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CONVERGENCE OF ARTIFICIAL INTELLIGENCE IN BIOTECHNOLOGY: INNOVATIONS AND PROSPECTS

Convergence of artificial intelligence with bionanotechnology shifts the «green» microbial synthesis of nanoparticles from an empirical approach to rational, data-driven design, enhancing reproducibility and technological maturity of the processes. The ***aim*** *of this work was to summarize current knowledge and outline the role of AI, machine learning, and deep learning methods in multifactorial optimization of biosynthesis conditions, prediction of nanoparticle properties prior to their production, guided self-assembly and engineering of producer strains, as well as in ensuring the safety of nanomaterials in line with the Safe-by-Design concept.* ***Methods.*** *Publications from 2020—2025 in PubMed, ACM, ScienceDirect, Google Scholar, and Scilit databases were analyzed, applying double screening and thematic synthesis. It was established that the use of AI significantly reduces the number of experiments, enables coordinated control of process parameters, ensures transfer of synthesis conditions between laboratory and pilot-scale setups, and allows ex-ante prediction of nanoparticle stability, bioactivity, and antimicrobial action. In particular, for La-doped ZnO nanoparticles, model accuracy reached $R^2 \approx 0.96$. A promising direction is programmed self-assembly of nanoscale structures, algorithmic selection of surface functionalization, and control of the protein «corona,» which determines biocompatibility and immune response. Another important result is the unification of toxicological data and improvement of regulatory compliance of products owing to explainable AI methods and integration with real-time process analytical control, as well as process design with quality built in from the outset. Thus, the convergence of artificial intelligence and «green»*

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microbial synthesis establishes a platform for precision engineering of biogenic nanomaterials with predictable properties, where strategic success depends on high-quality data, algorithm transparency, and interdisciplinary collaboration.

Keywords: *artificial intelligence; machine learning deep learning; bionanotechnology; green synthesis; microorganisms; nanoparticles; digital twins; environmental safety; Safe-by-Design.*

Convergence of artificial intelligence (AI) with bionanotechnology marks a qualitatively new stage in the evolution of scientific inquiry and technological innovation. The synergy of these two fields — each already a self-sufficient driver of progress — creates the foundation for solutions that until recently belonged to the realm of science fiction. For a correct assessment of this convergence, it is useful to briefly outline the intellectual genealogy of the fields. AI, as a subdiscipline of computer science, focuses on the development of systems capable of imitating key human cognitive functions — perception (of images, sounds, texts), analysis, planning, decision-making, and learning from experience. Historically, two major approaches are distinguished: symbolic AI (rule-based/logical inference) and statistical AI, which relies on probabilistic models and optimization methods (Amin et al., 2023; Dinu et al., 2024).

Within statistical AI, a subfield of machine learning (ML) emerged, where algorithms improve their performance through data without explicit programming of solution steps. ML is divided into supervized learning (models trained on input—target pairs), unsupervised learning (discovery of hidden structures without labels), and reinforcement learning (an agent optimizes the policy of action through a system of rewards/penalties) (Malik et al., 2025; Sang et al., 2022). The further development of ML led to deep learning (DL) — the use of multilayer artificial neural networks capable of automatically extracting feature hierarchies from high-dimensional data and achieving state-of-the-art performance in computer vision, speech, and prediction tasks. The relationships between AI—ML—DL and some key application areas are illustrated in Fig. 1.

Architectural choices are determined by the nature of the data. For images, the basic choice is convolutional neural networks (CNNs), which — thanks to local convolution and weight sharing of convolutional filters (and, if necessary, biases) — successfully recognize spatial patterns and provide high accuracy in classification, detection, and segmentation (Liu et al., 2023).

For sequences (text, time series), recurrent neural networks (RNNs/LSTMs) were traditionally the mainstay; however, transformers have now become the standard. Using the self-attention mechanism, they better model long-range dependences and scale effectively to large datasets derived from open web sources (Alomar et al., 2024).

In summary: CNNs are the natural choice for visual tasks; transformers dominate in natural language processing (NLP) and increasingly in multimodal settings; RNNs retain niche roles in certain streaming applications (Colliard-Granero et al., 2023).

Bionanotechnology — an integrative field at the intersection of biology and nanoscience — offers a platform for developing materials and devices with unique properties relevant to medicine, energy, and the environment. Central to this is the synthesis of nanomaterials, where quantum size effects, a high surface-to-volume ratio, and controllable morphology determine functionality. Traditional synthesis methods, despite their maturity, are often energy-intensive and involve toxic reagents, raising concerns of environmental sustainability. Against this background, green synthesis — using biological entities or their extracts as bioreductants and stabilizers — emerges as an eco-oriented alternative. Microorganisms (bacteria, fungi, algae) act as «living nanofactories,» enabling the reduction of metal ions and encapsulation of nuclei under mild conditions (Ahmad et al., 2024; Al-Shammari et

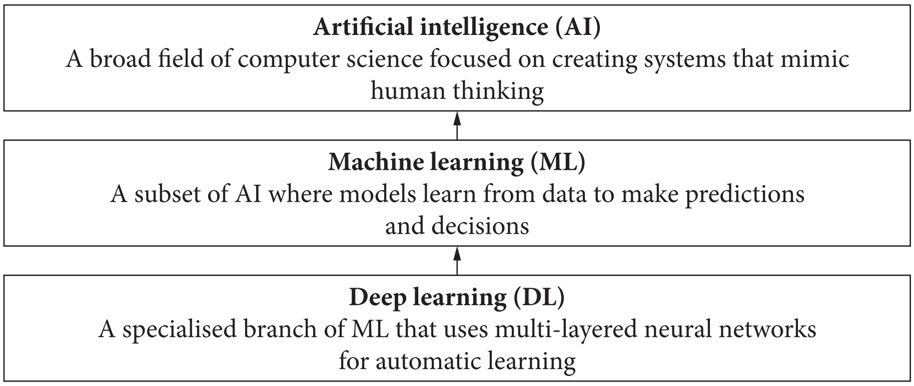

Fig. 1. Relationships among artificial intelligence (AI), machine learning (ML), and deep learning (DL)

al., 2022; Alsaiari et al., 2023; Tsekhmistrenko et al., 2020; Tymoshok et al., 2023).

In this context, the AI → ML → DL chain acquires applied significance. At the «upper» AI level, methods are employed for modeling nanobiointeractions (NP interactions with cellular barriers, protein corona), optimization of nanoparticle parameters for targeted delivery, and development of clinical decision-support systems in nanomedicine. At the ML level — regression models, decision trees, SVMs, clustering, and ensembles — support the analysis of large volumes of experimental and simulation data: predicting toxicity and biocompatibility, candidate selection, and automated classification of spectroscopic and microscopic data, thereby accelerating identification of structure and properties. The deepest level (DL) unlocks new opportunities for high-dimensional and multimodal data, typical for nanobiosystems: CNNs automate the TEM/SEM image analysis and morphometry extraction; RNNs/LSTMs process biosensor signals in real time; transformers generate candidate nanostructures *in silico* and predict their functional parameters based on sequences, graphs, and textual descriptions (Behgounia et al., 2020; Naik et al., 2024). Thus, the AI—ML—DL hierarchy in bionanotechnology is not only a conceptual framework but also a practical pipeline from data to material: from intelligent analysis and modelling to rational design of nanoplatforms with specified properties for biomedical applications.

Finally, the visual scheme of interconnections (Fig. 1) — «AI ⟷ ML ⟷ DL» — captures the hierarchy of approaches and application maps, emphasizing that modern bionanotechnology increasingly operates as a data-driven discipline, where knowledge is extracted from large volumes of heterogeneous data, translated into models, and returned to the laboratory as hypotheses, synthesis parameters, or validation protocols — in a closed design—build—test—learn loop. This defines the framework of the entire article: from the fundamentals of green synthesis to its intelligent optimization; from applied biomedicine to ecological and agricultural scenarios; and from advantages to challenges and prospects of implementation.

Materials and Methods. Searching for online repositories is a crucial stage in performing a systematic literature review on the convergence of bionanotechnology and AI. The process began with formulating a structured search string, developed according to established systematic review protocols. The search string used a combination of key terms. In particular, the following query was applied: («Artificial Intelligence» (MeSH) OR «Machine Learning» (MeSH) OR «deep learning») AND («Nanoparticles» (MeSH) OR nanoparticle OR nanomaterial OR «bio-nanotechnology») AND («Green Chemistry»

(MeSH) OR biogenic OR microbial OR biosynthesis) AND («2020/01/01» (Date - Publication): «2025/12/31» (Date — Publication)) AND (English [Language]) AND (Journal Article [Publication Type] OR Review [Publication Type]). Using this search string, a comprehensive search was performed across leading online repositories: PubMed (https://pubmed.ncbi.nlm.nih.gov/), ACM (https://dl.acm.org), ScienceDirect (https://www.sciencedirect.com/), Google Scholar (https://scholar.google.com), and Scilit (https://www.scilit.com/). These platforms were chosen due to their wide coverage of scientific literature on technology and applied sciences. Following identification, an initial screening stage was conducted to exclude irrelevant or duplicate studies. Articles most relevant to our study were analyzed. From the total of 286 identified works, 75 articles were selected by double screening. All included papers were carefully examined, and the results were studied and presented in this review

Fundamentals of Green Synthesis of Nanomaterials. Green synthesis of nanomaterials is an environmentally oriented paradigm for obtaining nanostructures through the use of biological entities or natural compounds that act as reducing and stabilizing agents of metallic precursors (Kirubakaran et al., 2025). In contrast to conventional physicochemical routes, which often require high temperatures and pressures or involve toxic reagents, the green approach relies on non-toxic, biodegradable media and energy-efficient regimes, substantially reducing the environmental footprint of production and facilitating subsequent integration of materials into biomedical applications (Gunasena et al., 2025). Central to this approach are biomolecules, such as enzymes, proteins, polysaccharides, and other metabolites, which, on the one hand, initiate and direct the reduction of metal ions to the zero-valent state or oxide nuclei formation and, on the other hand, stabilize nuclei and growing particles, preventing aggregation and determining the morphogenesis and surface chemistry of nanoparticles (Saxena et al., 2025).

A special role is played by microorganisms — bacteria, fungi, algae, and yeasts — as «living nanofactories» capable of producing nanoparticles under mild cultivation conditions. Compared to conventional methods, microbially mediated synthesis is more economically feasible and technologically sustainable: typical producers growing on inexpensive media, and the bioprocess itself does not require aggressive physicochemical influences (Tsekhmistrenko et al., 2020). Two complementary mechanisms are realized — intracellular and extracellular. In the intracellular pathway, metal ions are transported into the cell and reduced by cytosolic enzymes; in the extracellular pathway, they are adsorbed on the cell surface or in the periplasm and reduced by secreted enzymes and proteins (Tymoshok et al., 2025). An example is *Streptomyces* spp., which demonstrate the ability to form zinc, gold, manganese, silver, and copper oxide nanoparticles; at the same time, such fungi as *Fusarium oxysporum*, *Aspergillus flavus*, and *Cladosporium cladosporioides* are well known for their high yields of extracellular protein fractions, which encapsulate and stabilize particles, providing controlled morphology and narrower polydispersity (Ahmad et al., 2024). Algae and other microorganisms complement this toolkit, expanding the spectrum of available biogenic nanomaterials and increasing the ecological compatibility of the processes (Tsekhmistrenko et al., 2020).

The properties of biogenic nanoparticles — primarily size, shape, degree of crystallinity, ζ-potential, and surface chemistry — are finely tuned by selecting the type of producer and controlling process parameters such as pH, temperature, precursor salt concentration, ionic strength of the medium, and incubation time (Monteiro et al., 2025). Accordingly, targeted regulation of these factors enables the production of nanomaterials with specified performance characteristics for particular applications — from catalytic and sensing platforms to targeted delivery systems. Importantly, biogenic particles often display intrin-

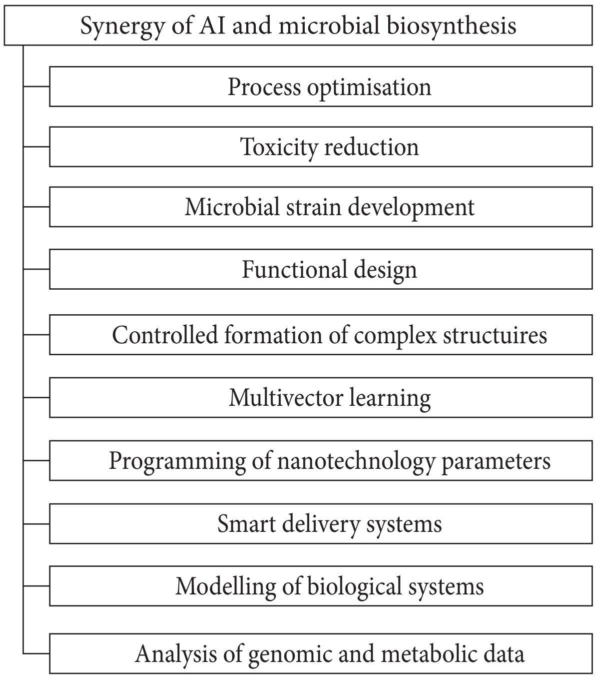

Fig. 2. Synergy of AI and microbial biosynthesis

sic functionality in biological systems, including participation in redox regulation and related signaling networks, which underlies their antibacterial and antifungal effects and opens additional opportunities for therapeutic use (Bityutsky et al., 2020). In the context of the global problem of antibiotic resistance, metal oxide nanoparticles (Ag, CuO, ZnO, etc.) are considered promising agents; however, to fully realize their potential, a deep understanding of the relationships among synthesis conditions, surface chemistry, protein corona formation, and mechanisms of antimicrobial action is required to ensure rational design and reproducibility of target properties (Ahmad et al., 2024; Tsekhmistrenko et al., 2021).

Overall, green synthesis establishes a reliable methodological foundation for sustainable nanomaterial production, where biological producers and their biomolecules act as sources of controlled nucleation, growth, and stabilization of particles, and process condition optimization enables the engineering of functionalized biocompatible nanostructures with predictable properties (Gunasena et al., 2025; Tsekhmistrenko et al., 2020; 2021). Such an integrative platform is a key prerequisite for further convergence with data-driven AI approaches, promising to accelerate the transition from empirical screening to rational design of «green» nanomaterials with high reproducibility and technological maturity (Tymoshok et al., 2025).

Synergistic Integration: AI Expands the Capabilities of Green Synthesis in Bionanotechnology. The integration of AI methods with «green» microbial synthesis creates a productive synergy that shifts nanomaterial production from an empirical domain to data-driven process engineering (Fig. 2).

Machine learning (ML) and deep learning (DL) algorithms make it possible to simultaneously optimize a multifactorial control space — culture conditions, pH, temperature, reaction time, ionic strength, and precursor concentrations — taking into account nonlinear interactions between parameters and target product properties (yield, size/polydispersity, morphology, stability). This significantly enhances the reproducibility and scalability of biogenic nanostructures. Generalized reviews focusing on biomineralization and «green» bio-routes of production confirm the relevance of AI as a meta-level control tool for microbial synthesis and post-synthetic functionalization (Chandrasekar et al., 2025).

At the process optimization level, the application of artificial neural networks (ANNs) and design-of-experiments approaches enables the identification of «windows» of optimal regimes without exhaustive grid screenings. Notably, ANNs have been successfully applied to the analysis, prediction, and validation of chitosan nanoparticle biosynthesis on microbial and plant substrates, facilitating the selection of conditions for maximum yield and target characteristics (El-Naggar et al., 2022; 2023). In continuous microfluidic systems, combining ML with hydrodynamic indicators (Re, Dean/Re) allows the prediction of the AgNP size based on input flow rates and composition, reducing the number of experiments and accelerating the transfer of conditions across setups (Nathanael et al., 2023).

AI expands materials design beyond synthesis: models based on composition/surface chemistry descriptors, processing conditions, and mechanistic features enable *ex ante* prediction of stability, reactivity, and bioactivity of biogenic nanoparticles, thereby focusing experimentation on narrow parameter ranges. A representative example is the use of ensemble algorithms (Extremely Random Trees) to predict the survival of *E. coli*, *P. aeruginosa*, and *S. aureus* under exposure to La-doped ZnO NPs, where key features included bacterial type, band gap width, ζ-potential, and incubation time ($R^2 \approx 0.96$). This shifted the emphasis from the «smaller = more aggressive» paradigm to the electronic and surface properties of the material (Navarro-López et al., 2024). In catalysis and sensing, data-driven models allow the prediction of mass/charge transfer parameters at the interface (e.g., for Au/Ag systems), thereby linking synthetic control «knobs» to functional performance.

The synergy of AI with constructive self-assembly opens pathways to controlled superstructures. Reviews on «AI-guided programmable assembly» in binary colloidal systems describe algorithmic design of binding rules and topology, enabling the generation of complex architectures with specific collective properties (Li et al., 2025). Parallel studies on DNA-directed binary self-assembly confirm the feasibility of such «programmed» colloidal molecules at the experimental level. At the interface of bioengineering and nanomedicine, combining AI-designed NPs with CRISPR navigation provides microenvironment-sensitive delivery platforms that respond to specific molecular signals in target cells (Sheikh et al., 2024; Bandaru et al., 2024; Srujana et al., 2025) — a direction rapidly progressing from *in silico* hypotheses to *in vitro/in vivo* validation.

Importantly, AI closes the loop from data to material: omics datasets (genomics/proteomics/metabolomics) and high-throughput screens (microfluidics, robotic platforms) are transformed into machine-readable feature spaces. These are used to train models for producer strain selection, metabolic pathway, and regulatory circuit design, as well as for prediction of the protein corona and immune interactions. The use of generative agents (LLM/CoT approaches) accelerates hypothesis generation and identification of synthesis/crystallization conditions (demonstrated for MOF/COF), while multimodal architectures enable integration of heterogeneous data on material, environment, and biological response (Chen et al., 2023; Bai et al., 2024; Lin et al., 2023; Morgan et al., 2024; Olawade et al., 2024; Serov et al., 2022; Singh et al., 2020). Together, this establishes a «digital loop» of design—build—test—learn, in which parameters determined by AI are implemented in automated bioreactor and microfluidic platforms with feedback, ensuring quality stability at scale.

Finally, the ecological and biomedical relevance of this integration is confirmed by applied case studies: from predicting the antimicrobial activity of doped oxide NPs and their effects on pathogens — to guided self-assembly of colloidal «molecules» with predefined optical/catalytic functions and from optimization of chitosan NP biosynthesis under mild conditions — to digital selection of regimes in microfluidic synthesizers (El-Naggar et al., 2022; Nathanael et al., 2023; Li et al., 2025). Collectively, this demonstrates how AI transforms green synthesis from a set of local practices into a systemic platform for rational design and scaling of biogenic nanomaterials

Synergy of AI and Microbial Synthesis. The integration of AI methods with «green» microbial synthesis shifts nanomaterial production from predominantly empirical practice to data-driven process engineering, where the multifactorial control space (producer strain/genotype, nutrient medium, pH, temperature, ionic strength, time, precursor and cofactor concentrations) is optimized in a coordinated manner and with consideration of nonlinear interactions.

In this approach, ML models serve as a «meta-level» of control that reduces the number of experiments, increases reproducibility and batch-to-batch quality stability, and accelerates the transfer of conditions from laboratory to pilot scale (Praveen Chakravarthi et al., 2024; Sheikh et al., 2024). Comprehensive reviews confirm that AI — from classical ensemble methods to deep architectures — aligns best with biomineralization routes and green bioprocesses, integrating with experimental design and process analytics (Chandrasekar et al., 2025).

At the synthesis optimization level, ANNs have proven effective in predicting «windows» of parameters for the biosynthesis of chitosan nanoparticles in both microbial and phytogenic systems, enabling targeted size/polydispersity and yield without exhaustive grid screenings (El-Naggar et al., 2022; 2023). In continuous microfluidic platforms, combining ML with hydrodynamic descriptors (Re, Dean/Re) provides prediction of AgNP size based on flow rates and reaction stream composition and demonstrates generalizability across setups (Nathanael et al., 2023).

AI also extends material design into the pre-synthesis stage: models based on composition and surface chemistry descriptors, processing regimes, and mechanistic features predict the stability, reactivity, and bioactivity of biogenic nanoparticles (NPs) before their production. A representative case is La-doped ZnO: the ensemble algorithm Extremely Random Trees predicted the survival of *E. coli*, *P. aeruginosa*, and *S. aureus* ($R^2 \approx 0.96$), shifting the focus from the simplistic «smaller = more aggressive» paradigm to electronic and surface properties (Navarro-López et al., 2024). For noble metals, multimodel ML approaches have reliably predicted energy/charge transfer parameters at the nanometal—acceptor interface, critical for catalysis and sensing (Demers et al., 2024; Prasad et al., 2024).

Significant progress is also evident in guided self-assembly: reviews on «AI-guided programmable assembly» in binary colloidal systems describe algorithmic design of binding rules and topologies, enabling reproducible construction of complex architectures with novel collective properties (Li et al., 2025). At the intersection of materials science and scientometrics, synergy between human experts and large language models (LLMs) accelerated the search for synthesis regimes to improve crystallinity of MOF/COF (Chen et al., 2023), while modern DL tools eliminate the «bottleneck» of image annotation by automating classification/segmentation of TEM/SEM nanoparticles (Colliard-Granero et al., 2023).

In strain bioengineering, ANNs and multitask models employ genomic and metabolic data to rank producers, predict protein localization/functions, and guide CRISPR editing, thereby enabling the construction of strains for NP synthesis with specified optical, catalytic, or therapeutic properties (Bandaru et al., 2024; Srujana et al., 2025; Bai et al., 2024; Lin et al., 2023; Sheikh et al., 2024). The evidence base for combining AI-designed NPs with CRISPR delivery in precision medicine is rapidly expanding (Srivastav et al., 2025).

The design—build—test—learn loop is closed through automated analysis of large omics datasets and robotic screening: AI extracts patterns governing nucleation/growth, protein corona formation, and immune interactions, and identifies critical factors to manipulate in order to improve yield and particle uniformity (Morgan et al., 2024; Olawade et al., 2024; Serov et al., 2022; Singh et al., 2020; Bag et al., 2025). Additionally, in nanomedicine, AI applied to the prediction of «material—drug—biofluids—immune system—endothelium—membranes» interactions provides tools for rational selection of composition/functionalization and application regimes (Adir et al., 2020), while in microfluidic/microbial syntheses it has been shown to accelerate condition transfer between devices and reduce the randomness of exploration (Nathanael et al., 2023; El-Naggar et al., 2023).

An important ecological-toxicological dimension illustrates how ML helps unify heterogeneous nanosafety data: from QSAR approaches for mixed «nano-oxide + heavy metal» systems to meta-models that generalize conflicting toxicological findings on nanosilver from different studies; this strengthens regulatory compliance of products and supports the principles of Safe-by-Design (Sang et al., 2022; Bilgi et al., 2023). In parallel, predictive ML models developed for bioremediation of selenium using *Bacillus selenatarsenatis* demonstrate how data-driven optimization can scale environmentally relevant processes (Behera et al., 2025).

Collectively, the integration of AI with microbial green synthesis establishes a systemic platform where process optimization, material design, guided self-assembly, strain engineering, and safety evaluation are addressed within a single closed cycle. This shifts biogenic nanomanufacturing toward a reproducible, scalable, and regulatorily viable technology with predictable functional outputs (Bandaru et al., 2024; Srujana et al., 2025; Chen et al., 2023; Chandrasekar et al., 2025; Li et al., 2025).

Prospects and Applications of Microbial «Green» Synthesis Guided by AI. The integration of AI with microbial «green» synthesis opens a qualitatively new level of controllability and reproducibility of biogenic nanomaterials: from strain selection and cultivation conditions to targeted tuning of particle size, morphology, surface chemistry, and stability for specific applications in biomedicine, agriculture, and environmental remediation. At the process level, AI enables the identification of «windows» of optimal regimes and reduces the number of experiments required for scaling. Notably, for chitosan NP biosynthesis, neural networks have been applied both to Streptomyces strains (maximization of yield and stability) and phytogenic systems based on Olea europaea (multifactor optimization with prediction validation) (El-Naggar et al., 2022). In continuous microfluidic platforms, ML models align hydrodynamic descriptors (Re, Dean/Re) and kinetic constants of growth/nucleation with output parameters (size, plasmon resonance), thereby accelerating condition transfer across devices and improving reproducibility of AgNP synthesis (Nathanael et al., 2023). Data-driven predictive assessment of properties allows elimination of non-constructive combinations before synthesis: for La-doped ZnO, ensemble models (Extremely Random Trees) reproducibly predicted the survival of *E. coli, P. aeruginosa,* and *S. aureus* ($R^2 \approx 0.96$), highlighting electronic and surface features (band gap width, ζ-potential, incubation time) rather than merely geometric particle size, which is directly useful for the design of antimicrobial platforms and sensing applications (Navarro-López et al., 2024).

Beyond «classical» synthesis optimisation, AI significantly broadens material and superstructure design. Recent reviews demonstrate how «AI-guided programmable assembly» in binary colloidal systems defines binding rules and topologies for reproducible binary self-assembly with complex architectures and novel collective properties — a direction organically coupled with biogenic nanoparticle production and subsequent oriented functionalization (Li, C. et al., 2025). At the level of bio-objects and bioprocesses, the synergy of AI with biomineralization is outlined as the key to «eco-friendly» NP fabrication with controlled core—shell/surface layer (quality-by-design in the «green» paradigm), accelerating the shift from empiricism to predictive bioengineering of synthesis (Chandrasekar et al., 2025). In parallel, a general «materials-AI» methodology is being formed in materials science for rapid discovery, optimization, and manufacturing, which can be directly transferred to biogenic systems (multimodal features «composition—process—structure—properties,» active learning, closed design—build—test—learn loop) (Madika et al., 2025). Using the example of microbially synthesized nanomaterials, recent reviews highlight their therapeutic (targeted delivery, immunomodulation), antibacterial, and diagnostic applications, emphasizing that data-driven optimization is the key to reproducible quality in scaling and clinical relevance (Pan et al., 2025). Table 1 presents specific examples of recent studies where AI was applied to improve or optimize the green synthesis of nanomaterials.

Additional interdisciplinary reviews on biomaterials and regenerative medicine highlight that AI is already serving as a «meta-optimizer» for the selection of compositions, topologies, and processing routes required for targeted optical, catalytic, and therapeutic effects — from surface engineering to corona control in biofluids and *in vivo* immune interactions (Varshney et al., 2025).

In applied scenarios, this synergy has three main vectors: biomedicine, agriculture, and environmental remediation. In biomedicine, microbially synthesized and AI-tuned NPs are used as targeted carriers for drugs/nucleic acids, antimicrobial agents, contrast labels, and sensors — owing to fine control over size/morphology/functionalization and the ability to algorithmically predict «material—protein corona—cellular barrier—immune system» interactions. Combined with CRISPR navigation, this forms «smart» platforms responsive to molecular signals of the target. In agriculture, microbially synthesized NPs are applied for precision plant nutrition/protection and biocontrol of pathogens, where ML models link particle properties with phytotoxicity/efficacy and soil—climate conditions. Environmental remediation foresees the use of biogenic NPs for sorption/reduction of pollutants in water and soil (heavy metals, dyes, organic pollutants), where AI optimizes the balance «activity ⟷ safety,» predicting kinetics, sorbent regeneration, and environmental matrix effects. Overall, AI-guided optimization reduces resource intensity, increases yield and uniformity, provides tools for targeted property engineering, and enhances regulatory readiness of products through transparent traceability of model decisions and validation on independent datasets. Existing case studies — ANN optimization of chitosan NP biosynthesis (on *Streptomyces* and *Olea europaea* extracts), ML-driven microfluidic fabrication of AgNPs with targeted plasmon resonance, prediction of antimicrobial activity of La:ZnO against clinically relevant bacteria — demonstrate the practical feasibility of this paradigm and set the trajectory toward industrial scale via robotization and PAT/QbD quality control loops (El-Naggar et al., 2022)

The Growing Role of AI in Materials Science and Biotechnology. AI and ML have become key drivers of progress in materials science and biotechnology, as they enable a shift from the empirical «trial-and-error» approach toward data-driven design of materials and bioprocesses (Goswami et al., 2023; Holzinger et al., 2023). In numerous energy and chemical applications — from solar cells and catalysis to batter-

Table 1. **Use of AI to improve/optimize green synthesis of nanoparticles using biomaterials**

Nanomaterial	Biomaterial Used	AI Technique Applied	Achieved Specific Outcome/Improvement	Reference
Chitosan NPs	*Streptomyces microflavus*	AI Technique Applied	Maximized yield of nanoparticle biosynthesis	El-Naggar et al., 2022
Silver NPs	Plant extract (*Olea europaea*)	AI Technique Applied	Analysis, validation, and prediction of nanoparticle biosynthesis	El-Naggar et al., 2023
Silver NPs	Microfluidic system	Machine Learning	Optimized synthesis parameters (flow rate, concentrations) for predicting desired plasmon resonance	Nathanael et al., 2023
La-doped ZnO NPs	Bacteria (*E. coli*, *P. aeruginosa*, *S. aureus*)	Machine Learning	Predicted bacterial survival against nanoparticles; identified key attributes influencing antibacterial activity	Navarro-López et al., 2024

ies and carbon capture, utilization, and storage (CCUS) — AI has been shown to substantially accelerate candidate selection and optimization of formulations/processes, particularly through scalable models based on graph representations of crystals and compounds, active learning, and self-driving laboratories (Chen et al., 2023; Madika et al., 2025; Ma et al., 2025; Tawalbeh et al., 2025; Tobias et al., 2025).

Conceptually, AI/ML encompasses a spectrum of methods — from ensemble models and support vector machines to deep architectures, evolutionary/genetic algorithms, clustering methods, and multitask models. In materials science, graph neural networks (GNNs) have become especially important: they operate on atomistic-crystalline graphs and achieve high accuracy in predicting properties and stability (Xue et al., 2025). Scaling such approaches has dramatically expanded the «candidate space» of stable crystals (Nature GNoME: 2.2 million structures, of which ≈381,000 are stable) and linked it to robotic synthesis (A-Lab) in a closed design—build—test—learn loop (Madika et al., 2025).

In parallel, physics-informed neural networks (PINNs) integrate equations of state and mass/charge/energy balance constraints directly into the loss function, improving generalizability and data efficiency in tasks where costly experiments or simulations limit dataset size. Recent reviews (2025) highlight mature PINNs/PIDL applications in heat and mass transfer, phase transitions, and geoenergy, which are directly relevant to the design of synthesis processes and material performance (Diao et al., 2025; Ma Wang et al., 2025; Wang et al., 2025).

Another significant trend is the combination of AI with autonomous «self-driving» laboratories: reviews from 2024—2025 systematized the architectures of digital/«lean» twins, active experimental design, and closed robotic cycles for chemistry and materials, radically improving reproducibility and the **speed** of obtaining high-fidelity data (Tobias et al., 2025).

At the level of applied demonstrations, integrated AI frameworks for heterostructures in photocatalytic hydrogen production in 2025 showed that combining composition/texture selection, traceable synthesis optimization, and predictive models improves efficiency and reproducibility (Belkhode et al., 2025). In CCUS**,** published perspectives/reviews emphasize the role of ML in screening adsorbents, membranes, and solvents in digital twins of absorption/regeneration processes and in energy optimization (Ma et al., 2025; Tawalbeh et al., 2025).

In biotechnology, multimodal and explainable models (XAI) accelerate the shift from correlations to mechanistically consistent hypotheses, supporting FAIR data exchange and federated learning in sensitive domains; this directly impacts the rational design of biomaterials, diagnostic platforms, and personalized therapies (Holzinger et al., 2023; Parvin et al., 2025).

In summary, the synergy of AI with materials science and biotecnology today represents not only accelerated discovery of new compounds/structures but also guided engineering of synthesis routes, integrated quality control, and scaling through automation. Critically important remain data reliability and prediction validation: cases of exaggerated claims in climate/material applications remind us of the need for strict verification and transparency of data—model—process pipelines, while successful cases (GNoME → A-Lab) demonstrate the reality of a «digital-robotic» conveyor from hypothesis to material (Tobias et al., 2025).

Application of ML in Nanomaterials Research. Nanotechnology involves manipulating matter on the scale of 1—100 nm. Predicting synthesis parameters, structure, properties, and applications is a cascade process in nanomaterials research, where each stage is interrelated and correlatively influences the others. Traditionally, the «trial-and-error» approach in nanomaterials research has several limitations, including duration, labor intensity, and resource consumption.

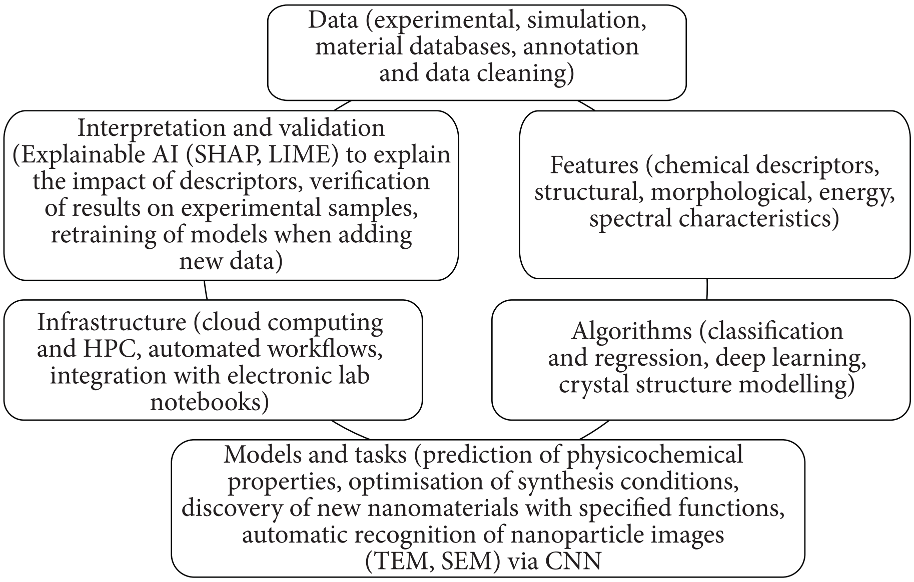

Fig. 3. Key elements of machine learning in nanomaterials research

The use of ML methods in nanomaterials research opens new opportunities for accelerated discovery and optimization of materials with desired properties (Diao et al., 2025). In nanomaterials studies, ML is applied to analyze large sets of experimental and simulation data, predict properties, and optimize synthesis processes (Dhoble et al., 2024). Key elements include several parameters (Fig. 3).

The foundation of this approach is data derived from experimental measurements (spectroscopy, microscopy, mechanical, electronic, and magnetic characteristics) and from computer modeling, including quantum mechanics methods (DFT), molecular dynamics, and Monte Carlo simulations. Centralized materials databases (Materials Project, AFLOW, NOMAD, OQMD) are gaining importance, providing access to standardized sets of structural and physicochemical data suitable for model training. A crucial component is data preprocessing, including noise removal, annotation, and format unification.

The second fundamental element is the selection of informative features (Wang H. et al., 2024). For nanomaterials, these may include chemical descriptors (atomic radius, electronegativity, valence), structural parameters (type of crystal lattice, symmetry, topological characteristics), morphological features (size, shape, nanoparticle distribution), energetic characteristics (formation energy, surface energy), and spectral profiles (UV-Vis, FTIR, Raman, XRD). Proper selection and combination of features largely determine the accuracy and interpretability of models (Diao et al., 2025).

The methodological foundation comprises various classes of algorithms (Kuznetsova et al., 2024). For regression and classification tasks, Random Forest, SVM, and XGBoost are applied; for analysis of complex nonlinear dependences, deep neural networks are actively used. Graph neural networks (GNNs) play a special role, as they can directly operate on atomic structure information of crystals (Xue et al., 2025). For new material discovery, active learning and Bayesian optimization methods are promising, reducing the number of experiments via targeted sample selection. When detecting hidden patterns in large datasets is required, unsupervised methods — principal component analysis (PCA) and various clustering approaches — are employed.

Practical tasks addressed with ML include the prediction of physicochemical properties (hardness, conductivity, catalytic activity), optimization of synthesis conditions (temperature, solvents, precursors), and identification of promising materials with novel functionalities. Another direction is automatic image analysis of nanoparticles obtained by TEM or SEM, performed using convolutional neural networks (CNNs).

The effectiveness of these approaches is supported by modern infrastructure: high-performance computing (HPC), cloud services, robotic laboratories, and integrated electronic lab notebooks. However, practical implementation requires not only accurate models but also their interpretability (Tao et al., 2021). Explainable AI (XAI) methods such as SHAP and LIME allow determination of the contribution of individual features to predictions, while experimental confirmation of obtained results and continuous model updating as new data become available are mandatory.

Integration of ML into nanoscience forms a multi-level system that includes data, features, algorithmic methods, application models, infrastructural solutions, and validation mechanisms. This system significantly increases the efficiency of discovery and development of nanomaterials, reducing the time and financial costs of traditional experimental research (Yang et al., 2024).

El-Naggar et al. (2023) describe the optimization of chitosan nanoparticle biosynthesis based on AI: the use of ANNs for analysis and prediction of the biosynthesis process of chitosan nanoparticles using *Olea europaea* leaf extract allowed the determination of optimal conditions to maximize NP yield. Moreover, AI has proven invaluable in material characterization and analysis. AI-driven computer vision technologies can analyze and interpret data from various microscopy methods, such as scanning electron microscopy (SEM), transmission electron microscopy (TEM), and atom probe tomography (APT), to identify material structures and obtain essential information about their properties (Kalinin et al., 2022; Wang et al., 2024; Unruh et al., 2022; Ziatdinov et al., 2022).

AI systems have been adapted for automatic counting and measuring of nanoparticles in microscopic images, significantly accelerating research and improving measurement reliability. In biotechnology, AI is transforming diverse aspects, including drug discovery, protein engineering, and genome sequencing. AI-powered platforms can analyze large compound databases to accelerate the identification of potential drug candidates and improve lead optimization (Fu et al., 2025). The role of AI in predicting and screening new therapeutic targets and drugs remains a highly promising research area (Papavassiliou et al., 2024). For years, AI has been proclaimed a transformative tool to accelerate drug discovery, development, and testing, substantially shortening research timelines. Currently, numerous AI-based drug development pipelines are entering the clinical phase worldwide (Alfa et al., 2024; Kundranda et al., 2024; Sun et al., 2020).

AI contributes to progress in nanoscience, including new approaches to the design, synthesis, and characterization of nanomaterials, as well as their applications (Hassan et al., 2023). AI integration can significantly accelerate innovation in this dynamic field.

AI algorithms are also used to predict protein structures, analyze genomic data to identify disease-associated mutations, and optimize metabolic pathways in synthetic biology (Praveen Chakravarthi et al., 2024).

Artificial intelligence is revolutionizing the design and optimization of smart multifunctional nanocarriers (SMNs). AI-based design promotes personalized medicine and enhances therapeutic efficacy (Noury et al., 2025). The strength of AI lies in its ability to process and analyze vast amounts of data, detect complex patterns, and generate predictions. This capability is highly valuable for accelerating research and development in both materials science and biotechnology. The ability of AI to predict material properties before their actual synthesis has the potential to substantially reduce the time and costs associated with traditional trial-and-error experiments. By using ML models trained on existing data, researchers can perform virtual screening of numerous potential materials and identify promising candidates for synthesis, thereby optimizing experimental efforts and resource allocation.

Biomedicine: Diagnostics, Imaging, Delivery, and «Copilots». Within the convergence of nanotechnology and artificial intelligence (AI), a new paradigm of anticancer strategies is emerging, particularly for hepatology. A comprehensive review (Bhange et al., 2025) shows that combining AI tools with nanomaterials provides synergistic advantages at all stages of the clinical continuum — from early diagnosis and patient stratification to precision drug delivery and continuous monitoring of therapeutic response. AI-guided nanoplatforms enable improved targeted transport of therapeutic agents to liver tumors with reduced systemic toxicity and side effects through optimization of carrier size, surface chemistry, and navigational properties.

In oncological imaging, the integration of AI models and algorithms with numerical—physical modeling of nanomaterials improves sensitivity, specificity, and accuracy of treatment monitoring; these trends are noted in enhanced therapeutic metrics (Chow, 2025; Das, 2023). Across the drug discovery chain — from target validation to candidate optimization — the impact of AI/data methods has been systematized (Khan et al., 2024), while a `vision of computational precision medicine integrating multimodal biomedical data for clinical decision-making is presented in (Moingeon et al., 2022). Multimodal AI architectures demonstrate convincing examples of accelerating the development of diagnostic protocols, new biomaterials, and personalized therapeutic schemes (Parvin et al., 2025). A distinct class of «smart» nanocarriers for drug and gene delivery has been outlined, whose parameters adaptively respond to tumor microenvironments via AI algorithms (Noury et al., 2025). Additionally, the deployment of generative «copilots» — software assistants working alongside researchers and clinicians — accelerates biomedical nanoengineering by suggesting design hypotheses and predicting functional properties of materials and systems (Wang et al., 2025).

Rational design of catalytic nanoparticles (nanozymes) and their applications in biosensors and biomedicine benefit significantly from ML methods. A review (Gao et al., 2024) summarizes current approaches to structure—property relationships, while the transition from empirical searches to AI-guided design is detailed in (Yu et al., 2025). The development of bio-inspired sensory receptors capable of collecting complex signals for subsequent interpretation by AI systems forms the basis of new nanobiosensor platforms (Bag et al., 2025).

At the intersection of sustainable engineering and the Internet of Things (IoT), «green» approaches to the synthesis of graphene materials and their integration into sensors and flexible electronics set an environmentally responsible trajectory for diagnostic devices (Banerjee et al., 2022). A critical module of biointeractions is the protein corona of nanoparticles; its formation determines pharmacokinetics, cellular uptake, and immune response. The potential of AI/ML in high-precision corona characterization and nanobiointeraction control directly affects the safety and efficacy of nanotherapies (Kopac et al., 2025).

Regarding safety, automated extraction of toxicological data and nanotoxicity prediction have been implemented (Ha et al., 2025), while transforming «raw» toxicological datasets into knowledge through AI and numerical simulations is demonstrated in (Yan et al., 2023). The methodological foundations of computational nanotoxicology, necessary for implementing the Safe-by-Design paradigm in nanomedicine, are described in (Singh et al., 2020). Collectively, these results conceptually align with reviews on the convergence of AI and nanotechnology in liver cancer treatment (Bhange et al., 2025), emphasizing the systemic shift from fragmented experimental practices to integrated, data-driven platforms for diagnostics, imaging, delivery, and AI «copilot» decision support. Together, this ensures a continuous cycle of data translation into clinical solutions (Fig. 4).

At the first stage, biomedical data are used — omics profiles, medical images (TEM, SEM, MRI, CT), and clinical records. Next, AI/ML/DL models are applied, enabling analysis, prediction, and generation of new solutions: from classical algorithms (regression, decision trees, SVM, clustering) to deep architectures (CNN, RNN, LSTM, transformers). The third stage produces nanoplatforms — nanoparticles, nanocarriers, and biosensors — optimized by AI for high efficiency and biocompatibility. The final stage comprises clinical endpoints, including early diagnostics, personalized therapy, and treatment monitoring. In this logic, AI functions not as a replacement but as a «copilot,» supporting researchers and clinicians in performing tasks faster and more accurately.

Thus, this integration demonstrates how the synergy of nanotechnology and AI paves the way for a new era of precision, adaptive, and safe biomedicine.

Advantages of AI in the Development of Sustainable Nanomaterial Production. Integrating AI into microbial «green» synthesis of nanomaterials establishes a systemic basis for sustainable nanomanufacturing, combining ecological, economic, and technological benefits. From an ecological perspective, green synthesis inherently reduces waste generation, energy consumption and excludes toxic reagents typical of traditional chemical routes. Embedded AI algorithms amplify these effects: they optimize bioprocess parameters (medium composition, pH, temperature, aeration/agitation, incubation time, metal precursor dosage), ensuring more efficient resource use and further waste minimization.

Economically, the use of microorganisms combined with AI is cost-optimal: microbial cultures can be cultivated on relatively inexpensive media,

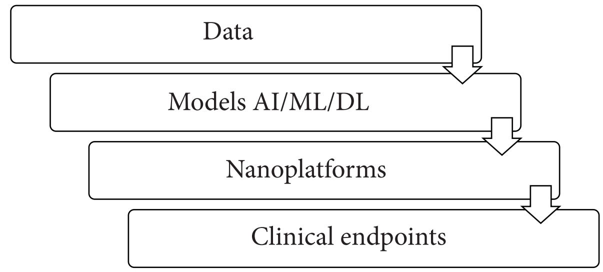

Fig. 4. Data translation into clinical decisions

while intelligent optimization reduces the need for numerous costly trial-and-error experiments, shortening development time and material consumption. Thus, AI directly enhances techno-economic efficiency at the stages of strain screening, biosynthesis condition selection, and scaling.

An important advantage is an improved quality control of target nanomaterials. Through predictive modeling and control methods (e.g., Bayesian optimization, evolutionary strategies, active learning), AI enables fine-tuning of size, polydispersity, morphology, purity, and surface functionalization. The result is reproducible batches with desired characteristics, critical for reliable applications in sensing, catalysis, drug delivery, and diagnostics. Reducing batch-to-batch variability increases productivity and stability of material properties (Yadavalli et al., 2025).

AI also provides scalability for green processes through automation and integration with real-time control systems (PAT/QbD, digital twins). Parameters optimized by models are implemented in automated bioreactor regimes that maintain consistently high quality during the transition from laboratory to semi-industrial and industrial production. This approach addresses one of nanotechnology's key challenges — reproducing laboratory results in manufacturing.

In summary, the synergy of green synthesis and AI simultaneously resolves ecological constraints, improves process economics, and ensures higher and more stable product quality. By optimizing the use of available biological resources and automating production stages, AI makes nanomanufacturing more economically viable, while precise control of synthesis parameters becomes more manageable and reproducible (Yadavalli et al., 2025). It has been proven that AI significantly enhances process optimization, quality control, and scalability in nanofabrication (Nandipati et al., 2024).

Together, these advantages outline the transition from empirical, resource-intensive approaches to sustainable, data-driven production platforms that meet modern requirements for environmental safety and industrial reproducibility — key prerequisites for regulatory implementation and wide adoption of bionanomaterials.

Challenges and Considerations for Implementing AI in «Green» Bionanotechnology. Integrating AI into microbial green synthesis of nanomaterials opens significant opportunities but is accompanied by methodological, data-related, engineering, and ethical challenges. First, modern large language models (LLMs) and generative models show limitations in causal reasoning and a tendency toward «hallucinations» (false but plausible answers), making their application in knowledge-intensive domains (bionanotechnology, nanotoxicology) risky without verification procedures, uncertainty calibration, and external grounding on validated sources (RAG). Reviews and clinical guidelines on LLMs confirm both the mechanisms of hallucination emergence and strategies for mitigation (fact-checking, self-consistency, instruction fine-tuning) (Huang et al., 2025). Thus, transferring LLMs into complex biological scenarios must be accompanied by thorough validation on independent datasets and reproducibility protocols.

The second critical block is data. AI model performance directly depends on the availability of large-scale, high-quality, standardized datasets. In green synthesis, such datasets are often lacking: experiments differ in media matrix, strains, cultivation regimes, precursors, and characterization approaches. The absence of unification complicates reliable predictive model construction and meta-analysis. Relevant frameworks to mitigate this problem are the FAIR principles (Findable, Accessible, Interoperable, Reusable), which extend not only to raw data but also on algorithms, tools, and workflows leading to these data (Wilkinson et al., 2016). Compliance with FAIR principles, along with open protocols of experimental reporting, forms the foundation for building models that generalize across laboratories.

The third block concerns the consistency and reproducibility of biologically mediated synthesis. Green synthesis is sensitive to the source of biological resources (microbial strains, plant extracts), season, cultivation, and extraction conditions, leading to batch-to-batch variability in size, morphology, and surface chemistry of nanoparticles. Systematic reviews and experimental studies confirm substantial variability both in plant-mediated synthesis and industrial nanomaterials, directly affecting product safety and functionality and complicating the development of generalized AI models (Hosseingholian et al., 2023). Accordingly, standardized characterization panels (size/polydispersity, ζ-potential, surface groups, protein corona) must be incorporated into training datasets.

The fourth block is the integration of AI with robotics and automation. To cross the laboratory—industry boundary, model-optimized parameters must be implemented in automated bioreactor/synthetic platforms supported by process analytical technologies (PAT) and quality-by-design (QbD) approaches. Current reviews note the role of PAT as the «nervous system» of continuous monitoring of critical quality attributes and the driver of QbD; combining it with autonomous or semi-autonomous analytical circuits increases reproducibility and resilience of 24/7 processes (Sathiyapriyan et al., 2025). In nanomedicine, «Quality by Digital Design» and nanoinformatics are also advancing, systematizing digital twins of processes and materials for accelerated, sustainable development — frameworks that naturally integrate with ML/DL (Roustan et al., 2025).

The fifth block addresses ethics, bias, and privacy. Ethical dimensions include algorithmic bias (arising from data imbalance), protection of confidential and sensitive information, and transparency of decision-making. Publications in clinical domains emphasize that LLM integration must rely on clear frameworks of responsible use, risk assessment, and oversight procedures (human-in-the-loop), including explicit reporting of model uncertainty and data lineage traceability (Roustan et al., 2025).

Therefore, effective implementation of AI in green bionanotechnology requires: (1) combining models with external grounding and validation procedures; (2) building open, FAIR-compliant, standardized data repositories; (3) reducing batch-to-batch variability through unified synthesis and characterization protocols; (4) integrating AI with PAT/QbD, digital twins, and robotic platforms; (5) applying clear ethical and regulatory frameworks. Only such data-driven and engineering-oriented integration will enable the transition from isolated laboratory successes to reproducible, scalable, and safe industrial production of nanomaterials.

Limitations. Despite significant advances in the convergence of AI and bionanotechnology, several limitations hinder widespread adoption. First, data quality and availability remain critical factors: insufficient standardization of experimental conditions, discrepancies in formats, and data heterogeneity complicate model training. Second, interpretation of AI decisions is often limited, reducing trust in models for clinical and biotechnological applications. Third, scaling microbial green synthesis from laboratory to industrial level requires not only algorithmic optimization but also stable bioreactor infrastructure. Additional limitations include regulatory barriers, high costs of implementing digital platforms, and the need for interdisciplinary teams combining expertise in microbiology, nanotechnology, informatics, and engineering.

Future directions. Development prospects lie in creating integrated «digital twins» of bioprocesses, enabling real-time prediction and correction of synthesis parameters. Physics-informed neural networks (PINNs), which incorporate conservation laws of mass and energy, are expected to expand, providing more reliable predictions under limited data. The use of multimodal AI architectures capable of combining microscopic images, spectroscopic profiles, and omics data into unified analytical systems is intensively developing. In biomedicine, «smart» nanoplatforms for precision delivery of therapeutic agents, guided by AI algorithms and capable of adapting to tumor microenvironments or pathological changes, are anticipated. In agriculture, the application of microbially synthesized nanoparticles for biocontrol and enhanced fertilization efficiency, considering soil—climate factors, will be key. Finally, safety and toxicology studies of nanomaterials will gain particular importance, where AI can help unify data and ensure the Safe-by-Design principle.

Conclusions. The synergy of artificial intelligence and microbial green synthesis forms a qualitatively new paradigm for the development of bionanotechnology. AI enables the transition from empirical practices to rational, data-driven design of nanomaterials, enhancing reproducibility, reducing resource intensity, and opening new opportunities in biomedicine, agriculture, and environmental remediation. Despite existing limitations, AI integration ensures a closed design—build—test—learn loop, where data are translated into knowledge, knowledge into models, and models into practical solutions. This defines the strategic trajectory of the field, where key success factors remain high-quality data, algorithmic transparency, regulatory compliance, and interdisciplinary collaboration.

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КОНВЕРГЕНЦІЯ ШТУЧНОГО ІНТЕЛЕКТУ В БІОНАНОТЕХНОЛОГІЇ: ІННОВАЦІЇ ТА ПЕРСПЕКТИВИ

Інтеграція штучного інтелекту з біонанотехнологією переводить «зелений» мікробний синтез наночастинок від емпіричного підходу до раціонального дано-керованого проєктування, підвищуючи відтворюваність і технологічну зрілість процесів. **Метою** роботи було узагальнити сучасні дані та окреслити роль методів AI, машинного та глибинного навчання в багатофакторній оптимізації умов біосинтезу, передбаченні властивостей наночастинок до їх одержання, керованій самозбірці й інженерії штамів-продуцентів, а також у забезпеченні безпечності наноматеріалів відповідно до концепції Safe-by-Design. **Методи.** Для цього було проаналізовано публікації 2020—2025 років у базах PubMed, ACM, ScienceDirect, Google Scholar та Scilit, проведено подвійний скринінг та тематичний синтез. **Встановлено,** що використання AI дозволяє суттєво зменшити кількість експериментів, узгоджено керувати параметрами процесу, забезпечувати перенесення умов синтезу між лабораторними і пілотними установками, а також здійснювати ex-ante прогноз стабільності, біоактивності та антимікробної дії наночастинок, зокрема для La-допованих ZnO наночастинок точність моделей сягала $R^2 \approx 0{,}96$. Перспективним напрямом є програмована самозбірка нанорозмірних структур, алгоритмічний підбір функціоналізації поверхні та контроль білкової «корони», що визначає біосумісність і імунну відповідь. Важливими результатами є також уніфікація токсикологічних даних і підвищення регуляторної придатності продукції завдяки методам пояснюваного AI та інтеграції з аналітичним контролем процесу в реальному часі та проєктування процесу так, щоб якість була закладена із самого початку. Таким чином, конвергенція штучного інтелекту та «зеленого» мікробного синтезу формує платформу прецизійної інженерії біогенних наноматеріалів із прогнозованими властивостями, де стратегічний успіх залежить від якісних даних, прозорості алгоритмів та міждисциплінарної співпраці.

Ключові слова: *штучний інтелект, машинне навчання, глибинне навчання, біонанотехнології, зелений синтез, мікроорганізми, наночастинки, цифрові двійники, екологічна безпека, Safe-by-Design.*