiple plugins simultaneously does not degrade accuracy, and the full-plugin configuration consistently attains the highest performance across all tasks. Together, these findings confirm that our plugin architecture successfully propagates the advantages of low-level multimodal sensing to high-level semantic reasoning.

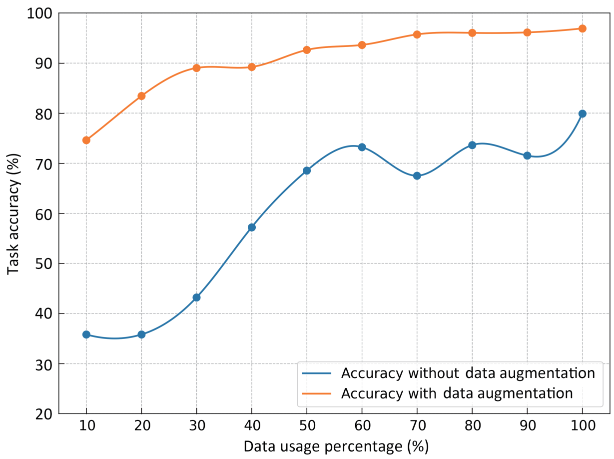

Fig. 4 Comparison of task accuracies with and without data augmentation.

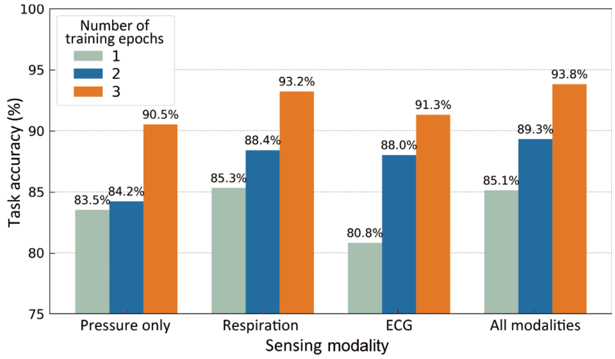

Fig. 5 Task accuracy improvements of posture classification under different sensing modalities.

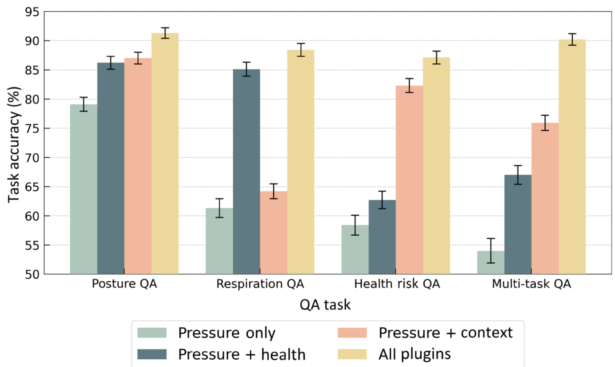

Fig. 6 Accuracies across QA tasks under different plugin combinations.

Second, for the context-aware edge scheduling layer, our specific algorithm is validated through a comprehensive comparative analysis in Figs. 7 and 8. This analysis benchmarks our RL-based scheduler against multiple baselines: A greedy policy that transmits raw data to establish an upper bound on accuracy, a random policy, and several fixed-ratio compression schemes. Figure 7 plots the communication delay as a function of available bandwidth. While all strategies show a delay reduction with increasing bandwidth, our RL-driven scheduler consistently achieves the lowest delay across the entire spectrum, confirming its superiority in optimizing data transmission efficiency.

However, low latency is only meaningful if task accuracy is preserved. Figure 8 depicts this crucial trade-off. The greedy policy, by ignoring latency constraints, serves as the accuracy upper bound. The results demonstrate that our RL-driven adaptive scheduler's accuracy approaches this upper bound once sufficient bandwidth is available, while still significantly outperforming fixed-ratio compression schemes in the low-bandwidth regime. Taken together,

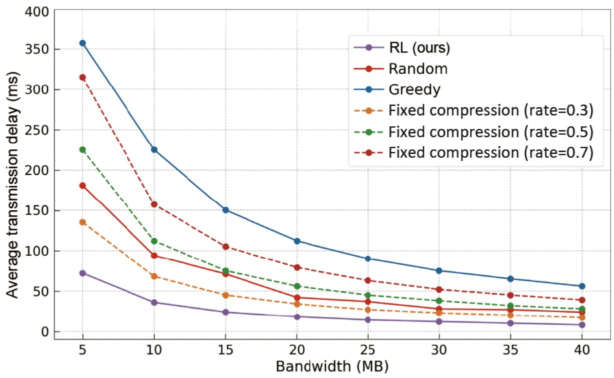

Fig. 7 Transmission delays under different sampling strategies with varying bandwidths.

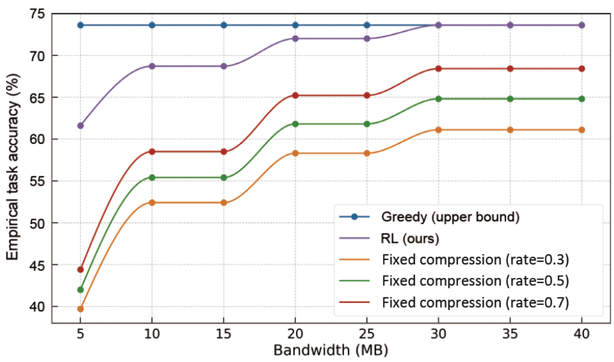

Fig. 8 Empirical accuracy retentions under different sampling strategies with varying bandwidths.

these findings confirm that our adaptive strategy successfully navigates the latency-accuracy trade-off, simultaneously achieving low-latency communication and high-fidelity transmission, thereby confirming the effectiveness of our adaptive design choice over simpler, non-adaptive variants.

6.2 Semantical qualitative analysis

To further understand the behavior of the application layer, we visualize the semantic embedding space using t-SNE, as shown in Figs. 9 and 10.

Figure 9 illustrates the distribution of the questions in our constructed QA pairs within the semantic embedding space. The embeddings associated with sitting and lying postures form highly compact clusters, while those for left-leaning and right-leaning postures are located in neighboring regions. This arrangement reflects the internal semantic organization of the large

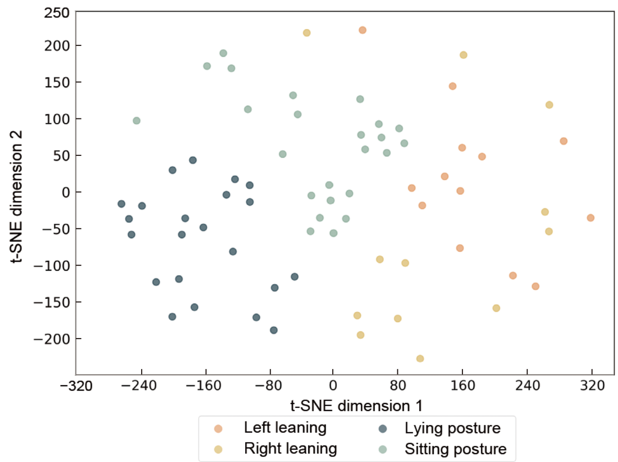

Fig. 9 t-SNE visualization of posture-related QA pairs. Each point represents the embedding of a question in posture QA pairs.

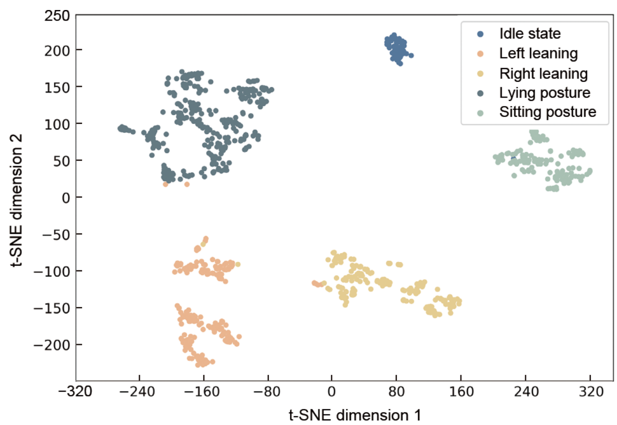

Fig. 10 t-SNE visualization of posture-related embedding of QA pairs in application layer.

language model; because left-leaning and right-leaning postures differ only in direction, they share a high degree of semantic similarity and thus tend to overlap in the embedding space. Furthermore, the relatively wide spread of points within each color-coded cluster demonstrates the linguistic diversity of the query formulations, which enables broader coverage of user expressions and improves the system's robustness.

Figure 10 presents the corresponding embeddings produced during the inference of QA pairs, mapping the multimodal sensor data to the learned semantic space. The results show a clear and discriminative structure. Among the five task categories, the idle class, representing sensor noise, is clustered specially, while the embeddings of other postures are more diverse. Notably, the sitting-posture cluster is clearly separated from the remaining categories. These patterns confirm the realism and discriminative strength of the learned semantic space, providing qualitative evidence that the plugin-enhanced LLM is successfully mapping complex sensor inputs to meaningful, well-separated representations.

7 Discussion and Future Work

Meta Fiberverse introduces a fabric-computing-centric architecture for intelligent terminal systems, achieving seamless integration across flexible sensing, low-latency communication, and semantic-level application intelligence. Preliminary evaluations demonstrate the system's feasibility and practicality in scenarios requiring fine-grained human–machine integration. Nonetheless, several limitations remain, highlighting opportunities for future research.

First, the current LLM backbone remains fixed; future extensions may involve multi-stage co-training or Low-Rank Adaptation (LoRA) of the LLM for domain-specific tasks.

Second, the system's perception capabilities are currently focused on physical-layer signals such as posture and vital signs. It lacks mechanisms for capturing higher-order semantic states such as emotional cues, cognitive intent, or social context. Developing unified multimodal abstraction frameworks that encompass both low-level physiological signals and high-level human intent will be critical for enabling more natural and meaningful human–machine collaboration.

Third, our evaluation reflects a trade-off between classification granularity and model robustness. While in-bed human postures are highly variable and can be categorized into many fine-grained classes, our focus on three primary categories was a strategic choice to ensure robust generalization within the scope of our collected data. Nevertheless, we acknowledge that this does not cover the full spectrum of dynamic behaviors. A crucial priority for future work is to conduct larger-scale data collection. This expanded dataset will enable us to tackle the more challenging task of fine-grained posture classification, moving beyond the three foundational classes validated in this work and enhancing the system's real-world applicability.

Fourth, a practical consideration for deployment is the computational cost of the LLM backbone. Our current work offload LLM inference to a powerful server, and our optimization focuses on the data transmission pipeline between the edge sensor and the server. Therefore, we did not profile the LLM's inference cost, memory, or energy consumption. One of future work is to explore the deployment of the full system on resource-constrained edge devices. This will involve investigating techniques such as model quantization, knowledge distillation, and the use of specialized hardware accelerators to create lightweight, edge-native efficient LLMs.

8 Conclusion

In this work, we present Meta Fiberverse, a human-centric intelligent fabric platform that unifies multimodal sensing, adaptive communication, and semantic reasoning within a cohesive system architecture. By addressing key limitations in existing wearable and edge intelligence systems, such as rigid task pipelines, poor semantic generalization, and limited comfort, our framework introduces a fabric-computing paradigm that emphasizes adaptability, modularity, and user-aligned intelligence.

Meta Fiberverse integrates ambient and wearable modalities into a shared semantic space, enabling digital twin modeling and natural language–driven task coordination through a plugin-style LLM interface. Experimental results demonstrate its effectiveness in balancing accuracy, latency, and energy efficiency under real-world constraints. This work lays the foundation for a new class of reconfigurable, semantically autonomous edge terminals, and opens future research directions in high-level abstraction, personalized adaptation, and large-scale deployment across domains such as healthcare, interactive robotics, and ubiquitous computing.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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Yue Wang received the BEng degree from South China University of Technology, China, in 2024, where he is currently a PhD candidate in artificial intelligence. His current research interests include fabric computing, edge intelligence, and large language models.

Jia Liu received the BEng degree in computer science and technology from University of Electronic Science and Technology of China, China, in 2020. She is currently a PhD candidate at Embedded and Pervasive Computing Laboratory and School of Computer Science and Technology, Huazhong University of Science and Technology, China. Her research interests include Internet of Things (IoTs), fabric computing, and edge computing.

Lejun Ai received the BEng degree from South China University of Technology, China, in 2024, where he is currently a PhD candidate in artificial intelligence. His current research interests include fabric computing, automatic sleep staging, and Large Language Models (LLMs).

Xiao-Kun Wu received a PhD degree in communication from Shanghai University, China, in 2010, and another PhD degree from South China University of Technology, China, in 2022. She is currently a professor at School of Journalism and Communication, Renmin University of China, China. She has authored three academic books and over 30 research papers in her research areas. Her research interests include online collective actions and communication models, as well as mass communications. She is a member of IEEE.

Wenjing Xiao received the PhD degree from Huazhong University of Science and Technology, China, in 2023. She is currently a research assistant professor at School of Computer, Electronic and Information, Guangxi University, China. Her Google scholar citations has reached more than 600 with an H-index of 15. Her research interests include efficient artificial intelligence, edge intelligence, on-device artificial intelligence, IoTs, and wireless network.

Salman A. Alqahtani received the PhD degree in computer science and Engineering from King Fahd University of petroleum and Minerals (KFUPM), Saudi Arabia, in 2007. He is currently a full professor and new emerging technologies and 5G network and beyond research chair at Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Saudi Arabia. His research interests include radio resource management for wireless and cellular networks (Fourth Generation (4G), Fifth Generation (5G), IoTs, Industry 4.0, Long-Term Evolution (LTE), LTE-advanced, femtocell, cognitive radio, and cyber sovereignty) with a focus on call admission control, packet scheduling, radio resource sharing, and the quality of service guarantees for data services.

Min Chen received the PhD degree from South China University of Technology, China, in 2004, where he is currently a full professor at School of Computer Science and Engineering. He was the director of the Embedded and Pervasive Computing Laboratory, Huazhong University of Science and Technology (HUST), China. Before joined HUST, he was an assistant professor at School of Computer Science and Engineering, Seoul National University, Republic of Korea. His Google scholar citations have reached more than 53 000 with an H-index of 102. His top paper has been cited more than 5600 times. He is a Fellow of Institution of Engineering and Technology (IET). He was a recipient of the IEEE Communications Society Fred W. Ellersick Prize in 2017, the IEEE Jack Neubauer Memorial Award in 2019, and the IEEE ComSoc APB Oustanding Paper Award in 2022. He is the founding chair of the IEEE Computer Society Special Technical Communities on Big Data and the chair of IEEE Globecom 2022 eHealth Symposium. He was selected as a highly cited researcher from 2018 to 2025. He is a Fellow of IEEE.

Guangming Tao received the PhD degree from University of Central Florida, Orlando, FL, USA, in 2014. He is currently a professor at Wuhan National Laboratory for Optoelectronics and School of Optical and Electronic Information, Huazhong University of Science and Technology, China. He is the director of the Center for Fiber Optoelectronics (CFO), and serves as the director for the Sport and Health Initiative (SHI) at the Optical Valley Laboratory, China. His research interests include interdisciplinary research on fiber optoelectronics for medical fiberbot, passive thermal management, and intelligent fabric. He is the editorial board member of *Laser and Optoelectronics Progress* and *Textile Research Journal*; an associate director of the Division of Fiber Materials and Composite Technology, Chinese Materials Research Society; and an associate editor of *Advanced Fiber Materials*.