

The Global Market for Artificial Intelligence (AI) Battery Technology 2027-2037

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Abstracts

Artificial intelligence is rapidly becoming a core technology across the battery value chain. It is changing how batteries are discovered, designed, tested, manufactured, managed, reused and recycled. The market for AI-driven battery technology spans AI software, AI-enabled services and AI-specific hardware, such as vision inspection systems and edge-AI battery management processors. It is set for strong growth over the next decade, as battery demand expands and AI becomes embedded in every stage of the lifecycle. The past twelve months have marked a turning point. AI has moved from pilot projects to company-wide transformation programmes at the world's leading cell makers, with targets for large productivity gains and AI governance overseen at board level. Recent developments include:

Generative AI in R&D. Materials foundation models and generative design tools have entered commercial battery R&D. Battery developers now offer AI-driven materials discovery platforms that screen millions of candidate electrolytes and electrode materials.

Sodium-ion. Sodium-ion batteries have entered mass production for passenger vehicles. Solid-state batteries are approaching commercial launch, and both chemistries rely heavily on AI-accelerated development.

Regulation and trade. The EU battery passport, due from February 2027, is turning battery state-of-health data into a regulated asset. Export controls on advanced battery technology have made data, models and process know-how matters of national strategy.

New demand. AI data centres, humanoid robots, drones and electric aircraft

have emerged as new sources of battery demand. Each needs sophisticated battery intelligence.

Looking ahead, the fastest growth is expected in:

Second-life assessment, as the first large wave of retired EV batteries arrives after 2030;

Recycling, under circular-economy regulation;

Digital twins, linking data across the battery lifecycle;

Materials informatics, driven by next-generation chemistries.

Stationary storage and data centres are becoming the fastest-growing customer groups. On-edge AI will take a rapidly rising share of battery analytics as neural processors spread through battery management hardware. Adoption will follow three waves:

Analytics and BMS intelligence in the late 2020s.

AI-native manufacturing and accelerated materials discovery in the early 2030s.

Autonomous laboratories and fully digital-twin-based development by the mid-2030s.

Competitive advantage will go to companies that combine proprietary battery data, deep electrochemical expertise, validated physics-informed models and integration across the full battery lifecycle. Battery development is moving from an experiment-centred process to a data-centred one, and AI capability is becoming as strategically important as manufacturing scale.

The Global Market for Artificial Intelligence (AI) Battery Technology 2027–2037 is a comprehensive analysis of how AI is transforming every stage of the battery lifecycle, and of the commercial opportunities this creates. The report analyses nine AI use-case arenas:

materials informatics;

cell and pack design;

cell testing and modelling;

manufacturing and quality control;

BMS and battery analytics;

application operation;

digital twins;

second-life assessment;

recycling.

Report contents include:

Global market forecasts 2027–2037 by use case, AI technique, deployment, offering, chemistry, end use and region

Bear, base and bull scenario analysis and value-pool distribution across the technology stack

Analysis of machine learning, deep learning, physics-informed models, generative AI, foundation models and agentic AI for batteries

Battery data infrastructure, public datasets, advanced sensing, BMS silicon and edge-AI processors

AI-driven materials discovery, universal interatomic potentials and autonomous laboratories

AI in cell and pack design, testing, lifetime prediction and gigafactory manufacturing

Next-generation BMS, cloud analytics, on-edge AI and battery health certification

AI for EV charging, V2G, BESS dispatch and data-centre battery management

Battery digital twins across the lifecycle

Second-life assessment, regrouping and AI in recycling

AI opportunities by battery chemistry and end-use market

Regional policy ecosystems, battery passports, AI regulation, safety standards and export controls

AI adoption by cell makers, EV OEMs and platform companies

Competitive landscape, partnerships, funding, M&A and patent analysis

Profiles of 95 companies. Companies profiled include About:Energy, ACC (Automotive Cells Company), ACCURE Battery Intelligence, Addionics, Aegis Critical Energy Defence, Aionics, Altilium, Anabatic Semi, Analog Devices, Atinary Technologies, B2U Storage Solutions, BASF, BattGenie, Blue Solutions, BMW Group, Bosch, Breathe Battery Technologies, Brightfield AI/Voltus, Brill Power, CATL, Chemix, Circular, Circunomics, Citrine Informatics, Cling Systems, Cognex, Connected Energy, CuspAI, Dassault Syst?mes, DellCon, DNV (Veracity), DP Technology, Dragonfly Energy, Dukosi, Dunia Innovations, Eatron Technologies, EcoPro, Electra Vehicles, Elisa IndustrIQ, Elysia Battery Intelligence (Fortescue Zero), EnPower Greentech, enspired, Envision AESC, Eonix Energy, EthonAI, EVE Energy, Fluence Energy, Gaussion, GBatteries, Glimpse Engineering, Google DeepMind, Huawei Digital Power, Intellegens and more....

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