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SPECIAL REPORT

2026 MARKET FORECAST: FOCUS ON AI AND WIRELESS

SPECIAL REPORT

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2026 Market Forecast: Focus on AI and Wireless

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Figuring out where the markets are headed this year is a challenge because of the turmoil due to wars, tariffs, and politics. These issues may impact the speed at which new technology is delivered, but it's often a matter of adjusting the level of the trend rather than a radical course change.

This year we asked our contributors to focus on a narrow topic rather than a broad, AI-in-everything overview. The contributions for this Special Report focus on markets such as healthcare, physical AI, data centers, and wireless communication. These markets are all seeing new technologies emerge, refinement of existing technologies, and opening new applications courtesy of the latest products and services.

CHAPTER 1

Connected Care: 3 Predictions for the Future of Wireless Healthcare

As Bluetooth and other wireless technologies enable continuous health monitoring, the lines between consumer and medical electronics are blurring.

DAMON BARNES, Director, Technical Marketing, *Bluetooth SIG*

Samsung Electronics

The future of wellness will be increasingly wireless. Bluetooth and other short-range wireless technologies are now central to the evolution of modern healthcare. What began with step counters and early fitness trackers has expanded into a diverse ecosystem of connected devices that support personal wellness, help people manage chronic conditions at home, and create new models of clinical care delivery.

The scale of this shift is what stands out. According to ABI Research, 477 million wireless wearables are expected to ship annually by 2029, highlighting the widespread adoption of these devices and how they're becoming central to people's daily health routines.

Looking ahead, several distinct trends are shaping the future of connected healthcare. Together, the predictions presented below point toward a landscape where personal devices, home health tools, and structured clinical monitoring programs increasingly work together to deliver continuous, data-informed insight.

Prediction #1: The Rise of Wearables for Personal Health and Wellness

Wearables have long served as the average consumer's first foray into connected health. Early devices centered on simple activity and sleep tracking. However, improvements in sensing, battery life, and wireless connectivity have transformed them into multi-sensor systems capable of gathering in-depth information about a person's health throughout the day.

Market research and forecasts from the 2025 Bluetooth market update reflect this expanding role. Forecasts suggest that 34 million sports, fitness, and wellness trackers equipped with Bluetooth will be shipped this year alone, and adoption continues to accelerate.

Smaller and more discreet form fac-

More than 70 million Bluetooth-enabled smart rings will be shipped annually by 2029, according to ABI Research.

tors are emerging as serious alternatives to wrist-worn devices. Bluetooth smart rings, for example, are projected to grow rapidly, with more than 70 million units expected to ship annually by 2029. The ability to wear them all day long gives them an advantage in collecting continuous physiological data with minimal user friction.

These devices aren't replacing traditional wearables but complementing them. Together, they reflect a broader trend: People are increasingly comfortable integrating passive health insight into everyday life. Reliable wireless performance plays an important role here, enabling wearables to synchronize frequently without interrupting battery life or user experience.

By 2029, annual shipments of Bluetooth wearables for healthcare purposes will reach 200 million, according to ABI Research.

Prediction #2: Consumer Electronics Expand Medical Insights Beyond the Clinic

Beyond consumer-oriented wearables, a significant number of devices are designed specifically to support people managing their health at home. This includes blood pressure monitors, pulse oximeters, thermometers, connected scales, glucometers, and a growing class of wearable patches.

These devices may not always be worn continuously, but they support self-management through periodic measurements that help people track chronic conditions or monitor recovery.

These categories are growing in parallel with wellness wearables. By 2029, 200 million Bluetooth healthcare wearables are expected to ship globally, representing a substantial share of the broader wearables landscape. At the same time, 60 million Bluetooth home health-monitoring devices will ship annually by the end of the decade, reflecting the steady adoption of tools that help people record key health metrics in home environments.

This segment illustrates a critical bridge between personal wellness and more structured healthcare use. It includes both continuous and intermittent measurement devices. While they're often used independently, many form the technological base for more formal care models.

Prediction #3: Remote Patient Monitoring Becomes a Pillar of Medical Care

Remote patient monitoring (RPM) programs represent the convergence of personal healthcare devices and clinical workflows. They make it possible for providers to observe chronic conditions over time, track recovery after procedures, and intervene earlier when concerning patterns emerge.

Growth projections indicate the rise of RPM. Estimates show that 26 million Bluetooth patient monitoring devices will ship annually by 2029, including connected blood-pressure cuffs, pulse oximeters, continuous glucose monitors, ECG patches, and other sensors designed for clinical-grade data collection. These devices gather longitudinal information rather than single in-clinic measurements, giving clinicians a more complete view of a patient's condition over time.

Demographic forces also reinforce this shift. The World Health Organization estimates that 1.4 billion people will be 60 years or older by 2030, rising to 2.1 billion by 2050. As populations age and health systems face rising demand for chronic care management, scalable wireless monitoring tools will play a critical role in supporting care outside traditional facilities.

RPM doesn't rely exclusively on

ABI Research estimates that approximately 475 million wearable devices will be shipped with Bluetooth per year by 2029.

wearables. Still, wearables increasingly enhance monitoring programs by offering continuous context around movement, sleep, recovery, heart rate variability, and other trends that support early detection. In practice, RPM blends a mix of intermittent home devices and continuous wearable sensors, each delivering different types of insight.

The Connected Health Ecosystem Ahead

Across wellness wearables, home health devices, and remote patient monitoring systems, wireless connectivity will continue driving a shift from episodic check-ins to a more continuous view of personal health.

As these devices become more embedded in daily routines, they will be expected to operate reliably with minimal power, integrate smoothly with smartphones and cloud platforms, and produce measurements that remain consistent across environments. Comfort and ease of use will remain essential, since continuous data depends on tools people can adopt without friction.

Looking to 2026 and beyond, the momentum behind connected health is set to accelerate. Wearables will evolve further, and household devices will become an even more common part of self-management. On top of that, remote patient monitoring will expand as care models move toward more distributed, data-driven approaches.

The future of connected health will be shaped by how effectively these technologies work together to deliver timely insight, support clinical decisions, and help people stay healthier wherever they're located.

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CHAPTER 2

Data Center Storage in 2026: When Storage, AI, and Compute Converge

New workload demands are turning data handling into a system-level design challenge rather than a back-end afterthought.

SCOTT SHADLEY, Director of Leadership Narrative and Evangelist at *Solidigm*

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As the industry looks toward 2026, data center architects and system designers face a convergence of pressures that make storage design more critical than ever. AI workloads continue to drive unprecedented demand for data movement, capacity, and performance, just as power, thermal, space, and component availability constraints tighten across global supply chains.

Storage can no longer be treated as a passive layer behind compute. It has become an active system component that directly influences performance, efficiency, and overall design risk.

For engineers and engineering managers planning systems that will ship in the next several years, decisions made today around storage architecture will shape not only AI performance, but also power envelopes, rack density, cooling strategies, and time-to-market. Understanding how storage fits into the broader AI infrastructure ecosystem is essential to building resilient and scalable data centers.

As AI and storage technologies converge, organizations must deal with new performance, scalability, and management challenges. SNIA is uniquely positioned to help the industry navigate these changes through standards development, technical guidance, and collaborative initiatives. This article discusses the emerging challenges at the intersection of AI and storage, the role of standards and best practices, and how SNIA is assisting the industry adapt and innovate.

AI Changes the Storage Equation

Traditional data center architectures evolved around a compute-first model. Storage systems were designed primarily for capacity and reliability, optimized to feed general-purpose workloads with predictable access patterns. AI disrupts this model.

Training and inference pipelines demand high bandwidth, low latency, and sustained data delivery across distributed systems. Storage performance variability can stall expensive compute resources and undermine overall system efficiency.

At the same time, data volumes continue to grow rapidly. AI models require access to massive datasets that may span hot, warm, and cold tiers, often distributed across multiple physical locations. As a result, storage decisions now affect network design, interconnect selection, and memory hierarchy planning. Engineers must evaluate storage not in isolation, but as part of an integrated system.

Constraints Shape Design Choices

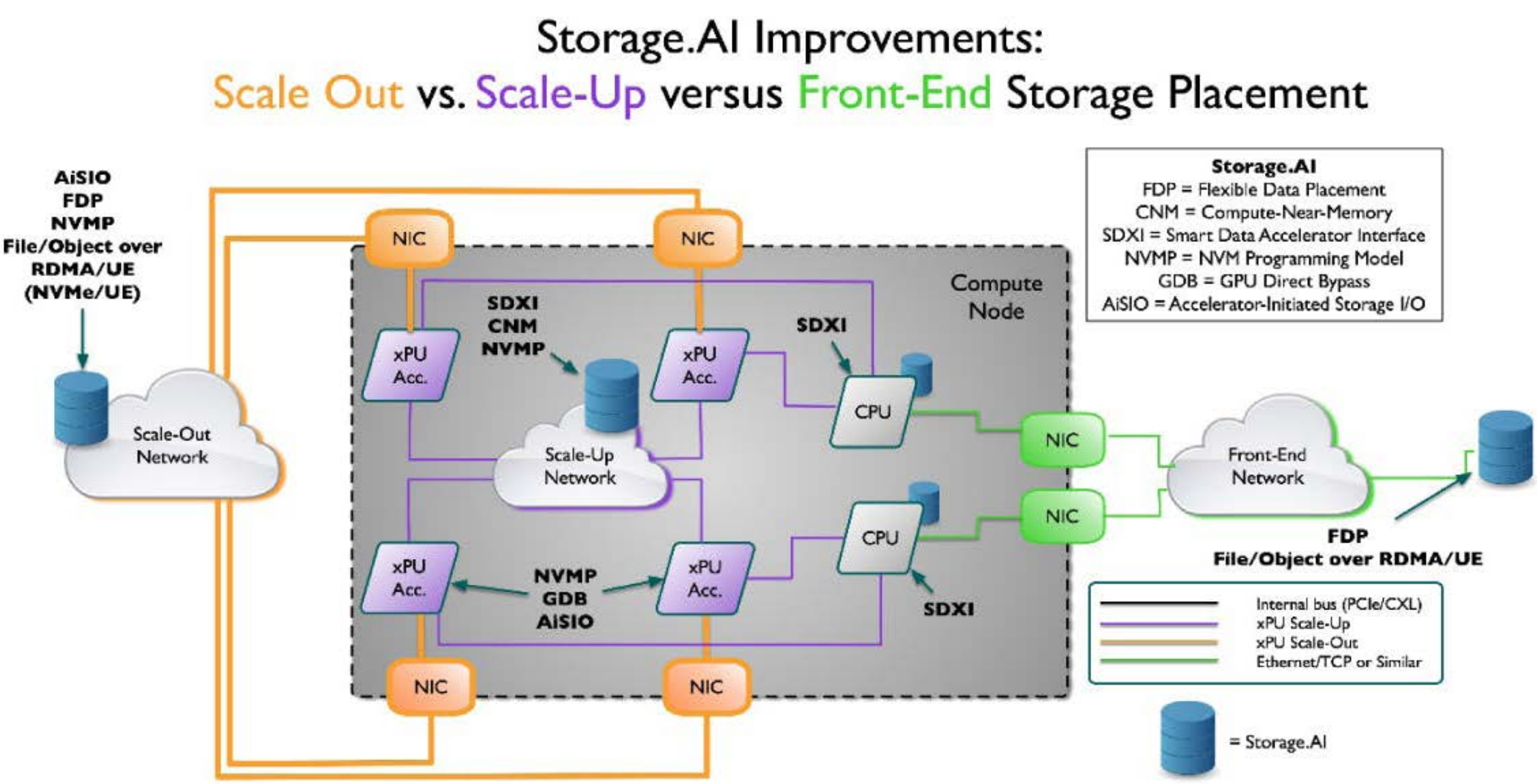
As 2026 unfolds, forecasts indicate increasing constraints across multiple dimensions of data center design. Power availability is becoming a gating factor in many regions, forcing tighter power budgets per rack and per workload. Thermal limits further restrict how densely systems can be deployed. Space constraints, particularly in urban or retrofit environments, add another layer of complexity.

Component availability also plays a growing role. Extended lead times for certain storage technologies, including high-capacity hard-disk drives (HDDs), require earlier design commitments, and limit flexibility. These realities are pushing architects to reconsider hybrid storage strategies that combine HDDs, solid-state disks (SSDs), and emerging technologies to balance capacity, performance, power consumption, and availability.

Evaluating Storage Technologies for 2026

HDDs remain essential for cost-effective, high-capacity storage, particularly for large datasets used in AI training and long-term retention. However, long lead times and power considerations require careful planning. [SSDs offer significant advantages in performance and latency]() and are increasingly used to replace or complement HDDs in performance-sensitive tiers. The tradeoffs include higher cost per bit and different thermal and endurance considerations that must be addressed at the system level.

Beyond traditional media, the industry continues to explore alternative archival technologies, including novel approaches designed for long-term data retention with minimal power consumption. While these technolo-



Next-generation data center designs integrate storage, AI accelerators, and compute nodes across scale-up and scale-out networks to support data-intensive AI workloads. SNIA gies aren't yet mainstream, their development highlights the need for flexible architectures that can incorporate new storage classes as they mature.

Storage as a System-Level Design Problem

One of the most significant shifts driven by AI is the need to address storage challenges holistically. Storage bandwidth, latency, and reliability directly influence network congestion, compute utilization, and overall system efficiency. Design decisions at the drive, enclosure, and interface level cascade upward to affect board layouts, interconnect choices, and software architecture.

This system-level view is central to SNIA's StorageAI initiative created to address a growing gap in how AI infrastructure challenges are analyzed and solved. While many efforts focus on individual domains such as compute accelerators, networking fabrics, or storage devices, StorageAI examines how these elements interact under real workloads and real constraints.

StorageAI looks specifically at data movement, placement, and accessibility across the AI pipeline, from ingestion and training to inference and long-term retention. It evaluates where bottlenecks emerge when storage, networking, and compute aren't co-designed, and how architectural choices at one layer ripple through the rest of the system. For engineers, this perspective helps translate abstract AI requirements into concrete design considerations at the component, board, enclosure, and system levels.

Rather than prescribing a single architecture, StorageAI provides a framework for understanding tradeoffs (**see figure**). It highlights how storage bandwidth, latency, and endurance affect compute utilization, power efficiency, and scalability, especially as systems move toward more distributed and heterogeneous designs.

By grounding these discussions in standards-based approaches, StorageAI helps engineers and engineering managers identify balanced solutions that can be implemented, validated, and evolved over time in real-world designs.

The Role of Standards in Reducing Design Risk

As architectures grow more complex, standards play an increasingly important role in managing risk. Standards provide stable design targets, predictable interfaces, and interoperability across components and vendors. For engineering teams, this translates directly into fewer redesign cycles, easier validation, and improved supply-chain flexibility.

SNIA's long-standing work in areas such as form-factor definitions and storage interfaces has helped the industry adopt interoperable hardware designs through multi-vendor plugfests that scale across product generations. In the context of AI-driven data centers, standards enable engineers to focus innovation where it matters most, while relying on proven frameworks for integration and compatibility.

Standards also support collaboration across adjacent ecosystems, including compute architectures, networking fabrics, and system software. Alignment with organizations such as NVM Express, Open Compute Project (OCP), Ultra Ethernet Consortium (UEC), and the Linux Foundation helps ensure that storage designs integrate smoothly into broader platform roadmaps.

Designing for the New Normal

The data center of 2026 will not be defined by a single technology or architecture. Instead, it will reflect a balance of performance, capacity, power efficiency, and availability, guided by system-level thinking and standards-based collaboration. Engineers must design for constraints — not ideal conditions — and anticipate continued evolution in AI workloads and infrastructure requirements.

For storage, this means minimizing unnecessary fragmentation, increasing commonality of design through industry standards, and still leaving room for differentiated innovation. It also means planning architectures that can adapt to new, emerging storage technologies emerge and evolving AI workflows.

Looking Ahead: Storage and AI

As AI continues to reshape computing, storage will remain a critical enabler of performance and scalability. The choices engineers make today will determine how effectively data centers can support next-generation workloads under real-world constraints. Approaches such as SNIA's StorageAI help frame these decisions by encouraging system-level thinking across compute, networking, and storage, and by grounding architectural tradeoffs in standards-based collaboration.

By treating storage as an active design element rather than a passive resource, and by leveraging initiatives like StorageAI alongside established standards, engineering teams can reduce risk, shorten design cycles, and build AI infrastructure that's resilient, efficient, and ready for the challenges of 2026 and beyond.

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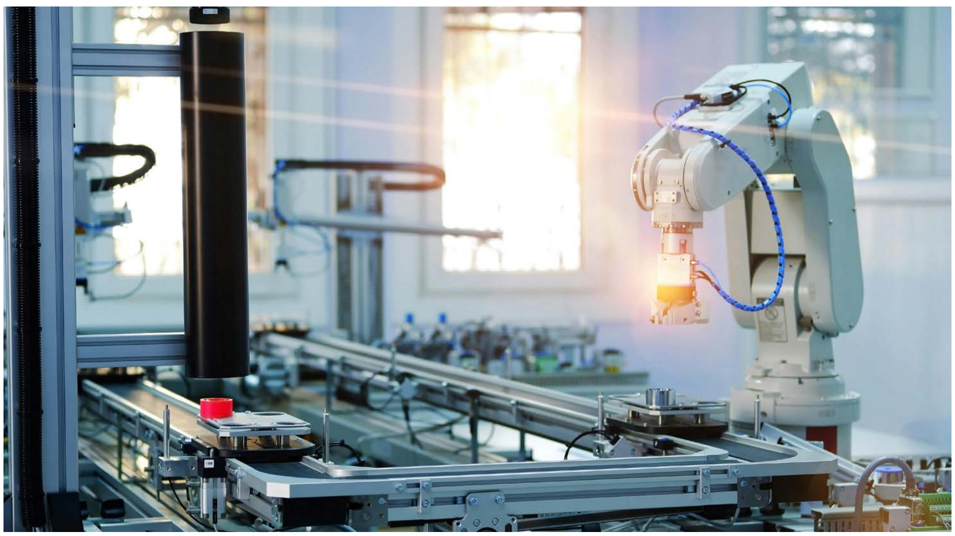
CHAPTER 3

Physical AI's Push Shifts into High Gear

As the move to physical AI speeds up, how do you make sure these capabilities become broadly accessible and not limited to only high-performance systems?

ARTEM AGINSKIY, General Manager, Jacinto High-Performance Compute, *Texas Instruments*



Texas Instrument

For a long time, AI models have had their heads in the cloud. Traditionally, these models have been trained and run inside data centers, and they could not directly affect the physical world. But as AI accelerators matured, edge devices started running models locally, capturing data close to the source to enable lower-latency inference. However, the output of those models still required direct human interaction to manifest in a physical action.

Today, innovations in safety, security, and reliability have made it possible for advanced driver-assistance systems (ADAS) in cars and industrial robots to act safely without humans in the loop. These innovations are helping AI transition from being a digital assistant that informs decisions to AI that can not only sense and think, but also act. This is where physical AI, sometimes referred to as embodied AI, comes into play.

But as the shift to physical AI accelerates, a question emerges: How do we ensure these capabilities become broadly accessible, not limited to only the most advanced or high-performance systems?

What is Physical AI?

The term physical AI refers to AI models that run on embedded hardware and directly influence a system's physical behavior.

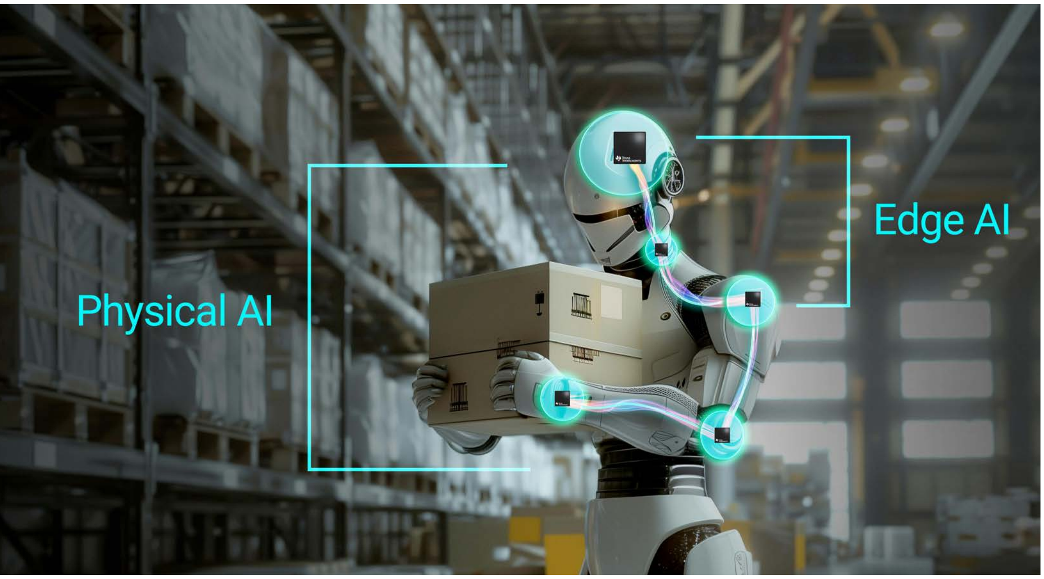
Physical AI isn't an entirely new concept. It pushes the concepts of edge AI and real-time control into systems that not only interpret their environment locally, but also use that interpretation to shape physical motion.

Figure 1 helps illustrate the difference between physical and edge AI. In a humanoid robot — one of the flagship physical-AI applications — physical AI is used to control the robot as it grabs and lifts a box, while edge AI covers the capabilities of the processors that locally run AI models.

Consider a driver approaching traffic that slows unexpectedly on a busy highway. Today, the vehicle's deterministic systems respond when the distance to the car ahead shrinks to a defined threshold, slowing the vehicle with the aim of stopping safely.

A physical-AI system changes when that happens. It analyzes emerging traffic patterns earlier and adjusts speed even before the defined threshold would have been crossed. The result is a smoother, more controlled change in motion enabled by the AI running directly on embedded hardware in the car. This sort of improvement is even more impactful when it

CHAPTER 3: **Physical AI’s Push Shifts into High Gear**



1. Physical AI builds on the concept of edge AI, encompassing not only perception of the physical world, but also interaction with it. Texas Instruments

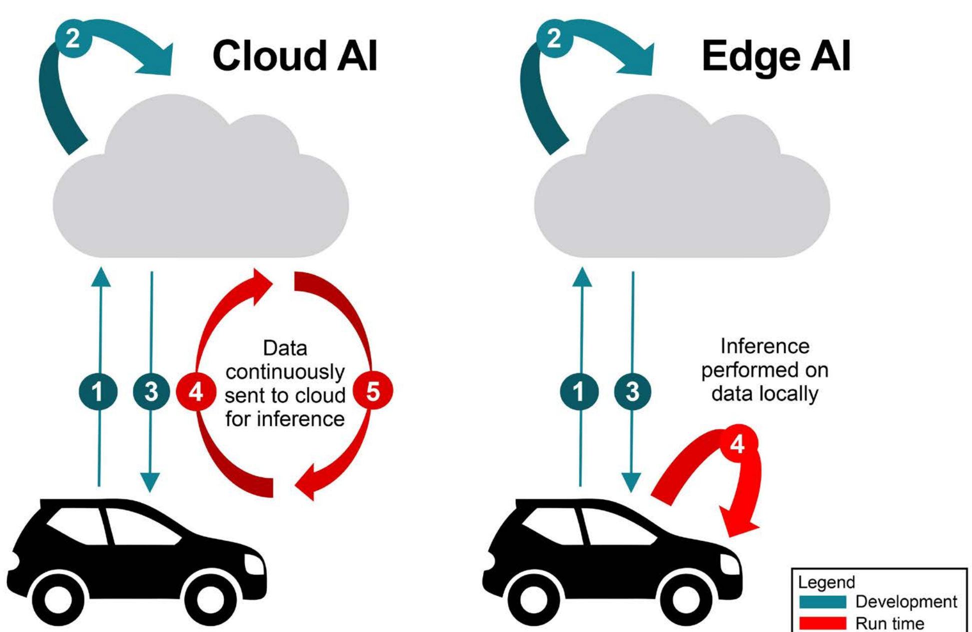
can appear in many vehicles, not just a few.

Every millisecond matters when AI analyzes and reacts to sensor and actuator data in real-time. Physical AI fills the need for local, near-instantaneous processing.

However, we still use massive amounts of computing and memory in the cloud to train and refine physical-AI models. For instance, [digital twins] are critical when it comes to training physical-AI models, including those used in robotics. By building a virtual version of a system, complete with its mechanics, electronics, and sensors, we can test and refine models before they interact with hardware.

Where Edge AI Ends and Physical AI Begins

Edge AI covers AI models that run locally on everything from smaller microcontrollers (MCUs) to embedded processors, pooling and processing data from sensors and then generating outputs without relying on remote servers. The concept is outlined in **Figure 2.**



2. A comparison of cloud-based AI and edge AI. Texas Instruments

What distinguishes physical AI is what happens after the model produces its output. Edge AI can classify an image, identify a sound, or interpret sensor data. Physical AI brings together perception with actuation to control how a system moves, reacts or adjusts in real-time. For instance, a car can react further ahead of time when physical AI interprets multiple cues from nearby traffic locally, supporting smoother changes in speed.

In the industrial world, warehouse robots are able to adjust their routes as people move near them because onboard models process the scene without network delay. Industrial equipment can fine-tune the torque, position, or speed of motors when local models evaluate sensor data continuously rather than deferring to AI models running in the cloud.

None of this is new. Engineers

have used predictive and even machine-learning models in embedded systems for years. But physical AI stands apart by integrating these capabilities at a deeper level into system designs, where local inference and actuation are tightly coupled. Because physical AI is being woven into a wide range of product families and at varying price points, engineers need approaches to hardware and software that scale.

Physical AI Hinges on Hardware/Software Co-Design

Physical AI generally breaks down into three fundamental parts: sense, think, and act. For instance, a self-driving car "senses" its surroundings using cameras, radar, LiDAR, and other sensors; "thinks" by processing data to plot out a safe path on the road ahead; and, finally, "acts" by controlling the steering, brakes, and throttle to execute the plan. Traditionally, AI models are used to sense and think about the surrounding world. But when AI models start to control movement, it changes the rules of system design.

In physical AI, engineers can no longer rely on constant wireless connectivity because these systems require predictable timing, accurate sensor data, and hardware that can respond in a matter of milliseconds.

Engineers face a mix of hardware and software design considerations. For instance, processors must be able to execute models within the timing requirements of the control loop, while the sensor chain must be able to deliver accurate, dependable data. Software needs to coordinate perception and actuation without introducing latency, and verification becomes more complicated, as errors now carry real-world consequences for reliability of the machinery and safety of the user.

Hardware and software shape each other in physical AI far more than in prior generations of embedded systems. As a result, physical-AI development is best approached as a co-design effort, in which hardware and software decisions are treated as tightly connected. A practical example helps illustrate the point.

Consider a small robotic arm designed to handle delicate components on a production line. The software team may want to deploy a larger model to improve grasp prediction, but that has implications for the hardware team, since the processor must still run inference within a tight control loop.

Conversely, the hardware team may want to adopt a new type of current sensor inside the motor to deliver higher-resolution data. That, in turn, pushes the software team to adjust the model and control logic so that the arm can take full advantage of the improved signal quality.

Through coordinated co-design, both sides of the engineering team can come to a solution where the AI model fits the compute budget, the sensors support the needed precision, and the control loop stays within its timing window. This ultimately allows the arm to move in a safer, more reliable way.

Hardware is Hard in Physical AI Systems

Semiconductors are the foundation for physical AI. These systems rely on embedded processors that run the AI model, signal-chain devices that capture sensor information with accuracy, and power technologies that maintain stable operation as loads shift. Each of these parts sets the limits for timing, precision, and consistency in a physical-AI design.

What I've seen in many designs is that improvements in one area ripple into others. A new sensing chain can enable more precise control. A processor that supports a slightly larger model can help a robot handle more complex scenarios. And a refined power architecture will help systems maintain consistent performance during rapid movements.

Fundamentally, physical AI depends on this interaction between components in terms of predictable processing, reliable sensing, and stable power systems.

Where is physical AI headed? I'm seeing trends across the industry that are shaping how physical AI systems take form. Designers are bringing sensing, computing, and control closer together to support predictable timing and consistent performance.

As discussed, simulation and digital-twin environments are increasingly common in development flows, giving teams a way to test behavior before hardware is available.

Today, physical AI is gaining momentum across several sectors:

- In buildings and infrastructure, engineers can build controllers to adjust mechanical systems based on environmental information.
- In robotics, onboard intelligence helps machines adjust their movement around people and equipment.
- In industrial automation, equipment adapts behavior based on live sensor input, helping processes stay stable under changing conditions.

In all of these situations, semiconductor companies like Texas Instruments play a vital role in shaping what physical-AI systems can accomplish. That's because their performance, accuracy and reliability depend on the underlying hardware — not only software.

Ultimately, they're the ones supplying the building blocks of the physical-AI era. And as these technologies spread into more types of devices and new tiers of products, their job is also to make sure these capabilities remain within reach for as many designers as possible.

If physical AI is to shape how machines move, react, and support us, improving safety and convenience, it must be broadly available on everyday devices and not just limited to high-performance systems.

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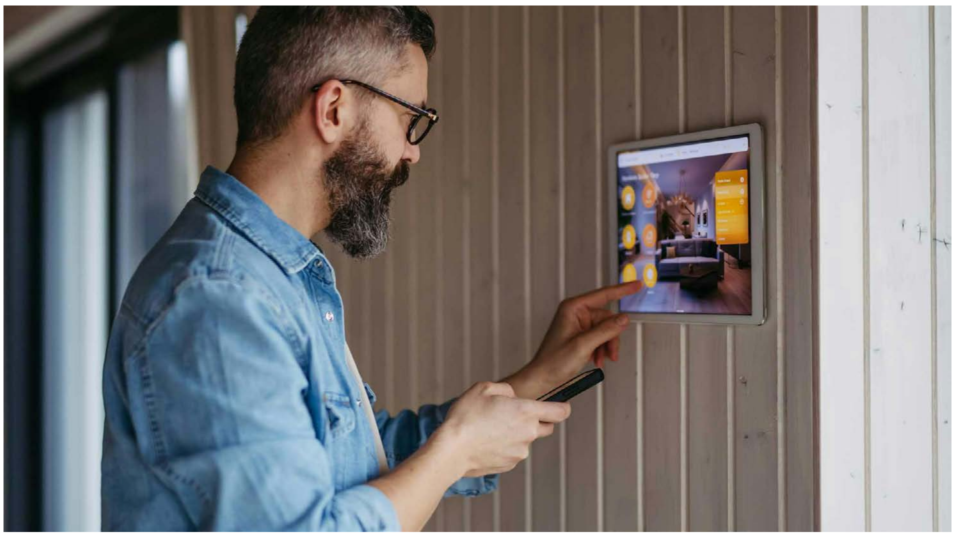
CHAPTER 4

What's Next for Wi-Fi: Key Trends for 2026

In 2026, several key developments will impact Wi-Fi, from wider Wi-Fi 7 infrastructure adoption to new peer-to-peer (P2P) capabilities and advances in sensing and locationing.

SIVARAM TRIKUTAM, SVP of Wireless Products, *Infineon Technologies*



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Wi-Fi continues to evolve as new standards, security requirements, and device capabilities reshape how designers build connected products. 2026 will see several key developments, from wider Wi-Fi 7 infrastructure adoption to new peer-to-peer (P2P) capabilities and advances in sensing and locationing. The growing focus on post-quantum cryptography (PQC) and improved power efficiency will also impact next-generation IoT designs.

Together, these trends signal a more capable, secure, and energy-efficient Wi-Fi ecosystem in the year ahead.

Wi-Fi 7 Will Become Mainstream

Wi-Fi 6 introduced orthogonal frequency-division multiple access (OFDMA), shifting Wi-Fi's design priorities from chasing peak data rates to improving overall network efficiency. It answered a simple question: Why build a faster car if it's stuck in traffic all the time?

Wi-Fi 7 extends that shift with Multi-Link Operation, which improves connection robustness and reduces latency. The feature is already available in most high-end smartphones and PCs, yet its benefits haven't been fully realized because access points (APs) and routers are still catching up.

Today, only expensive, high-end models support Wi-Fi 7. In 2026, adoption will broaden across APs and routers at all price points, while ISPs begin rolling out Wi-Fi 7 as the default option.

Wi-Fi Aware Will Create New P2P Use Cases

The traditional Wi-Fi model requires devices to communicate through an AP or router. Device-to-device communication has long been possible through neighborhood area networking (NAN), though adoption has been limited. This is expected to change in 2026. With Apple iOS now supporting Wi-Fi Aware, the door opens for a broader set of peer-to-peer use cases.

Smartphones will be able to communicate directly across iOS and Android ecosystems. They will also be able to connect to IoT devices such as printers, appliances, and door locks without joining the same Wi-Fi network. On top of that, Wi-Fi Aware's certified peer connections support one-touch onboarding, allowing personal devices, such as healthcare and medical monitors, to join a network simply by opening an app.

Getting Ready for PQC

As Wi-Fi connects more IoT devices to the internet, the attack surface expands, increasing the risk of botnets, lateral movement, supply-chain attacks, and similar threats. Hardware root of trust, secure onboarding and updates, and per-device attestation will become baseline expectations for IoT devices.

While these measures address today's security challenges, we're approaching a point where quantum computers could break current cryptographic protections. In 2026, device manufacturers will begin preparing for next-generation security through PQC.

PQC uses new classes of mathematical problems, such as lattice-based schemes that remain resistant to quantum attacks. Standards bodies have approved PQC algorithms so that device makers can begin migrating away from RSA (Rivest–Shamir–Adleman) and ECC (elliptic curve cryptography) well before quantum computers can defeat them.

Wi-Fi for Sensing and Locationing

Wi-Fi's role in sensing and locationing has been discussed for years. But because the underlying technologies weren't mature or reliable enough for large-scale use, broad deployment of these applications remained limited.

That's beginning to change. Several key protocols are now available: 802.11mc for basic locationing, 802.11az for improved three-dimensional positioning, and 802.11bf for exchanging channel state information to enable presence and motion detection. With microcontrollers that integrate edge-AI acceleration now widely available, the conditions are in place for the industry to build and deploy multi-modal sensing and locationing applications at scale.

Increase in the Number of Battery-Operated Devices

Improvements in both active and standby power consumption of Wi-Fi system-on-chip (SoC) devices are reducing the energy requirements of connected products. New features in Wi-Fi 6 and Wi-Fi 7 further lower power usage for always-on operation, which will ramp up the number of battery-powered Wi-Fi–connected devices. These devices are generally easier for DIY users to install, further accelerating adoption.

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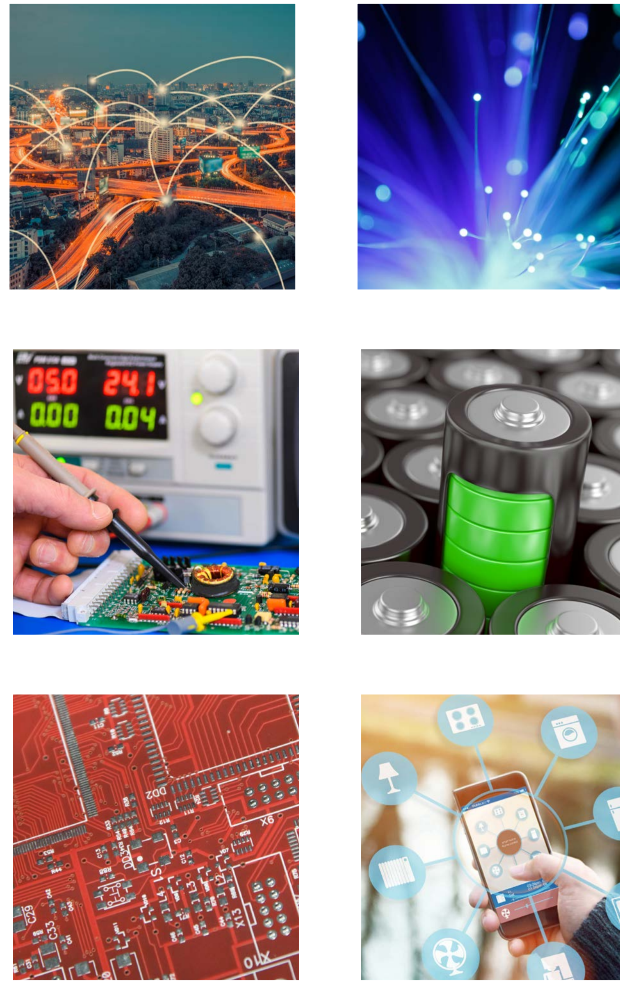

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