OPEN ACCESS
NIJBAS
ONLINE ISSN: 2992-5797
Publications 2025
PRINT ISSN: 2992-6122

NEWPORT INTERNATIONAL JOURNAL OF BIOLOGICAL AND APPLIED SCIENCES (NIJBAS)

Volume 7 Issue 2 Page 73-78, 2026



https://doi.org/10.59298/NIJBAS/2026/7.2.7378

# AI-Guided Design of Nanomedicines for Personalized Cancer Therapy

**Taliikwa Nicholas Ceaser**

**Department of Pharmacognosy Kampala International University Uganda**
**Email:ceaser.taliikwa@studwc.kiu.ac.ug**

## ABSTRACT

Personalized cancer therapy aims to tailor treatment strategies to the unique molecular, genetic, and phenotypic characteristics of individual patients. Nanomedicine has emerged as a powerful enabler of this paradigm by improving drug delivery, enhancing tumor selectivity, and reducing systemic toxicity. However, the rational design of effective nanomedicines is challenged by the complexity of cancer biology, interpatient heterogeneity, and the vast design space of nanomaterial properties. Artificial intelligence (AI) offers transformative tools to address these challenges by integrating large-scale biological, chemical, and clinical datasets to guide nanomedicine design and optimization. AI-driven approaches, including machine learning, deep learning, and reinforcement learning, can predict nanoparticle behavior, therapeutic efficacy, and patient-specific responses with unprecedented accuracy. This review examines the role of AI in guiding the design of nanomedicines for personalized cancer therapy. We discuss how AI enables data-driven nanoparticle engineering, patient stratification, and adaptive treatment strategies. Current applications, emerging platforms, and translational challenges are critically evaluated. By bridging nanotechnology and precision oncology, AI-guided nanomedicine holds significant promise for realizing truly personalized cancer treatment.

**Keywords:** artificial intelligence; nanomedicine; personalized cancer therapy; machine learning; precision oncology

## INTRODUCTION

Cancer is a highly heterogeneous disease characterized by extensive genetic, epigenetic, metabolic, and microenvironmental diversity both between patients and within individual tumors [1–3]. This heterogeneity underlies variable therapeutic responses and the frequent emergence of drug resistance, posing a major obstacle to effective cancer treatment [4–7]. Personalized cancer therapy seeks to overcome these limitations by tailoring interventions to patient-specific tumor features, informed by genomic, transcriptomic, proteomic, and clinical data[8]. While advances in molecular profiling have enabled more precise target identification, translating this information into optimized therapeutic delivery remains a critical challenge[9, 10].

Nanomedicine offers unique advantages for personalized therapy by enabling controlled drug delivery, improved pharmacokinetics, and selective tumor accumulation[11, 12]. Nanoparticles can be engineered with tunable size, shape, surface chemistry, and functional ligands to optimize circulation time, tumor penetration, and cellular uptake. Moreover, nanocarriers can co-deliver multiple agents, incorporate imaging functionality, and respond to tumor-specific stimuli[13]. Despite these advantages, the clinical impact of nanomedicine has been limited by inconsistent performance across patient populations and difficulties in rational nanoparticle design[14–16]. Traditional nanomedicine development relies heavily on empirical experimentation and trial-and-error optimization. Given the enormous combinatorial design space encompassing material composition, architecture, surface modifications, and payload combinations, this approach is inefficient and poorly suited for personalization[17, 18]. Furthermore, nanoparticle–biological interactions are highly complex and context-dependent, influenced by patient-specific factors such as protein corona formation, immune status, vascular permeability, and tumor microenvironment properties[19, 20]. These factors complicate the prediction of in vivo behavior and therapeutic outcome.

Artificial intelligence has emerged as a powerful framework for addressing complex, high-dimensional problems in biomedical research. By leveraging machine learning algorithms capable of identifying nonlinear patterns in large datasets, AI enables data-driven modeling and prediction beyond human intuition[21, 22]. In oncology, AI has already demonstrated value in image analysis, biomarker discovery, treatment response prediction, and clinical decision support. Extending these capabilities to nanomedicine design represents a logical and potentially transformative progression[22, 23].

AI-guided nanomedicine integrates data from materials science, cancer biology, pharmacology, and clinical outcomes to inform nanoparticle engineering decisions. Machine learning models can correlate nanoparticle physicochemical properties with biological performance metrics such as biodistribution, cellular uptake, toxicity, and efficacy[24, 25]. Deep learning approaches can extract features from imaging and omics data to guide patient stratification and therapy selection. Reinforcement learning can support adaptive optimization of nanoparticle design and dosing strategies over time[25, 26].



Importantly, AI enables personalization at multiple levels. At the design level, nanoparticles can be optimized for specific tumor phenotypes or molecular subtypes. At the patient level, predictive models can identify which nanomedicine formulation is most likely to be effective based on individual biological profiles. At the treatment level, AI can support dynamic adaptation of therapy in response to longitudinal patient data. Collectively, these capabilities position AI-guided nanomedicine as a cornerstone of next-generation precision oncology.

**2. AI Methodologies Applied to Nanomedicine Design**

A range of AI methodologies are being applied to the design and optimization of nanomedicines, each offering distinct strengths[27]. Machine learning (ML) techniques, including supervised, unsupervised, and semi-supervised learning, are widely used to model relationships between nanoparticle properties and biological outcomes. Supervised learning algorithms such as random forests, support vector machines, and gradient boosting are commonly employed to predict metrics like drug loading efficiency, stability, toxicity, and tumor accumulation[27].

Deep learning (DL), a subset of ML based on artificial neural networks with multiple layers, is particularly well suited for handling complex and high-dimensional data. Convolutional neural networks enable automated analysis of microscopy and medical imaging data, facilitating prediction of nanoparticle–cell interactions and treatment response[28, 29]. Recurrent and transformer-based architectures support temporal modeling of pharmacokinetic and longitudinal clinical data.

Unsupervised learning techniques, including clustering and dimensionality reduction, are valuable for identifying latent patterns in nanoparticle libraries and patient datasets. These approaches can reveal previously unrecognized structure–function relationships and support hypothesis generation[30]. Reinforcement learning, which optimizes decision-making through iterative feedback, is increasingly explored for adaptive nanoparticle design and treatment scheduling[30].

Crucially, the effectiveness of AI models depends on data quality, diversity, and interpretability. Integration of experimental, computational, and clinical datasets is essential for robust model training. Explainable AI approaches are gaining importance to ensure transparency, regulatory acceptance, and clinical trust[31].

**3. Data-Driven Engineering of Nanoparticle Properties**

Artificial intelligence (AI)–guided design has transformed nanoparticle engineering from a largely empirical process into a data-driven and predictive discipline[32]. The therapeutic performance of nanoparticles is critically influenced by physicochemical parameters such as size, shape, surface charge, elasticity, composition, and ligand density. These properties collectively govern biodistribution, circulation time, cellular uptake, intracellular trafficking, and clearance. AI-based modeling enables systematic optimization of these parameters, allowing rational design tailored to specific biological contexts[32].

Machine learning algorithms trained on large experimental datasets can uncover non-linear relationships between nanoparticle attributes and biological outcomes that are difficult to discern through conventional approaches[33]. For instance, AI models can predict optimal nanoparticle size ranges for tumor penetration by integrating data on vascular permeability, interstitial fluid pressure, and stromal density. Such predictions help balance competing requirements small sizes favor deep penetration, while larger particles may enhance retention and drug payload capacity[33].

Surface chemistry optimization represents another area where AI provides substantial advantages. Nanoparticle surface charge and functionalization strongly influence protein corona formation, which in turn affects immune recognition and targeting efficiency[34]. AI models trained on proteomic and physicochemical data can predict corona composition under different biological conditions, guiding surface modifications that enhance stealth properties while preserving active targeting. This enables the rational selection of polyethylene glycol alternatives, zwitterionic coatings, or biomimetic surfaces to optimize in vivo stability[34].

Material selection also benefits from AI-driven optimization. By analyzing performance metrics across polymeric, lipid-based, inorganic, and hybrid nanoparticle systems, machine learning models can recommend materials best suited for specific therapeutic goals, such as sustained release, imaging contrast enhancement, or

immune modulation[35]. These insights accelerate early-stage development and reduce reliance on costly trial-and-error experimentation.

Importantly, AI-guided nanoparticle engineering supports iterative refinement through closed-loop optimization. Predictive modeling informs experimental validation, and experimental results are fed back into models to improve accuracy[35]. This continuous learning process shortens development timelines, reduces resource consumption, and enables rapid customization of nanomedicines for different cancer subtypes or biological barriers. Collectively, data-driven engineering establishes a scalable and efficient framework for next-generation nanotherapeutic design.



**4. Patient Stratification and Personalized Nanotherapy Selection**

Beyond nanoparticle design, AI plays a pivotal role in aligning nanomedicine strategies with patient-specific biology. Cancer heterogeneity across patients—and even within individual tumors—significantly influences nanoparticle delivery efficiency and therapeutic response[36, 37]. AI-enabled patient stratification integrates multidimensional data, including genomics, transcriptomics, proteomics, radiomics, and clinical parameters, to identify patient subgroups most likely to benefit from specific nanotherapeutic formulations[37].

Predictive models can correlate tumor features such as vascular density, extracellular matrix composition, immune infiltration, and metabolic state with nanoparticle accumulation and penetration[38]. For example, AI analysis of imaging and histopathological data can identify tumors with enhanced permeability and retention characteristics suitable for passive nanoparticle targeting, while others may require active targeting or microenvironment-responsive systems[38].

AI-driven decision support systems further enable personalized nanotherapy selection by recommending optimal payloads, dosing regimens, and delivery strategies. By integrating toxicity profiles, pharmacokinetic data, and patient comorbidities, these systems help balance therapeutic efficacy with safety[39]. Such personalization is particularly valuable for complex nanomedicines carrying potent cytotoxic agents or immunomodulators.

Importantly, AI facilitates dynamic patient stratification over time. Longitudinal data analysis allows monitoring of tumor evolution, treatment response, and resistance development, enabling timely adaptation of nanotherapy strategies. By aligning nanomedicine design and deployment with individual patient biology, AI supports a paradigm shift from population-averaged treatments to truly individualized cancer care[39].

**5. AI-Guided Combination Nanomedicines and Adaptive Therapy**

Combination therapy has become a cornerstone of modern oncology, reflecting the multifactorial nature of cancer progression and resistance. AI-guided nanomedicine enables rational design of combination nanotherapeutics by modeling drug–drug interactions[40], synergistic effects, and toxicity profiles. Machine learning algorithms can predict optimal drug combinations, ratios, and release kinetics for co-delivery within a single nanoparticle, maximizing therapeutic synergy while minimizing adverse effects[40].

Nanoparticles provide a unique platform for synchronized delivery of multiple agents, overcoming pharmacokinetic mismatches that limit conventional combination therapies. AI models trained on preclinical and clinical data can guide the selection of payloads targeting complementary pathways, such as chemotherapy combined with immune checkpoint inhibition or metabolic modulation[41]. This systems-level optimization enhances therapeutic robustness and reduces the likelihood of resistance.

Adaptive therapy represents an emerging frontier in AI-guided nanomedicine. By continuously analyzing longitudinal patient data, including imaging, biomarkers, and clinical outcomes, AI systems can recommend real-time adjustments to treatment regimens[42]. Nanomedicines designed with modular architectures or stimulus-responsive release mechanisms are particularly well suited for adaptive strategies, as payload composition or activation can be modified in response to disease dynamics.

AI-driven feedback loops enable dynamic treatment optimization, adjusting dosing, scheduling, or therapeutic combinations based on patient response and toxicity signals[42]. This adaptive approach moves beyond static treatment protocols, offering a responsive and personalized strategy for managing cancer as an evolving disease.

**6. Translational Challenges and Clinical Integration**

Despite significant promise, the clinical translation of AI-guided nanomedicine faces several challenges. Data scarcity and heterogeneity remain major obstacles, as robust AI models require large, standardized datasets encompassing nanoparticle properties, biological responses, and clinical outcomes[43]. Variability in experimental protocols and reporting further limits model generalizability and reproducibility.

Regulatory frameworks for AI-driven design and decision-making are still evolving. Questions surrounding model validation, interpretability, and accountability must be addressed to ensure patient safety and regulatory acceptance[44]. Transparent and explainable AI models will be critical for building clinical trust and facilitating regulatory review.

Manufacturing scalability and reproducibility pose additional challenges, particularly for highly customized nanomedicines designed through AI optimization. Ensuring consistent quality while accommodating personalization requires advances in manufacturing technologies and quality control systems[45]. Ethical

considerations, including data privacy, algorithmic bias, and equitable access to AI-enabled therapies, must also be carefully managed.

Overcoming these challenges will require close collaboration among materials scientists, clinicians, data scientists, regulators, and ethicists. Standardized data infrastructures, early regulatory engagement, and integrated translational pipelines will be essential for realizing the full clinical potential of AI-guided nanomedicine in precision oncology.

**7. Conclusion and Future Perspectives**



AI-guided design of nanomedicines represents a paradigm shift in personalized cancer therapy. By integrating advanced computational intelligence with nanotechnology and oncology, this approach enables rational, data-driven optimization of therapeutic delivery tailored to individual patients. AI enhances every stage of nanomedicine development, from material selection and design to patient stratification and adaptive treatment. While significant translational challenges remain, ongoing advances in data integration, model interpretability, and regulatory science are steadily paving the way toward clinical implementation. As these barriers are addressed, AI-guided nanomedicine is poised to become a central pillar of precision oncology, offering more effective, safer, and truly personalized cancer therapies.

**REFERENCES**

1. Abolhassani, H., Eskandari, A., Saremi Poor, A., Zarrabi, A., Khodadadi, B., Karimifard, S., Sahrayi, H., Bourbour, M., Tavakkoli Yaraki, M.: Nanobiotechnological approaches for breast cancer Management: Drug delivery systems and 3D In-Vitro models. Coord. Chem. Rev. 508, 215754 (2024). https://doi.org/10.1016/j.ccr.2024.215754
2. Aljabali, A.A.A., Obeid, M.A., Gammoh, O., El-Tanani, M., Mishra, V., Mishra, Y., Kapre, S., Srivatsa Palakurthi, S., Hassan, Sk.S., Nawn, D., Lundstrom, K., Hromić-Jahjefendić, A., Serrano-Aroca, Á., Redwan, E.M., Uversky, V.N., Tambuwala, M.M.: Nanomaterial-Driven Precision Immunomodulation: A New Paradigm in Therapeutic Interventions. Cancers. 16, 2030 (2024). https://doi.org/10.3390/cancers16112030
3. Tufail, T., Uti, D.E., Aja, P.M., Offor, C.E., Ibiam, U.A., Ukaidi, C.U.A.: Utilizing Indigenous Flora in East Africa for Breast Cancer Treatment: An Overview. Anticancer Agents Med. Chem. 25, 99–113 (2025). https://doi.org/10.2174/0118715206338557240909081833
4. Uti, D.E., Atangwho, I.J., Alum, E.U., Ntaobeten, E., Obeten, U.N., Bawa, I., Agada, S.A., Ukam, C.I.-O., Egbung, G.E.: Antioxidants in cancer therapy mitigating lipid peroxidation without compromising treatment through nanotechnology. Discov. Nano. 20, 70 (2025). https://doi.org/10.1186/s11671-025-04248-0
5. Divella, R., De Luca, R., Abbate, I., Naglieri, E., Daniele, A.: Obesity and cancer: the role of adipose tissue and adipo-cytokines-induced chronic inflammation. J. Cancer. 7, 2346–2359 (2016). https://doi.org/10.7150/jca.16884
6. Fawzy, M.P., Hassan, H.A.F.M., Amin, M.U., Preis, E., Bakowsky, U., Fahmy, S.A.: Deploying nucleic acids-loaded plant-derived exosomes as green nano gadget in cancer gene therapy. Mater. Adv. 6, 1230–1261 (2025). https://doi.org/10.1039/D4MA01189A
7. Etrych, T., Janoušková, O., Chytil, P.: Fluorescence Imaging as a Tool in Preclinical Evaluation of Polymer-Based Nano-DDS Systems Intended for Cancer Treatment. Pharmaceutics. 11, 471 (2019). https://doi.org/10.3390/pharmaceutics11090471
8. Alum, E.U.: AI-driven biomarker discovery: enhancing precision in cancer diagnosis and prognosis. Discov. Oncol. 16, 313 (2025). https://doi.org/10.1007/s12672-025-02064-7
9. Uti, D.E., Ugwu, O.P.-C., Alum, B.N., Edeh, F.O., Ainebyoona, C.: Unveiling the microbial orchestra: exploring the role of microbiota in cancer development and treatment. Discov. Oncol. 16, 646 (2025). https://doi.org/10.1007/s12672-025-02352-2
10. Omang, Bawa, I., Ugwu, O.P.-C., Idowu, A.O., Atangwho, I.J., Egbung, G.E.: Theranostic Nanoparticles in Prostate Cancer: Disrupting Hypoxia-Induced Glycolysis by Targeting Hypoxia-Inducible Factor-1 Alpha and Downstream Metabolites. Cancer Med. 15, e71519 (2026). https://doi.org/10.1002/cam4.71519
11. Agrahari, V., and Hiremath, P.: Challenges Associated and Approaches for Successful Translation of Nanomedicines Into Commercial Products. Nanomed. 12, 819–823 (2017). https://doi.org/10.2217/nnm-2017-0039
12. Hou, J., Xue, Z., Chen, Y., Li, J., Yue, X., Zhang, Y., Gao, J., Hao, Y., Shen, J.: Development of Stimuli-Responsive Polymeric Nanomedicines in Hypoxic Tumors and Their Therapeutic Promise in Oral Cancer. Polymers. 17, (2025). https://doi.org/10.3390/polym17081010
13. Nwuruku, O.A., Ugwu, O.P.-C., Uti, D.E., Edwin, N.: Harnessing nature: plant-derived nanocarriers for targeted drug delivery in cancer therapy. Phytomedicine Plus. 5, 100828 (2025). https://doi.org/10.1016/j.phyplu.2025.100828

14. Ahmar, H.: Nonenzymatic Electrochemical Detection of Glucose Using Screen-Printed Electrode Modified with Pd–Au Nanoparticles Encapsulated on Dendrimer Grafted Multi-Wall Carbon Nanotubes. Curr. Appl. Sci. 2, 67–78 (2024). https://doi.org/10.22034/cas.2022.343533.1019
15. Cheng, T.-M., Chu, H.-Y., Huang, H.-M., Li, Z.-L., Chen, C.-Y., Shih, Y.-J., Whang-Peng, J., Cheng, R.H., Mo, J.-K., Lin, H.-Y., Wang, K.: Toxicologic Concerns with Current Medical Nanoparticles. Int. J. Mol. Sci. 23, (2022). https://doi.org/10.3390/ijms23147597
16. Ying, S., Guan, Z., Ofoegbu, P.C., Clubb, P., Rico, C., He, F., Hong, J.: Green synthesis of nanoparticles: Current developments and limitations. Environ. Technol. Innov. 26, 102336 (2022). https://doi.org/10.1016/j.eti.2022.102336
17. Ramos, T.I., Villacis-Aguirre, C.A., López-Aguilar, K.V., Santiago Padilla, L., Altamirano, C., Toledo, J.R., Santiago Vispo, N.: The Hitchhiker's Guide to Human Therapeutic Nanoparticle Development. Pharmaceutics. 14, 247 (2022). https://doi.org/10.3390/pharmaceutics14020247
18. Moradi Kashkooli, F., Bhandari, A., Gu, B., Kolios, M.C., Kohandel, M., Zhan, W.: Multiphysics modelling enhanced by imaging and artificial intelligence for personalised cancer nanomedicine: Foundations for clinical digital twins. J. Controlled Release. 386, 114138 (2025). https://doi.org/10.1016/j.jconrel.2025.114138
19. Parvin, N., Aslam, M., Joo, S.W., Mandal, T.K.: Nano-Phytomedicine: Harnessing Plant-Derived Phytochemicals in Nanocarriers for Targeted Human Health Applications. Molecules. 30, (2025). https://doi.org/10.3390/molecules30153177
20. Gessner, I.: Optimizing nanoparticle design and surface modification toward clinical translation. Mrs Bull. 46, 643–649 (2021). https://doi.org/10.1557/s43577-021-00132-1
21. Maleki Varnosfaderani, S., Forouzanfar, M.: The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century. Bioengineering. 11, 337 (2024). https://doi.org/10.3390/bioengineering11040337
22. Rashidi, H.H., Pantanowitz, J., Hanna, M.G., Tafti, A.P., Sanghani, P., Buchinsky, A., Fennell, B., Deebajah, M., Wheeler, S., Pearce, T., Abukhiran, I., Robertson, S., Palmer, O., Gur, M., Tran, N.K., Pantanowitz, L.: Introduction to Artificial Intelligence and Machine Learning in Pathology and Medicine: Generative and Nongenerative Artificial Intelligence Basics. Mod. Pathol. 38, 100688 (2025). https://doi.org/10.1016/j.modpat.2024.100688
23. Houssein, E.H., Gamal, A.M., Younis, E.M.G., Mohamed, E.: Explainable artificial intelligence for medical imaging systems using deep learning: a comprehensive review. Clust. Comput. 28, 469 (2025). https://doi.org/10.1007/s10586-025-05281-5
24. Guan, C., Mendes, B.B., Conniot, J., Dias, A.L., Hammad, L., Thambi, T., Langer, R., Rodrigues, T., Conde, J., de la Fuente-Nunez, C.: Accelerating discoveries in cancer nanomedicine using AI. Cell Biomater. 1, 100279 (2025). https://doi.org/10.1016/j.celbio.2025.100279
25. Samathoti, P., Kumarachari, R.K., Bukke, S.P.N., Rajasekhar, E.S.K., Jaiswal, A.A., Eftekhari, Z.: The role of nanomedicine and artificial intelligence in cancer health care: individual applications and emerging integrations—a narrative review. Discov. Oncol. 16, 697 (2025). https://doi.org/10.1007/s12672-025-02469-4
26. Han, Y., Kim, D.H., Pack, S.P.: Nanomaterials in Drug Delivery: Leveraging Artificial Intelligence and Big Data for Predictive Design. Int. J. Mol. Sci. 26, (2025). https://doi.org/10.3390/ijms262211121
27. Serrano, D.R., Luciano, F.C., Anaya, B.J., Ongoren, B., Kara, A., Molina, G., Ramirez, B.I., Sánchez-Guirales, S.A., Simon, J.A., Tomietto, G., Rapti, C., Ruiz, H.K., Rawat, S., Kumar, D., Lalatsa, A.: Artificial Intelligence (AI) Applications in Drug Discovery and Drug Delivery: Revolutionizing Personalized Medicine. Pharmaceutics. 16, 1328 (2024). https://doi.org/10.3390/pharmaceutics16101328
28. Ali, M., Benfante, V., Basirinia, G., Alongi, P., Sperandeo, A., Quattrocchi, A., Giannone, A.G., Cabibi, D., Yezzi, A., Di Raimondo, D., Tuttolomondo, A., Comelli, A.: Applications of Artificial Intelligence, Deep Learning, and Machine Learning to Support the Analysis of Microscopic Images of Cells and Tissues. J. Imaging. 11, 59 (2025). https://doi.org/10.3390/jimaging11020059
29. Dipankar, P., Salazar, D., Dennard, E., Mohiyuddin, S., Nguyen, Q.C.: Artificial intelligence based advancements in nanomedicine for brain disorder management: an updated narrative review. Front. Med. 12, (2025). https://doi.org/10.3389/fmed.2025.1599340
30. Mim, J.J., Mamun, A.A., Nayem, M.H., Mahmud, S., Nath, A., Rahman, S.M., Fidal, S.A., Hossain, N.: Machine learning-driven advances in nanotechnology: From materials design to process optimization – A review. Mater. Today Commun. 50, 114485 (2026). https://doi.org/10.1016/j.mtcomm.2025.114485
31. Bhat, A.R., Ahmed, S.: Artificial intelligence (AI) in drug design and discovery: A comprehensive review. Silico Res. Biomed. 1, 100049 (2025). https://doi.org/10.1016/j.insi.2025.100049
32. Suksaeree, J.: A Review of Artificial Intelligence (AI)-Driven Smart and Sustainable Drug Delivery Systems: A Dual-Framework Roadmap for the Next Pharmaceutical Paradigm. Sci. 7, (2025). https://doi.org/10.3390/sci7040179

33. Kopac, T.: Leveraging Artificial Intelligence and Machine Learning for Characterizing Protein Corona, Nanobiological Interactions, and Advancing Drug Discovery. Bioengineering. 12, 312 (2025). https://doi.org/10.3390/bioengineering12030312
34. González-García, L.E., MacGregor, M.N., Visalakshan, R.M., Lazarian, A., Cavallaro, A.A., Morsbach, S., Mierczynska-Vasilev, A., Mailänder, V., Landfester, K., Vasilev, K.: Nanoparticles Surface Chemistry Influence on Protein Corona Composition and Inflammatory Responses. Nanomaterials. 12, 682 (2022). https://doi.org/10.3390/nano12040682
35. Shen, C., Zhang, M., Lu, M., Chang, E., Gao, Z., Ban, W., Liu, Q., Zuo, Z., Jiang, C.: Machine learning empowered formulation design, optimization and characterization of nanoparticulate drug delivery systems: Current applications, challenges, and future perspectives. Acta Pharm. Sin. B. (2025). https://doi.org/10.1016/j.apsb.2025.12.011
36. Younas, A., Wang, S., Asad, M., Al Mamun, A., Majeed, S., Sharif, A., Zhou, Q., Liu, Y., Geng, P., Shao, C., Xiao, J.: Recent advances in cancer nanomedicine: From smart targeting to personalized therapeutics - pioneering a new era in precision oncology. Mater. Today Bio. 36, 102660 (2026). https://doi.org/10.1016/j.mtbio.2025.102660
37. Gupta, V., Kumar, D., Gupta, S., Tanwar, R., Jaiswal, N.K., Islam, M.M., Singh, S., Choudhary, N., Gowri, S., Webster, T.J., Faiyazuddin, M.: Nanotechnology-Driven Cancer Therapies for Precision Oncology: Advances and Clinical Outlook. Int. J. Nanomedicine. 21, 1–33 (2026). https://doi.org/10.2147/IJN.S568254
38. Henke, E., Nandigama, R., Ergün, S.: Extracellular Matrix in the Tumor Microenvironment and Its Impact on Cancer Therapy. Front. Mol. Biosci. 6, 160 (2020). https://doi.org/10.3389/fmolb.2019.00160
39. Chitoran, E., Rotaru, V., Gelal, A., Ionescu, S.-O., Gullo, G., Stefan, D.-C., Simion, L.: Using Artificial Intelligence to Develop Clinical Decision Support Systems—The Evolving Road of Personalized Oncologic Therapy. Diagnostics. 15, (2025). https://doi.org/10.3390/diagnostics15182391
40. Zhang, M., Liu, E., Cui, Y., Huang, Y.: Nanotechnology-based combination therapy for overcoming multidrug-resistant cancer. Cancer Biol. Med. 14, 212–227 (2017). https://doi.org/10.20892/j.issn.2095-3941.2017.0054
41. Singh, H., Balusamy, S.R., Sukweenadhi, J., Shrivastav, A., Mohanprasanth, A., Saravanan, M., Mijakovic, I., Singh, P.: Engineering combination nanomedicines to overcome cancer resistance. RSC Adv. 16, 5128–5167. https://doi.org/10.1039/d5ra08728g
42. Trasca, D.-M., Dorin, P.I., Carmen, S., Varut, R.-M., Singer, C.E., Radivojevic, K., Stoica, G.A.: Artificial Intelligence in Biomedicine: A Systematic Review from Nanomedicine to Neurology and Hepatology. Pharmaceutics. 17, (2025). https://doi.org/10.3390/pharmaceutics17121564
43. Chou, W., Canchola, A., Zhang, F., Lin, Z.: Machine Learning and Artificial Intelligence in Nanomedicine. Wiley Interdiscip. Rev. Nanomed. Nanobiotechnol. 17, e70027 (2025). https://doi.org/10.1002/wnan.70027
44. Mennella, C., Maniscalco, U., De Pietro, G., Esposito, M.: Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon. 10, e26297 (2024). https://doi.org/10.1016/j.heliyon.2024.e26297
45. Shirzad, M., Shaban, M., Mohammadzadeh, V., Rahdar, A., Fathi-karkan, S., Hoseini, Z.S., Najafi, M., Kharaba, Z., Aboudzadeh, M.A.: Artificial Intelligence-Assisted Design of Nanomedicines for Breast Cancer Diagnosis and Therapy: Advances, Challenges, and Future Directions. BioNanoScience. 15, 354 (2025). https://doi.org/10.1007/s12668-025-01980-w

**CITE AS: Taliikwa Nicholas Ceaser (2026). AI-Guided Design of Nanomedicines for Personalized Cancer Therapy. NEWPORT INTERNATIONAL JOURNAL OF BIOLOGICAL AND APPLIED SCIENCES 7(2):73-78. https://doi.org/10.59298/NIJBAS/2026/7.2.7378**