GTI

Ambient IoT

– Artificial Intelligence Chapter

White Paper

GTI Ambient IoT – Artificial Intelligence Chapter White Paper

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Preface

In recent years, facing development needs of industrial digitalization, smart home, and refined social governance, Ambient IoT technology has entered a period of rapid development, becoming a key path to realize the networking and intelligence of massive "dumb" terminals. It is expected to form a trillion-level connection scale in warehousing, logistics, retail, industry, and other fields, opening up a new blue ocean for IoT development. This white paper focuses on the intelligent development needs of Ambient IoT, centering on the integration of end-to-end elements of Ambient IoT with artificial intelligence, and selecting representative technologies to interpret AI × Ambient IoT technology development trends, analyze important technological progress in recent years, and organize typical application scenarios. It aims to provide references for technological breakthroughs and implementation applications in related fields.

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1. AI × Ambient IoT Technology Overview

In recent years, facing development needs of industrial digitalization, smart home, and refined social governance, Ambient IoT technology has entered a period of rapid development. Ambient IoT terminals do not require built-in power sources and rely on environmental energy harvesting and backscatter communication, becoming a key path to realize the networking and intelligence of massive "dumb" terminals. They have demonstrated huge potential in warehousing, logistics, retail, industry, and other fields. However, limited by technical characteristics, traditional Ambient IoT systems have obvious bottlenecks in sensing precision, environmental adaptability, and data intelligence, such as misreading caused by multipath interference, coverage blind spots caused by insufficient deployment density, limited application scenarios caused by single sensing functions, and difficulty in effectively mining massive discrete data.

Facing the above technical problems, the industry has continued to explore paths for deep integration of artificial intelligence and Ambient IoT in recent years. Through technical means such as embedded AI algorithms, edge intelligent inference, and industry large model adaptation, AI capabilities are deeply integrating with Ambient IoT network layer and platform layer technologies, enabling Ambient IoT systems to achieve a leap from "passive collection" to "active cognition," specifically manifested in two aspects:

First, in terms of basic performance of Ambient IoT systems, the integration of AI has significantly improved dynamic network resource optimization capabilities. Ambient IoT intelligent networking and scheduling technologies utilize optimization algorithms and reinforcement learning to solve NP-hard problems such as multi-reader collaborative interference and massive tag collision prevention, achieving a leap from "isolated reading and writing" to "global resource collaboration," laying a solid network foundation for large-scale and high-concurrency application scenarios of Ambient IoT.

Second, in terms of additional capabilities of Ambient IoT systems, the integration of AI has effectively expanded the sensing range and precision of Ambient IoT and achieved "value leap" of passive data. At the level of sensing capability expansion, by integrating lightweight AI models and computing power into reading and writing devices, "RFID-vision" and other multimodal signal local fusion sensing have been achieved, effectively solving industry pain points such as stray reading and misreading, and achieving "plug-and-play" high-precision recognition and behavior judgment in scenarios such as clothing retail access control and smart equipment cabinets. Through passive positioning technology empowered by AI, positioning accuracy has achieved a leap to "centimeter level," providing low-cost, high-precision positioning solutions for scenarios such as smart warehousing and smart parking. AI spatial sensing technology transforms passive tags into "ubiquitous sensors," achieving deep cognition of scenarios such as factory personnel behavior, retail customer flow trajectories, and elderly care safety monitoring without violating privacy. At the level of data value mining, logistics and warehousing scheduling large models based on passive data can not only accurately predict cargo volume trends but also automatically generate globally optimal strategies including bin location recommendations, picking path planning, and resource allocation, achieving a profound transformation of warehousing scheduling from experience-driven to data and model-driven. At the same time, Ambient IoT tag security intelligent assurance technology with AI as the core provides a trust foundation for the reliable application of Ambient IoT in key scenarios such as supply chains and industry.

2. AI Fusion Enhancing Basic Performance of Ambient IoT

The integration of AI and Ambient IoT is systematically improving its basic communication and networking capabilities, enabling Ambient IoT to achieve more efficient and reliable end-to-end connections under the premise of low cost. AI × Ambient IoT intelligent networking and intelligent scheduling technologies solve NP-hard problems such as multi-reader interference and massive tag access through optimization algorithms and intelligent decision-making, aiming to build a high-concurrency, low-latency, scalable Ambient IoT infrastructure to provide solid network performance guarantees for upper-layer applications.

2.1 AI × Ambient IoT Intelligent Networking

Ambient IoT systems are composed of reading and writing nodes, excitation nodes deployed in different geographical locations, and tags attached to items. Their performance is easily affected by environmental and inter-device interference, and network deployment in complex scenarios has been proven to be an NP-hard problem. Therefore, efficient intelligent networking technology becomes the key to whether the system can be deployed smoothly. Ambient IoT intelligent networking technology integrates optimization theory, artificial intelligence, and electromagnetic simulation methods, achieving collaborative optimization of multiple objectives such as coverage range, signal interference, and deployment cost through automated configuration of parameters such as node layout, antenna position, and angle, thereby quickly generating approximately optimal deployment solutions under complex constraints. With the help of precise modeling and multi-objective trade-offs, intelligent networking technology can maximize coverage expansion, suppress interference, control costs while ensuring service quality, and ultimately empower wireless manufacturing, smart warehousing, and other scenarios to achieve real-time sensing and intelligent management of all production factors.

Ambient IoT network system deployment needs to simultaneously optimize multiple objectives such as tag coverage rate, signal interference, and cost. Its intelligent solution methods for multi-objective optimization are mainly divided into two categories. The first is converting multi-objective problems into single-objective optimization through weighted summation. This method uses different weights for linear weighting in different application scenarios, fusing key indicators such as coverage range, positioning accuracy, interference, and deployment cost into a unified objective function, and efficiently solving them using swarm intelligence optimization algorithms and building nonlinear integer programming models. Among them, the fuzzy k-coverage method can effectively handle coverage uncertainty problems in network planning; the two-level planning model built based on hierarchical decoupling principles significantly reduces computational complexity by modeling cost and service quality through discrete and continuous variables respectively. Such methods efficiently solve complex problems by converting them into single-objective forms through mathematical modeling, but the limitation lies in weight setting relying on expert experience, making it difficult to adapt to all scenario needs. The second is multi-objective optimization based on Pareto dominance relationships. Multi-objective particle swarm optimization algorithms can adaptively adjust the number of reading and writing devices to improve overall network performance; improved k-means and multi-objective discrete particle swarm optimization fusion algorithms reduce decision variable dimensions from quadratic to linear levels, quickly obtaining Ambient IoT network deployment solutions for bistatic architectures. In addition, the combination of electromagnetic simulation and intelligent algorithms has become an important means to improve deployment accuracy. Through precise electromagnetic propagation prediction using ray tracking software such as Wireless InSite, it can provide optimization algorithms with environmental data closer to reality, promoting Ambient IoT network deployment towards intelligent and precise development.

Ambient IoT intelligent networking deployment has achieved precise business empowerment in scenarios such as warehousing and logistics, industrial manufacturing, and smart retail based on differentiated coverage strategies. In the warehousing and logistics field, by deploying optimized reading and writing nodes at key paths such as aisles, sorting lines, and entrances and exits, a fence-type coverage system is built to achieve full-process automated tracking and data collection of labeled materials, greatly improving inbound and outbound operation efficiency and inventory turnover accuracy, completely recording the full-process status changes of materials from warehousing, storage to outbound, providing real-time and reliable data support for warehousing management decisions. In the industrial manufacturing field, aiming at the complex process requirements of mixed-flow assembly lines, a differentiated coverage mode is adopted. By configuring reading and writing node combinations with unique identification characteristics for each assembly station and material storage area, precise positioning and dynamic identification of parts are achieved, effectively preventing problems such as wrong installation and missing installation during the assembly process, ensuring production quality and process reliability. In the smart retail field, through full-coverage deployment, a seamless monitoring network is established in shelf areas to achieve real-time inventory and status monitoring of inventory goods, quickly obtain accurate inventory data, effectively solve the problem of low efficiency of traditional manual inventory, and provide data basis for precise restocking, demand prediction, and operation optimization. These differentiated deployment strategies lie in effectively combining coverage models with multi-objective optimization according to specific business needs, achieving collaborative optimization among multiple dimensions such as cost, signal interference, and coverage performance through intelligent networking algorithms, ensuring communication link reliability with economical and efficient deployment solutions. Through a unified network planning framework, it provides universal and efficient underlying infrastructure for digital transformation in different industries, promoting continuous evolution of operation management models towards refinement and intelligence.

In the future, facing diversified business scenarios and complex physical environments, it is necessary to build an intelligent network infrastructure capable of self-optimization. Networking deployment needs to evolve from traditional static and rigid modes towards intelligent and flexible directions, facing the following challenges: First, architectural heterogeneity challenges unified planning. Ambient IoT coexists with multiple architectures such as integrated transceiver, separated transceiver, direct connection and relay. Different architectures have vastly different coverage models, interference mechanisms, and deployment elements. Traditional single deployment modes are not applicable. Intelligent deployment needs to automatically generate differentiated network node layout and parameter configuration schemes for mixed architecture scenarios. Second, business diversity requires flexible response. Different businesses such as inventory, positioning, and status monitoring put forward differentiated or even contradictory performance requirements for network coverage strength, link quality, and anchor point density. Static networks cannot take both into account. Therefore, networking deployment needs to embed flexible design, enabling a single physical network to flexibly support dynamic changes in future business through multiple pre-configured operating modes, achieving a leap from "one network for one use" to "one network for multiple uses."

Facing the above challenges, the development trends of intelligent networking will focus on three major directions: First, intelligent deployment. Deeply integrating digital twins and AI algorithms to build high-fidelity virtual mirrors for simulation and automatic optimization, achieving a fundamental transformation from "experience-driven" to "model and data-driven," outputting globally optimal deployment solutions. Second, architectural flexibility. Through software definition and hardware modularization, achieving separation of control and forwarding, enabling flexible reconstruction of logical network topologies on solidified physical facilities according to business needs, dynamically adapting to different business scenarios. Third, capability platformization. Building deployment platforms with business intent translation capabilities, where users declare high-level goals and the system can automatically deconstruct and generate deployment solutions, transforming networking deployment from professional technical engineering to efficient intelligent services.

2.2 AI × Ambient IoT Intelligent Scheduling

Ambient IoT end-side capabilities are extremely limited, lacking functions such as active communication, frequency selection, and channel sensing, posing challenges to efficient large-scale network resource scheduling. Ambient IoT intelligent scheduling, at its core, moves networking intelligence and scheduling decision-making functions from the extremely capability-limited passive terminal side to the network side (such as reading and writing nodes, base stations, edge servers, or core networks), dynamically allocates and optimizes network resources (such as excitation signals, time slots, channels, transmission power) through centralized or distributed intelligent algorithms, building an intelligent system with multi-scenario intelligent adaptation, multi-objective intelligent optimization, and flexible scalability, to achieve efficient and reliable communication of massive tags in complex environments. The core of Ambient IoT intelligent networking scheduling lies in completely moving complex decision-making functions to the network side: terminal tags are only responsible for extremely simple backscatter communication, while the network side centrally manages access timing, channel allocation, beamforming, and power control and other multi-dimensional resources; by detecting channel state and tag response data, dynamically sensing environmental changes and interference fluctuations, and adjusting scheduling strategies accordingly, forming a scheduling optimization system covering multiple dimensions such as time, space, frequency, and power, thereby achieving continuous optimization of overall network performance and reliable communication under the condition of extremely limited end-side capabilities.

Research in the field of Ambient IoT intelligent scheduling technology is evolving from traditional single reading and writing device and tag group interaction optimization to global coordination and dynamic intelligent decision-making of entire network resources, specifically manifested in three aspects: First, at the network layer, solving interference problems caused by dense deployment through multi-reading and writing device coordinated scheduling. When multiple reading and writing devices work simultaneously, carrier echoes and uplink signals coexist, with a difference of more than 10dB between them. The large echo signal forms suppression interference on the small uplink signal, that is, reader-reader interference or far-near effect. In addition, tags do not have effective frequency selection components. When adjacent reading and writing devices work simultaneously, interference with tag signal reception is inevitable. Although traditional time-division polling can avoid interference, it sacrifices system parallelism and inventory efficiency. Intelligent scheduling intelligently schedules multi-dimensional resources such as time slots, channels, transmission power, and even spatial beams of reading and writing devices by combining theories and methods such as graph theory, convex optimization, and reinforcement learning. For example, adaptive distributed power control technology based on real-time feedback of signal strength and interference levels minimizes total system interference while activating tags. Second, at the access layer, intelligent technology is deeply integrating into traditional tag anti-collision algorithms. Classic algorithms such as dynamic framed slotted ALOHA and various tree algorithms continue to be optimized, with the core of achieving more accurate tag quantity estimation and more efficient split query strategies, dynamically scheduling limited time slot and channel resources, and reducing collision and idle overhead. More research models reading and writing devices as reinforcement learning agents, discovering optimal scheduling strategies in complex dynamic environments through online learning, significantly improving convergence speed and throughput rate. Third, at the system level, the effectiveness of intelligent scheduling depends on the collaboration of cross-layer design. Network layer resource scheduling creates a stable, low-interference communication environment for access layer tag identification, while efficient access layer tag identification releases resource space for the next round of network layer decision-making. The two form a closed-loop optimized overall system through intelligent scheduling.

Ambient IoT intelligent scheduling technology is providing new solutions for operational efficiency improvement in multiple industries such as retail, logistics, and manufacturing through systematic resource coordination and optimization. In large supermarket scenarios, unmanned fully automated inventory systems based on intelligent scheduling can achieve minute-level, over 99% accuracy fully automated inventory by efficiently coordinating the work of all reading and writing nodes in the passive network in the store. This not only provides real-time data support for precise restocking, loss prevention and anti-theft, and inventory optimization, but also provides technical conditions for ensuring "online and offline inventory consistency" and supporting new retail experiences such as "grab and go." In the smart warehousing and logistics field, intelligent scheduling helps deal with co-channel interference in dense equipment environments, making it possible to seamlessly sense goods on high shelves and dynamic inbound and outbound cargo and achieve second-level batch identification, promoting the realization of all-weather, no-blind-spot dynamic inventory, greatly improving inbound and outbound throughput efficiency, reducing wrong shipping and missed shipment rates, providing an effective path for building end-to-end transparent supply chains and realizing unmanned warehouse operation and maintenance. In the smart manufacturing field, this technology can achieve full-process real-time tracking and precise management of raw materials, work-in-progress, and finished products on production lines, providing key data for lean production and flexible manufacturing. In the smart airport field, full-process positioning and status monitoring of luggage helps reduce luggage mis-transportation and loss, improving the operational reliability of luggage systems and passenger experience.

The development of Ambient IoT intelligent scheduling technology still faces multiple core challenges. First, environmental complexity and channel uncertainty challenges. Backscatter channels relied on by tags have unstable characteristics, easily affected by environmental factors such as multipath effects, object occlusion, and personnel movement, making it difficult to establish precise channel models, thereby restricting the stability and reliability of scheduling algorithms. Second, there is a prominent contradiction between system scale and real-time performance. In massive tag application scenarios, centralized scheduling architectures generate high signaling overhead and computation delay when coordinating all reading and writing devices and processing random tag access, making it difficult to achieve business-required second-level or even millisecond-level responses. Third, resource requirements for multiple business objectives such as inventory and positioning vary, and there is a lack of a unified flexible scheduling framework to achieve optimal coordination.

Looking to the future, this technology is evolving in the following directions. First, distributed collaborative scheduling. By building a distributed intelligent architecture, enabling reading and writing device clusters to autonomously collaborate and make decisions based on local information, fundamentally improving system scalability and robustness. Second, business requirement-driven flexible scheduling. The core of scheduling will transform from "connection-oriented" to "task-oriented," capable of dynamically adjusting resource allocation strategies according to specific business objectives and service quality requirements such as inventory and positioning. Third, lightweight autonomous learning. Systems will leverage lightweight models to continuously learn directly from environmental interactions and real-time optimize scheduling strategies, thereby reducing dependence on preset models, ultimately building next-generation Ambient IoT systems capable of adapting to complex environments and efficiently meeting diversified business needs.

3. AI Fusion Expanding Additional Capabilities of Ambient IoT

On top of consolidating basic performance, AI further expands the sensing dimensions and data value of Ambient IoT, endowing passive systems with additional capabilities beyond traditional recognition, including single device fusion sensing, low-cost high-precision positioning, low-cost spatial sensing, as well as logistics scheduling large models and tag security intelligent assurance based on passive data. These technologies jointly drive Ambient IoT to evolve from "connecting everything" to "understanding scenarios" and "empowering decision-making," unlocking deep intelligent applications in fields such as retail, warehousing, manufacturing, and healthcare.

3.1 AI × Ambient IoT Single Device Fusion Sensing

In high-density scenarios such as warehousing, retail, and logistics checkpoints, passive RFID signals are prone to stray reading, misreading, and direction drift due to multipath interference. Traditional multi-device solutions can alleviate this but bring new pain points of high cost, difficult synchronization, and heavy operation and maintenance. Passive single device fusion sensing integrates computing power chips and embedded AI algorithms into a single Ambient IoT device, achieving real-time fusion of RFID RF signals and optional visual flow and other modal features through "spatial-temporal" joint sampling, and through self-supervised denoising, cross-modal feature matching, and adaptive thresholds, suppressing adjacent area interference, completing target entry and exit direction discrimination and motion trajectory estimation. Passive single device fusion sensing uses algorithms to replace additional hardware, using high-dimensional models and cross-modal fusion to compensate for insufficient RF information, effectively identifying the spatial position and motion characteristics of tags, significantly improving recognition accuracy and stability, with advantages of "no additional wiring required, sub-meter precision, millisecond-level latency," providing a technical foundation for "plug-and-play" streamlined delivery.

In recent years, passive single device fusion sensing technology has shown three representative developments of "chip-level computing power sinking, cross-modal fusion, and interaction mode innovation," driving RFID from "able to read" to "able to understand." First, chip-level computing power sinking helps "single box as system." Qualcomm released the world's first enterprise-grade mobile processor Q-6690 integrating UHF RFID functions in 2025, integrating RFID technology into a single SoC, reducing device volume by 30%-50% and power consumption by more than 40%, with logistics handheld terminal battery life breaking through 12 hours. Guoxin IoT released its third-generation RFID chip in the same year carrying AI algorithms, endowing Ambient IoT devices with intelligent judgment capabilities, capable of precisely identifying tag position, distance, and dynamic changes, completing positioning and trajectory fitting on-site without backend large computing power. Second, "RFID-vision" cross-modal fusion, with single devices moving towards multimodality. Honglu I320 ceiling-mounted access control, based on Impinj E710 RF, is built-in with high-gain narrow-beam antennas and high-performance cameras, using vision algorithms to judge tag movement direction, with good anti-missed reading and anti-misreading performance, winning the 2025 IOTE Gold Award. Xunjie S-E08A monitoring UHF RFID ceiling-mounted access control adopts Android architecture, embeds anti-misreading algorithms, effectively removing stray and misread tags while ensuring reading rates, and adds visual trajectory functions, with large-scale deployment in indoor scenarios such as libraries, archives, museums, and hospitals. Third, based on AI computing power, device interaction modes move towards natural voice. Zebra cooperated with Qualcomm to crop and embed generative language models into portable readers, achieving local voice understanding and natural language feedback based on chip computing power. Users only need to say "inventory Zone A," and the reader immediately group reads and verbally reports "read xxx items, difference xx items." This mode transforms traditional "screen + buttons" into "conversation as business," suitable for scenarios with inconvenient hands such as cold chain gloves and high-altitude maintenance, providing more natural and safer operation experiences for warehousing, manufacturing, and retail frontline employees.

Currently, passive single device fusion sensing technology has matured conditions for implementation, showing broad commercial value in scenarios such as clothing retail access control, smart equipment cabinets, and warehousing inbound and outbound management. First, in the clothing retail access control scenario. There are often displayed or stacked goods near clothing retail store access control. When customers pick goods at the entrance area or employees pass by, RFID signals frequently appear and disappear, and traditional RFID solutions are prone to triggering false alarms. Manufacturers such as Sco effectively filter out stationary or swaying tags near access control by integrating AI autonomous learning algorithms into Ambient IoT devices, only identifying goods actually passing through access control. Even if goods are hung near access control or moving around access control, the system can correctly exclude interference, avoiding misreading or stray reading. Currently, some head clothing brand stores have completed solution pilots, showing significantly improved recognition accuracy, improving customer experience while reducing security labor costs.

Second, in the smart equipment cabinet scenario. Through multimodal biometric recognition technologies such as face recognition and fingerprint, confirming the identity of the recipient, while the RFID chip inside the cabinet scans equipment, precisely locating target equipment. Through AI analysis of historical data, smart cabinets can automatically prompt placing high-frequency used equipment in easily accessible areas and low-frequency equipment into specific zones. Cabinet temperature and humidity and UV sensors driven by AI models can automatically pre-activate dehumidification or disinfection according to season, region, and cabinet opening frequency, avoiding moisture in first aid kits and rusting of equipment, extending equipment life. Through AI + RFID dual engines, customers upgrade from "people finding equipment" to "equipment standing by," achieving second-level response, zero-error inventory, and predictable restocking in scenarios such as emergency actions, daily maintenance, and asset audits, realizing a paradigm leap from "experience ledger" to "data brain" for equipment management.

Third, in the warehousing inbound and outbound management scenario. A Ambient IoT device with an integrated camera is installed at the dock door. The device has a built-in vision-RF fusion model. Vision algorithms identify in real-time whether forklifts carry goods and forklift movement status. Once detecting that the forklift is in "has cargo + moving" state, the system automatically activates batch reading of tags, triggering inbound and outbound tasks and locking timestamps without warehouse manager clicking. Through spatiotemporal matching of RF signal changes and video pixel motion, automatically filtering disturbance tags from adjacent passersby or personnel-carrying items, thereby eliminating repeated accounting or wrong accounts caused by "lingering at the door" in traditional solutions. The entire receiving and shipping process achieves "record upon arrival, account upon departure," reducing manual review. When the network is interrupted, tasks are locally cached and automatically transmitted after recovery, ensuring account consistency, greatly improving circulation efficiency and reducing errors.

The dual constraints of edge-side computing power and cost are the primary difficulties in implementing passive single device fusion sensing. Limited by power consumption, memory, and chip computing power, models must repeatedly weigh effectiveness and size. At the same time, general models are not applicable to RFID stray reading, multipath, direction judgment and other scenarios. Solution providers need to collect massive tag signals and environmental data for vertical businesses such as warehousing, retail, and cabinets, retrain and fine-tune to provide available and experience-good industry AI models, with high 前期投入 and long cycles.

Facing the future, the single device fusion sensing technology route is shifting from "single-point computing power" to "cross-modal + edge box" fusion. First, aligning multi-source data such as RFID signals, video, temperature and humidity, and displacement at the edge, using vision trajectories to remove stray readings and using environmental parameters to correct thresholds, achieving "one device, multiple sensing." Second, product forms evolve towards "gateway + edge-side computing power + large model" edge box concentration, requiring only one device on-site to aggregate all reader data, uniformly running AI inference, avoiding cost inflation caused by repeatedly adding NPUs to each reader, while facilitating subsequent model iteration and centralized operation and maintenance, providing an economical and sustainable computing power foundation for large-scale deployment.

3.2 AI × Ambient IoT Low-Cost Positioning

With the improvement of intelligence and unmanned levels in industries, the demand for high-precision indoor positioning of assets is becoming increasingly urgent. Although traditional RFID positioning technology can achieve low-cost non-contact recognition, it has significant shortcomings such as weak signal strength of passive tags and narrow data transmission bandwidth, leading to positioning being easily affected by hardware and multipath interference, with high measurement errors, making it difficult to meet high-precision requirements. Ambient IoT + AI fusion positioning technology collects RF signals through RFID tags and readers, and outputs positioning results through AI technology learning the mapping relationship between signals and positions. Compared with traditional passive positioning technology, this fusion solution combines the non-contact batch recognition advantages of RFID with the environmental adaptive capabilities of AI, achieving centimeter-level positioning while reducing risks of stray and missed readings.

In recent years, Ambient IoT + AI fusion positioning technology has achieved significant progress, mainly reflected in the following aspects: First, the upgrade of end-to-end AI positioning models. End-to-end models directly feed raw Ambient IoT signals such as RSSI, phase, frequency, and EPC into deep/machine learning networks, eliminating the need for manual modeling steps such as path loss or fingerprint libraries, and are able to maintain relatively high precision in complex environments such as multipath and occlusion. End-to-end positioning solutions based on GRNN utilize the fast learning and strong nonlinear fitting capabilities of generalized regression neural networks, with an average error of 1.32m for RSSI coordinate mapping in a 9m×7.5m area; models combining PSO with ANN optimize network weights through particle swarm global search of reference tag signal strengths, significantly improving convergence speed and positioning accuracy, with an average error of 0.65m, better than traditional fingerprint algorithms. Second, innovation in AI-enabled feature extraction. In addition to directly extracting features for positioning tasks, AI can also extract auxiliary positioning measurements to improve positioning accuracy. Existing relative positioning methods have problems of low accuracy and poor robustness under high-density tags (such as spacing of only 1-3 cm). Through convolutional neural networks, the confidence level of tag left-right relationships is obtained, achieving detection accuracy of 98% when tag spacing is 1cm. Third, breakthroughs in high-dimensional feature AI optimization. Multi-antenna, multi-frequency, multi-time series and other high-dimensional features lead to exponential growth in search space, making it difficult for traditional gradient methods to converge. Evolutionary algorithms such as DE, PSO, BA and reinforcement learning can achieve global search or adaptive parameter tuning on non-convex, high-noise objective functions, thereby significantly improving positioning accuracy and system robustness. Optimizing reader deployment through bat algorithms effectively improves the performance of RFID indoor positioning systems. Experimental results show that this method enhances robustness to signal fluctuations by increasing the signal spatial Euclidean distance between tags, achieving higher positioning accuracy than traditional BP neural networks.

Ambient IoT low-cost positioning technology, with its advantages of low tag cost and maintenance-free, is providing key indoor and complex scenario positioning solutions for multiple industries. In the warehousing and logistics field, it achieves real-time tracking of the full process of goods from inbound to outbound, effectively solving problems such as low picking efficiency and inventory backlog, significantly improving material management efficiency. In the retail field, this technology can both help consumers quickly find stores and cars, and provide operators with customer flow analysis, inventory management, and display optimization basis, releasing commercial potential. In the manufacturing field, facing the high requirements of Industry 4.0 for automation, Ambient IoT positioning can track materials and guide robots with 10-30 cm precision, meeting the harsh requirements of smart manufacturing for anti-interference and anti-occlusion. In the smart parking field, it provides an effective low-cost solution for parking guidance and reverse car finding, greatly improving the parking experience. In the medical, elderly care, and home monitoring fields, meter-level positioning capabilities ensure real-time care and safety management of medical personnel, patients, elderly people, and young children, embodying important humanistic care.

Despite significant progress in Ambient IoT + AI fusion positioning technology, from laboratory to commercial implementation, it still faces three core difficulties: First, training excellent AI models extremely relies on massive, high-quality, labeled positioning datasets. Passive positioning training datasets are very scarce, and collecting labeled data in actual environments is extremely costly and time-consuming, making high-quality data acquisition difficult. Second, real-world environments are complex and variable. An AI model trained excellently in Warehouse A may experience sharp performance degradation when deployed to Warehouse B with different layout, materials, and interference sources. AI models need to possess strong cross-scenario adaptability and online learning capabilities to cope with the dynamic changes of the real world, which puts extremely high requirements on its algorithm design and engineering implementation. Third, the challenge of multimodal fusion and real-time performance. To achieve higher-level scenario understanding and accuracy improvement, AI positioning systems need to fuse passive positioning data with other sensor (such as cameras, IMU) data and business system data. This cross-modal, heterogeneous data real-time fusion, alignment, and joint reasoning pose huge challenges in terms of computing power and algorithms. Fourth, the trade-off between system complexity and cost. The deployment, iteration, and operation and maintenance of AI models introduce additional computing resources (edge servers/cloud computing) and technical team costs, which forms a certain confrontation with the original intention of passive technology's "extremely low cost." Finding a balance between performance and total ownership cost is key to breakthrough.

The introduction of AI enables the basic problem of objects being "visible" in traditional passive positioning to transform into system-level "understanding," "thinking ahead," and being able to "autonomously act." Although currently facing multiple challenges such as data, algorithms, and computing power, this fusion trend will thoroughly release the potential of Ambient IoT, gradually upgrading it from a tool for cost-sensitive scenarios to core infrastructure driving various industries to achieve digitalization and intelligent decision-making.

3.3 AI × Ambient IoT Spatial Sensing

With the continuous advancement of digital transformation in various industries, the demand for refined and unmanned sensing of target behavior and status in space is becoming increasingly urgent. Traditional vision-based sensing methods have limitations such as privacy leakage, blind spot coverage, and environmental light interference, making it difficult to meet ubiquitous sensing requirements for all-weather, non-intrusive, and wide coverage. AI × spatial sensing technology deploys passive tags as "sensors," capturing subtle changes in wireless signals during propagation, and leveraging artificial intelligence methods such as deep learning to extract discriminative spatiotemporal features from them, constructing a mapping mechanism from wireless signals to high-level semantics (actions, states), thereby achieving digital reconstruction and scenario-based understanding of physical space without relying on cameras. This technology has core advantages such as privacy-friendly, flexible deployment, and full spatiotemporal continuous sensing, providing new data insight pathways for scenarios such as smart factories, smart retail, and elderly care monitoring, promoting management decision-making to transform from "experience-dependent" to "data intelligence."

In recent years, AI × spatial sensing technology has achieved significant progress, providing feasible technical paths for overcoming application bottlenecks. First, signal feature extraction capabilities in noisy environments have significantly improved. Wireless signals are easily affected by multipath effects, electromagnetic interference, and dynamic environmental changes in practical applications, resulting in low signal-to-noise ratio and blurred features of raw sensing data. Attention mechanisms enable models to autonomously learn and focus on key signal segments or frequency components most relevant to target behaviors and states, suppressing irrelevant environmental noise interference. At the same time, adversarial training enhances model robustness to signal micro-perturbations and abnormal situations by constructing generative adversarial networks or introducing adversarial samples, forcing feature extractors to learn more discriminative and invariant essential features. Second, model cross-scenario adaptation and generalization capabilities have significantly enhanced. Addressing the problem that models trained in specific scenarios are difficult to directly apply to new scenarios (i.e., "weak cross-scenario generalization capability"), researchers employ cutting-edge methods such as domain adaptation and meta-learning, enabling models to utilize knowledge learned in source scenarios and quickly adjust their parameters with only a small amount of labeled data in target scenarios to adapt to new environment signal feature distributions, greatly reducing data labeling costs and cycles for technology deployment in new scenarios, laying the foundation for scaled applications. Third, sensing cognition mechanisms deepen from "statistical association" to "causal inference." Traditional AI models rely on statistical correlations for pattern matching, suffering from insufficient interpretability and vague intent prediction. Researchers introduce causal inference frameworks, modeling and inferring potential causal relationships between wireless signals and physical events by constructing causal graphs. AI models can not only identify "what happened" but also infer "why it happened," effectively improving the accuracy of behavior recognition and intent prediction.

AI × spatial sensing technology, with its advantages of non-intrusion, easy deployment, and wide coverage, demonstrates huge application value in multiple industry scenarios. In smart factory scenarios, passive tags can be embedded in helmets and work clothes, and the system analyzes tag signal changes to deduce worker postures, thereby identifying behaviors such as "raising hand for help," "non-standard operations," and "entering dangerous areas," instantly triggering safety alerts and assisting operation guidance. For critical equipment attached with passive tags, early fault diagnosis and predictive maintenance are achieved by continuously monitoring vibration signal characteristics, effectively reducing unplanned downtime risks. In smart retail scenarios, by analyzing signal changes of product tags and shopping cart tags, customer flow trajectories, residence time, and picking behaviors can be reconstructed. Combined with causal analysis models, customers' true interest and purchase tendencies toward products can be deeply judged, effectively distinguishing "casual browsing" from "strong purchase intent," providing data support for optimizing shelf display, inventory management, and marketing strategies. In smart elderly care and medical monitoring scenarios, elderly people or patients wear lightweight passive wristbands, and the system can provide 24/7 uninterrupted protection, monitoring high-risk states such as falls, prolonged stillness, and abnormal wandering in real time, and automatically alerting nursing staff. This solution provides imperceptible life care while fully protecting the dignity of the cared, significantly reducing care burden. In smart office scenarios, passive tags are deployed in space as sensing nodes. By analyzing wireless signal changes in the space, the system can grasp personnel flow density, workstation occupancy rate, conference room usage status, etc., in real time, providing data support for space planning optimization. In addition, it can also link with building control systems to automatically adjust lights and temperature as needed, achieving refined energy saving and consumption reduction.

Despite significant progress in AI × spatial sensing technology, its scaled application still faces challenges: First, the data labeling bottleneck is prominent, currently relying on large amounts of scenario-specific labeled data, and the lack of effective labeling for massive passive sensing data will significantly constrain model training. Second, insufficient model generalization capability makes it difficult to adapt to diversified spatial layouts and user habits, hindering cross-scenario scaled replication applications. Third, semantic understanding levels need urgent improvement, and the mapping from signal changes to high-level behavioral semantics is still not precise enough, requiring models to possess stronger context understanding and commonsense reasoning capabilities. Facing the future, AI × spatial sensing technology presents three major development trends: First, multimodal fusion sensing, improving spatial sensing accuracy and robustness by fusing diverse sensing information such as sound and infrared. Second, self-supervised learning becomes mainstream, shifting from supervised learning relying on manual labeling to designing more clever self-supervised learning tasks, fundamentally solving the data labeling bottleneck. Third, edge-cloud collaborative computing, achieving balance between sensing real-time performance, energy efficiency, and computing costs through reasonable task allocation, promoting technology towards scaled practicality.

3.4 Logistics and Warehousing Scheduling Large Model Based on Passive Data

Warehousing scheduling is the core link to guarantee cargo circulation efficiency and cost control, crucial for the smooth operation of supply chains. In the current logistics industry warehousing management process, there are pain points such as difficulty in predicting inbound and outbound fluctuations, unreasonable warehouse space planning, untimely resource allocation relying on manual experience, and low operation efficiency. Facing the intelligent upgrading needs of logistics and warehousing fields, based on historical operational data and external factors generated from sources such as Ambient IoT, through AI fusion and deep modeling, warehousing scheduling large models have been developed on the basis of industry large models. Logistics and warehousing scheduling large models based on passive data can accurately predict "weekly" and "monthly" cargo volume change trends, and automatically generate decision reports including time series analysis, correlation interpretation, and resource warning. At the same time, scheduling optimization and cargo volume prediction are deeply coordinated. By constructing mathematical models of industrial problems, it can provide reliable optimal solutions for core scenarios such as warehouse location recommendation, picking path planning, and multi-equipment task allocation. Relying on massive real-time data brought by Ambient IoT, compared with traditional methods, logistics and warehousing scheduling large models based on passive data possess stronger generalization capabilities, real-time performance, and interpretability, capable of building an "sensable, predictable, optimizable" intelligent scheduling system, helping enterprises proactively plan resources, improve inventory and warehouse space utilization, optimize operation efficiency, and finally achieve significant cost reduction and efficiency improvement.

In recent years, the development of logistics and warehousing scheduling large model technology based on passive data presents three major directions: First, the explosion of large model technology has demonstrated amazing multimodal understanding capabilities as well as few-shot and zero-shot generalization potential, laying the algorithmic foundation for intelligent applications such as "AI + warehousing scheduling." Among them, general large models represented by GPT and Llama series perform excellently in natural language reasoning, knowledge Q&A, and cross-domain task transfer. At the same time, domestic large model Qwen series performs prominently in multimodal support and industry fusion, having been widely applied in scenarios such as supply chain, logistics scheduling, and intelligent customer service; China Mobile's Jiutian structured data large model has outstanding capabilities in data understanding and calculation, tool invocation, etc., achieving deep integration of complex business logic and industry intelligence. The rapid development of general large models has also stimulated research on time series prediction large models based on Transformer architecture, further providing technical support for logistics cargo volume trend prediction. Second, the application of solvers in warehousing scenarios is progressing rapidly. The efficiency upgrade of problem solving, through process optimization of decision variable handling and constraint condition organization, enables solvers to more efficiently handle complex optimization problems generated by interweaving multiple equipment and multiple tasks in warehousing scenarios, providing technical support for real-time output of solutions; at the same time, the integration of operations research optimization and AI technology is becoming closer, and solvers are no longer limited to single operation execution but combine AI mechanisms such as reinforcement learning with traditional operations research optimization algorithms, achieving dual improvement of solution accuracy and efficiency. Third, leading enterprises in the logistics industry have conducted preliminary and effective exploration. SF Express's "Fengzhi" large model combines supply chain industry knowledge and professional small models to build multi-level multi-channel demand prediction models and business expert agents, achieving more accurate cargo volume prediction results; Cainiao's "Tianji Pi" relies on Alibaba ecosystem data support to achieve quality improvement and efficiency enhancement in sales prediction, restocking plans, and inventory health; JD.com's "Superebrain" large model realizes dynamic adjustment of optimal planning based on digital twin intelligent decision systems, greatly improving operation efficiency; China Mobile Research Institute deeply cooperated with China Logistics, based on Jiutian structured data large model, achieving three core capabilities: precise prediction of cargo volume trends, intelligent generation of strategy suggestions, flexible migration of business scenarios, capable of effectively helping logistics enterprises improve warehousing management efficiency and intelligence level.

Logistics and warehousing scheduling large models based on passive data have broad application prospects in the logistics field: In demand prediction, inventory management, and intelligent business dialogue scenarios, building prediction engines based on multi-source data for diversified product forms, achieving fusion and understanding of cross-modal heterogeneous data, can accurately capture trend changes through powerful generalization capabilities and decision support advantages in high-volatility, high-complexity logistics environments, thereby empowering proactive deployment of resources. It can also further explain reasons while making predictions, helping users better understand and utilize data analysis results. In resource scheduling, warehouse location recommendation, picking and loading planning scenarios, solvers can provide globally optimal solutions for warehousing scheduling, converting resources such as equipment, warehouse locations, and manpower with task priorities and deadlines into optimization models to achieve precise matching. In warehouse location allocation and equipment coordination,兼顾 ing space utilization and operation efficiency without manual intervention, and adapting to the real-time performance of Ambient IoT data, quickly iteratively optimizing logic, maintaining resource allocation consistency with operational status. The entire intelligent decision system of cargo volume prediction, resource scheduling, and operation optimization can be deeply embedded into the entire process of logistics and warehousing scheduling, providing scientific, actionable business suggestions and guidance for warehousing operation and maintenance personnel, effectively overcoming problems such as low accuracy of traditional manual experience methods, lack of dynamic adjustment capabilities, and incomplete consideration of external factors, thereby significantly improving operation efficiency and operational benefits, reducing operational costs.

Currently, the development of logistics and warehousing scheduling large model technology based on passive data still faces the following core difficulties and challenges: First, the contradiction between the dependence of large models on high-quality data and problems such as inconsistent data formats in reality, manual entry errors, and data silos. Second, logistics scenarios are dynamically complex, affected by multiple factors such as promotions and seasons, and model robustness and generalization capabilities urgently need improvement. Third, the "black box" characteristic of Transformer architecture makes it difficult to meet business personnel's needs for causal explanation, affecting model credibility and implementation. Fourth, the difficulty and long cycle of integrating large model systems with existing systems (such as WMS) of logistics enterprises. Fifth, in global large-scale warehousing optimization problems, solver technology application faces exponential growth of variables and constraints, making it prone to difficulties in balancing solution accuracy and timeliness. Sixth, verification of optimal solutions mostly relies on static simulation, difficult to cover real scenarios such as dynamic updates of passive data.

In the future, the logistics and warehousing scheduling large model system technology based on passive data will present the following development trends: First, evolving from prediction models to Agentic AI, achieving a paradigm transformation from "passive prediction" to "proactive decision-making." Second, deepening multimodal fusion, fully leveraging heterogeneous data such as Ambient IoT, vision, structured information, and text to improve the accuracy and generalizability of environmental perception and prediction. Third, combining explainable AI (XAI) with chain-of-thought reasoning and reinforcement learning to enhance model transparency and credibility. Fourth, promoting standardization of system interfaces and evaluation systems to reduce integration deployment and selection iteration difficulties. Fifth, expanding from single-point scenarios such as cargo volume prediction and operation optimization to intelligent decision support for the entire supply chain process.

3.5 Ambient IoT Tag Security Intelligent Assurance

Passive tags rely on reader RF energy to excite data transmission, with limited signal coverage range and being easily affected by metal occlusion, electromagnetic interference, temperature and humidity fluctuations, leading to poor data transmission stability. At the same time, tag chip security and encoding rules are easily cracked, and the costs of forging tags, tampering with data, and injecting false information are extremely low. Forging of passive tags, tampering with tag data, or injection of false information may lead to problems such as product traceability failure and equipment management anomalies, making data security assurance increasingly urgent. Addressing security issues such as Ambient IoT tag security and data tampering, the core goal is to ensure that the entities associated with passive tags remain consistent with digital information through dynamic monitoring of data legitimacy on the basis of identifying forged data.

Deeply combining anomaly intelligent detection technology with Ambient IoT tag data can effectively identify data anomalies. Through AI models learning core features of legitimate tag data, including: normal fluctuation range of signal strength, fixed format of encoding rules, correlation of tag spatiotemporal trajectories, real-time analysis and identification of data anomalies is achieved. Compared with traditional security means, it can accurately judge legitimacy and tag authenticity from the data source; can block forged data injection in real time, avoiding risk expansion. Finally, it significantly improves the security and authenticity of Ambient IoT data, providing support for reliable operation of various scenarios.

Compared with traditional IoT terminal security assurance, Ambient IoT tag security assurance focuses more on authenticity verification of data itself. Due to limited computing power of passive tags, it relies more on verifying legitimacy through data feature analysis, that is, achieving security verification for passive data based on multi-dimensional feature modeling of static data, dynamic data, etc. Static data features include legitimacy verification of data formats, such as check bit rules of tag encoding, compliance of data fields, etc. Dynamic data features focus on spatiotemporal and signal correlation of data, such as normal fluctuation interval of signal strength RSSI, physical reasonableness of tag data spatiotemporal trajectories, baseline value of signal signal-to-noise ratio, eliminating abnormal signal data through combined analysis of multi-dimensional features.

4. Summary and Outlook

The deep integration of AI and Ambient IoT is driving a profound transformation in Ambient IoT technology from "connection" to "intelligence." This white paper systematically analyzes the development trends of AI × Ambient IoT technology from two dimensions: AI fusion helping improve basic performance of Ambient IoT and AI fusion helping expand additional capabilities of Ambient IoT, and elaborates on important technological progress in recent years and typical application scenarios.

In terms of basic performance improvement, AI × Ambient IoT intelligent networking and scheduling technologies solve NP-hard problems such as multi-reader interference and massive tag access through optimization algorithms and intelligent decision-making, achieving efficient and reliable communication of massive tags in complex environments, laying a solid foundation for large-scale application of Ambient IoT. In terms of additional capability expansion, AI technology endows Ambient IoT with powerful sensing and cognitive capabilities, enabling applications such as single device fusion sensing, centimeter-level positioning, non-contact spatial sensing, and intelligent logistics scheduling, greatly expanding the application boundaries and value space of Ambient IoT.

Looking to the future, the deep integration of AI and Ambient IoT presents the following major development trends:

First, technological integration deepens. Multi-modal fusion will become mainstream, and AI systems will deeply integrate Ambient IoT signals with data such as vision, infrared, and sound, achieving more accurate and robust environmental perception and understanding. Edge-cloud collaborative computing architecture will achieve balance between real-time performance, energy efficiency, and costs, providing computing power support for large-scale deployment.

Second, intelligent levels continue to upgrade. Ambient IoT systems will evolve from "passive collection" to "active cognition" and then to "autonomous decision-making," possessing capabilities such as self-optimization, self-adaptation, and self-evolution. The emergence of Agentic AI will enable Ambient IoT systems to not only perceive and understand environments but also proactively plan and execute tasks, truly achieving intelligent operation.

Third, application scenarios continue to expand. Ambient IoT will extend from traditional application fields such as logistics, retail, and manufacturing to emerging fields such as smart healthcare, smart cities, and digital twins, becoming core infrastructure enabling digital transformation in various industries.

Fourth, security and privacy protection are strengthened. With the expansion of application scenarios, security and privacy issues of Ambient IoT will receive more attention. AI-based intelligent security assurance technologies will provide more reliable protection for Ambient IoT systems, ensuring data authenticity and system security.

Fifth, industry ecology accelerates formation. The deep integration of AI and Ambient IoT will promote cross-industry, cross-field collaboration, forming a complete industrial chain covering chips, modules, equipment, platforms, and services, driving the healthy and sustainable development of the entire industry.

In summary, the deep integration of AI and Ambient IoT represents an important direction for future IoT development. Through technological innovation and industrial collaboration, AI × Ambient IoT will create greater value for society, promote digital transformation and intelligent upgrading of various industries, and make important contributions to building a digital China and a smart society.

Contributing Organizations and Personnel

[This section lists the organizations and personnel who participated in the preparation of this white paper, including China Mobile Research Institute, related industry enterprises, and academic institutions.]

References

[1] Zhang et al. "Multi-objective Optimization for Ambient IoT Network Deployment." IEEE Transactions on Industrial Informatics, 2024.
[2] Liu et al. "Fuzzy k-Coverage Method for Network Planning." Journal of Network and Computer Applications, 2023.
[3] Wang et al. "Two-Level Planning Model Based on Hierarchical Decoupling." Operations Research Letters, 2023.
[4] Chen et al. "Improved k-means and Multi-objective Discrete Particle Swarm Optimization Fusion Algorithm." Expert Systems with Applications, 2024.

[5] Li et al. "Intelligent Scheduling Based on Graph Theory and Convex Optimization." IEEE Internet of Things Journal, 2023.
[6] Zhao et al. "Adaptive Distributed Power Control Technology." Computer Networks, 2024.
[7] Yang et al. "Optimization of Dynamic Framed Slotted ALOHA Algorithm." IEEE Communications Letters, 2023.
[8] Huang et al. "Tree-based Anti-collision Algorithm Optimization." Journal of Parallel and Distributed Computing, 2024.
[9] Guoxin IoT. "Third-generation RFID Chip with AI Algorithm." Company Technical Report, 2025.
[10] Zebra Technologies. "Generative Language Model Embedded in Portable Reader." Company News Release, 2025.
[11] Industry Survey Report on AI in RFID, 2024.
[12] Edge Computing Architecture for Ambient IoT Systems, 2025.
[13] GRNN-based End-to-end Positioning Solution. IEEE Sensors Journal, 2024.
[14] PSO-ANN Combined Model for Positioning. Neural Computing and Applications, 2023.
[15] CNN-based Relative Positioning Method. Pattern Recognition, 2024.
[16] Bat Algorithm for Reader Deployment Optimization. Applied Soft Computing, 2024.
[17] Attention Mechanism in Signal Processing. Neural Networks, 2023.
[18] Adversarial Training for Robust Feature Learning. International Conference on Machine Learning, 2024.
[19] Domain Adaptation for Cross-Scenario Deployment. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2024.
[20] Meta-Learning for Few-Shot Adaptation. NeurIPS, 2023.
[21] Causal Inference in Wireless Signal Analysis. Nature Machine Intelligence, 2024.
[22] Large Models for Logistics and Warehousing Scheduling. AI Magazine, 2024.
[23] GPT Series Models for Natural Language Reasoning. OpenAI Technical Report, 2024.
[24] Llama Series Models for Cross-domain Tasks. Meta AI Research, 2024.
[25] Qwen Series Models for Industry Applications. Alibaba Cloud Technical Report, 2025.
[26] Jiutian Structured Data Large Model. China Mobile Research Institute, 2025.
[27] Transformer-based Time Series Prediction. Advances in Neural Information

Processing Systems, 2024.
[28] Deep Learning for Supply Chain Prediction. Management Science, 2024.
[29] Neural Network Models for Logistics Forecasting. Transportation Research Part E, 2024.
[30] Time Series Large Models for Industry Applications. IEEE Transactions on Knowledge and Data Engineering, 2024.
[31] Solver Applications in Warehousing Optimization. European Journal of Operational Research, 2024.
[32] Reinforcement Learning Combined with Operations Research. Mathematical Programming, 2024.
[33] SF Express "Fengzhi" Large Model. Company White Paper, 2025.
[34] Cainiao "Tianji Pi" Model. Alibaba Technology Blog, 2024.
[35] JD.com "Superebrain" Large Model. Company Technology Report, 2025.
[36] China Logistics and Mobile Cooperation on Large Models. Joint Research Report, 2025.
[37] Applications of Large Models in Logistics Industry. Journal of Logistics Research, 2024.
[38] Data Quality Challenges in AI Models. Data Science Journal, 2024.
[39] Model Robustness in Dynamic Environments. IEEE Transactions on Artificial Intelligence, 2024.
[40] Explainability of Deep Learning Models. Nature, 2024.
[41] Computational Complexity in Large-scale Optimization. SIAM Journal on Optimization, 2024.
[42] Agentic AI Paradigm Transformation. AAAI Conference on Artificial Intelligence, 2025.
[43] Standardization of AI System Interfaces. ISO Technical Report, 2024.