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Artificial Intelligence–Driven Translational Nanomedicine in Oncology: Multistage Targeting Strategies, Clinical Advances, and Future Directions for Liver, Breast, Kidney, and Brain Cancers

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Abstract:

Artificial intelligence (AI) and translational nanomedicine are revolutionizing the field of precision oncology through the use of smart nanoparticles, personalization of drug delivery, and evidence-based therapeutic decisions. This review highlights some of the recent developments in AI-driven translational nanomedicine, with special emphasis on multistage targeting approaches and clinical utility in liver, breast, renal, and brain tumors. Machine learning, deep learning, radiomics, multimodal omics, and nanoinformatics are among the areas discussed in this review. Tumor heterogeneity, vascular barrier, immune microenvironment, renal clearance, and blood-brain barrier penetration in organs are considered in order to highlight the necessity for the development of personalized nanomedicine strategies. Despite the advancements that have been made by AI-guided nanomedicine in drug delivery, pharmacokinetics and safety, there are several obstacles that hinder the clinical application of such technology. The above review suggests future strategies which include standardization in nanoinformatics, patient-derived organoids, digital twins, federated learning, adaptive clinical trials based on biomarkers, and explainable AI for accelerating clinical translation. It may be concluded that the combination of AI and translational nanomedicine offers an attractive approach towards the development of safer and effective cancer treatment options.

Keywords: Artificial intelligence (AI); Translational nanomedicine; Precision oncology; Multistage targeting; Nanoinformatics; Personalized medicine; Clinical translation.

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1. INTRODUCTION

Cancer nanotechnology was conceived to enhance the therapeutic index of the anticancer drugs through modification of their solubility, circulation time, biodistribution, tissue uptake, and drug release rate[1]. Liposomes, protein nanocarriers, inorganic nanoparticles, albumin-based nanocarriers, polymers, micelles, and lipid nanoparticles have been investigated as carriers of small molecules, nucleic acids, proteins, imaging agents, and various combinations. The rationale for translation of nanomaterials is strong – a carrier may provide protection, limit the toxic effects on sensitive normal tissues, exploit characteristics of the tumor vasculature or molecular signatures of tumors, and facilitate controlled or responsive drug delivery[2]. Still, the development path of cancer nanomedicine has been bumpy. Some nanomaterials have reached clinical practice in oncology, but many others have failed due to heterogeneity of tumor targeting, inability to predict pharmacokinetics in humans, difficulties with reproducible manufacture, and lack of improvement compared to the current standard treatment.

AI provides a supplementary suite of technologies that can be employed to overcome these shortcomings[3]. Learning methods can predict connections between physicochemical characteristics and biological activity, discover phenotypes for imaging or molecular detection of nanoparticle uptake, select ligands and payload, simulate pharmacokinetics, recognize toxicity markers, and provide personalized therapy choices. The conceptual overlap between AI and nanotechnology thus leads to transformation of nanomedicine from a predominantly drug-delivery science into an integrated translational framework in which patient characteristics, carrier design, delivery confirmation, and therapeutic outcome are optimized simultaneously. Such an overlap is especially important in case of solid tumors, as biological interfaces responsible for nanoparticle function are multiscale and patient-specific.

1.1 Background and Context

The classical approach to passive tumor targeting exploiting the phenomenon of the enhanced permeability and retention (EPR) effect is frequently inadequate for clinical cancer treatment since different tumors demonstrate considerable variability in terms of their vasculature, tissue composition, immune environment, and drug diffusion[4]. Accordingly, the success of translational medicine using nanoparticles entails a multi-stage process encompassing patient selection, circulation stability, tumor permeation, cell targeting, and drug release within the cell, with AI playing a key role in integrating information in each stage. Liver, breast, kidney, and brain cancers need special attention due to particular biological obstacles.

1.2 Objectives of the Review

Goals for this review include:

- To elucidate the potential of AI to aid the development and application of multistage-targeted nanomedicines.
- To compile human and clinical-based evidence in the field of nanomedicine for liver, breast, kidney, and brain cancer.

- To compare approaches, translational advantages and disadvantages, in imaging, multi-omics, pharmacology, formulation science, and clinical trials.
- To highlight areas for further investigation and future directions without the need for animal-based evidence.

1.3 Importance of the Topic

The significance of this issue comes from the difference between the increasing complexity of nanotechnologies and the small number of formulation strategies which result in sustained therapeutic benefit. In order for AI to contribute to closing this gap, it needs to be tested against human data, understand mechanisms, and have a prospective evaluation of its benefits. A review that distinguishes between computational feasibility, human data-based validation, and therapeutic efficacy is thus required. This helps avoid one major flaw in the existing literature on this issue – equating the potential of formulation optimization or classification performance with therapeutic benefit. The translational approach requires an assessment of whether AI alters carrier selection, patient stratification, delivery confirmation, dose optimization, toxicity reduction, or survival/QoL improvement.

2. AI-ENABLED NANOMEDICINE DESIGN AND MULTISTAGE TARGETING

The use of AI in nanomedicine development is most accurately represented by a translational loop rather than a predictive approach[5]. Here, clinical and experimental data provide information about the target product profile, the computational models provide the candidate composition, assays test transport, uptake, release, and toxicity, and the generated data feedback to the models. The process may allow avoiding experimental testing, yet it requires high-quality datasets and validation to be credible.

2.1 AI for Material Selection, Formulation Optimization, and Payload Matching

Formulation development consists of a design space comprising high dimensions such as particle size, polydispersity, morphology, surface charge, composition of lipids/polymer, ligand density, drug-polymer ratio, encapsulation efficiency, release rate, colloidal stability, sterilization sensitivity, and storage properties[6]. Traditional design of experiments techniques is useful yet may be unproductive when there is a non-linear relationship among variables. While supervised learning maps formulation variables to output parameters like size, encapsulation, stability, release, and toxicity, Bayesian optimization and active learning suggest which experiment to conduct next. Generative techniques can suggest new material combinations; however, these must have strict constraints of chemical feasibility.

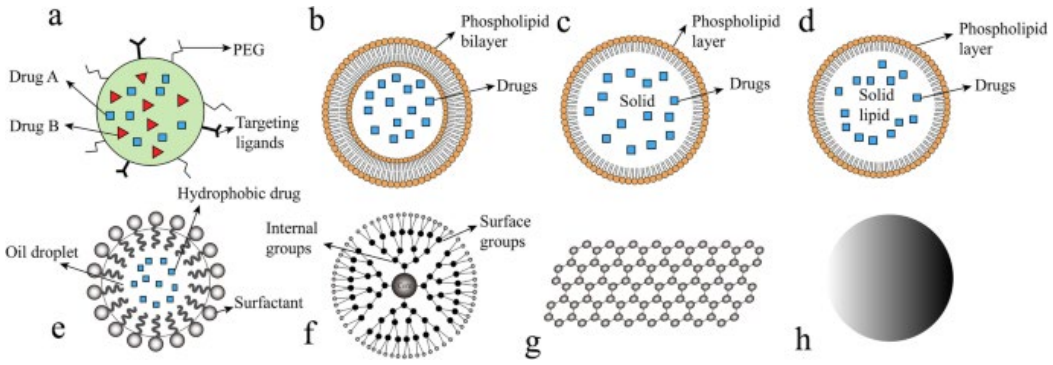

Figure 1. Representative nanocarrier platforms used in AI-enabled translational cancer nanomedicine

The compatibility of payloads is also critical. While one that can hold a hydrophobic cytotoxic drug might not be able to accommodate other payloads like mRNA, siRNA, proteins, or combinations thereof. AI can correlate the drug features, formulation characteristics, disease type, and mode of delivery. In cancer treatment, the relevant optimization model needs to maximize a multi-objective function rather than a singular objective. Good encapsulation alone does not justify the lack of efficient release, high complement activation, or organ non-specific accumulation. Multi-objective optimization allows you to tradeoff between potency, stability, manufacturing feasibility, predicted toxicity, and cost[7].

One of the most important advantages of AI formulation technology is the capability to discover interactions that are not easy to define through mechanistic equations[8]. On the other hand, one of the most significant limitations of this technology is sensitivity to small, heterogeneous and biased data sets. Nanomedicine research frequently publishes data using inconsistent units, assays, media, time points and endpoints. Thus, a model may learn laboratory specific signatures instead of the formulation principles.

2.2 Multistage Targeting: From Patient Selection to Intracellular Release

Multistep targeting understands the fact that a series of conditional events needs to be successful for achieving effective treatment. Any failure in any of the steps can render the subsequent steps irrelevant. The first step in this case is patient selection. The patient can be selected based on various radiomics, digital pathology, circulating biomarker, and multi-omics technologies that enable identifying vascular, stromal, receptor, metabolic, and immune phenotypes compatible with the nanomedicine[9].

The second step is systemic navigation. Protein adsorption, immune system recognition, coagulation, complement activation, and mononuclear phagocyte uptake modify the biological profile of nanoparticles following administration. Although machine learning approaches could predict protein corona composition and compatibility with blood from surface properties, they have to be developed using human plasma and tested across demographic and clinical variations[10]. The third step is tissue accessibility. Perfused, permeable, necrotic, and stromal properties obtained by imaging could help predict tumor exposure. In liver cancers, local arterial delivery and guided embolization can be considered; in brain tumors, the barrier permeability

and regions with abnormal vasculature should be determined; and in kidney tumors, vascularity and renal filtration are critical.

Intratumoral delivery and cellular targeting is the fourth step. Receptor binding, extracellular matrix density, endocytosis, and cell heterogeneity impact drug delivery. AI could be employed to choose ligands based on receptor specificity for HER2, folate receptor, transferrin receptor, integrins, mutant EGFR, or tumor-associated antigen receptors; however, the receptors need to be characterized in the patient population[11]. The fifth step is stimulus-responsive or intracellular release. Potential stimuli include pH, redox environment, enzymes, reactive oxygen species, temperature, ultrasound, magnetic field, and light, although there is variability with regard to intensity and distribution within patients. Therefore, models should predict the likelihood of a therapeutic release window rather than assume stimulus presence.

The last phase is adaptive response. Imaging information, biomarkers like circulating tumor DNA, toxicity, and pharmacokinetic information can all be combined to make adjustments to dosage or schedule. In this way, one ends up with an adaptive treatment strategy where the initial design is not fixed. The advantage of this approach lies in its individualized nature; the problem, however, is in the complexity of the process.

2.3 AI-Integrated Theranostics, Multi-Omics, and Human-Derived Models

Theranostic nanomedicine involves the combination of therapies and imaging or molecular sensing. Machine learning algorithms may be used for multiparametric imaging analyses to determine delivery, differentiate between effects and progression, and associate distribution patterns with outcomes. The potential ability of nanoparticle contrast or radiotracer technologies to detect if a lesion has received the delivery agent prior to administering any toxic dose of the treatment could prove to be particularly important where patient-to-patient variation is considerable[12].

Multi-omics could help to discover which pathways play a role in delivery, resistance, metabolism, immune response, and target expression. Genomics, transcriptomics, proteomics, metabolomics, and spatial data integration could allow choosing a nanomedicine on the basis of a subpopulation identified by the mechanism, not only by anatomy. Nevertheless, the use of high-dimensional data increases the risks of overfitting and discovery of false findings.

Human-based models serve as a critical link between computational prediction and clinical implementation. Human patient-derived organoids, tumor slices, microphysiological system models, and ex vivo models allow for assessing nanoparticle uptake, therapeutic efficacy, and toxicity without sacrificing tumor heterogeneity. Multimodal clinical data from patients, which include imaging data, pathology, multi-omics, pharmacokinetics, and toxicology data are analyzed using AI in order to fine-tune patient selection and therapy monitoring[13]. Unfortunately, inter-patient variability, receptor heterogeneity, imaging issues, and insufficient external validation constitute significant obstacles to translation into the clinic. Human-based models should therefore supplement prospective clinical trials in the validation of AI-driven precision nanomedicine.

3. ORGAN-SPECIFIC TRANSLATIONAL AND CLINICAL ADVANCES

The success of a nanomedicine is largely dependent on its organ-specific biology. This review focuses on human disease, imaging, pharmacology, approved nanomedicines, and clinical studies. Data obtained from animals is not considered when making any evaluations.

3.1 Liver Cancer

Hepatocellular carcinoma (HCC) frequently occurs in a cirrhotic liver, wherein there is perfusion change, fibrosis, portal hypertension, decreased hepatic reserve function, and immune compromise that make systemic therapy challenging. Moreover, the liver is a prime area for nanoparticle retention by Kupffer cells and sinusoidal endothelial cells. This may be helpful for hepatic targeting but may lead to decreased selectivity for tumors and increased liver toxicity. AI may utilize contrast enhanced CT and/or MRI for assessment of arterial enhancement, wash-out, necrosis, vascular invasion, and background of liver, and thus help choose suitable patients for either systemic or loco-regional nano-based therapies[14].

Targeting in HCC through a multistep process can involve characterization of vascular and molecular phenotypes through radiomics or multi-omics, then the selection of a vehicle that is compatible with the physiology of the liver. Locoregional delivery methods such as intra-arterial delivery or embolization-compatible vehicles can help to enhance local concentration and lower systemic dose. Treatment plan design using AI can incorporate anatomical structures like arteries, tumor load, liver physiology, and history of therapy.

The clinical translational process is hampered by heterogeneity of cirrhosis, variation in reticuloendothelial uptake, competition with mortality caused by liver failure, and fast-moving standard of care based on immunotherapy combinations[15]. It means that the nano formulation should demonstrate benefit over the active competitor, and not over the free drug alone. The most likely path forward would not be the universal nanoparticle for all HCC patients, but a biomarker-selective or image-selective formulation that enhances the delivery of an exact payload or locoregional treatment or lowers toxicity in HCC patients with decreased hepatic reserve. Human liver organoids and HCC tumor slices can aid in the study of uptake and hepatotoxicity; however, they should contain non-cancerous cirrhotic liver.

3.2 Breast Cancer

In terms of the clinical nanomedicine profile of the four cancers discussed, breast cancer appears to have the most developed. The use of liposomal anthracycline and albumin-bound paclitaxel have proven that nanomedicine has an effect on the pharmacokinetics of these drugs, decreasing toxicities and improving delivery of the medication. Still, the efficiency of the two drugs in clinical settings depends on disease subtypes and treatment settings.

The development of nanomedicine for breast cancer has been enhanced by AI through combining digital pathology, medical imaging, and multi-omics profiling to describe HER2 status, hormonal receptors, immune microenvironment, stroma architecture, and molecular heterogeneity. This enables identification of appropriate patient subpopulations for designing targeted nanoparticles, combination drugs, and nucleic acid delivery systems. Nanomedicine can

be especially useful in triple-negative breast cancer due to the high molecular heterogeneity of this disease, lack of specific drug targets, and chemotherapy and immunotherapy dependence[16].

Multistage approaches to cancer targeting are based on long-circulation nanocarriers with receptor-mediated targeting and drug release. However, even though active targeting increases cellular uptake more significantly than overall accumulation in tumors, pharmacokinetic testing, molecular validation, and imaging evaluation are necessary when conducting clinical trials. The focus of future studies should be on the use of patient biomarkers to individualize treatment.

3.3 Kidney Cancer

Renal cell carcinoma (RCC), in particular, clear-cell RCC is marked by properties of angiogenesis, metabolic shift, and immune modulation. Treatment in today's era makes use of immune checkpoint inhibitors and anti-vascular endothelial growth factor inhibitors. Thus, nanotechnology drug discovery should be placed in the framework of combination therapies as opposed to being just an alternative to traditional treatments[17]. AI can fuse together information from histology, radiomics, circulating biomarkers, and genomics to delineate angiogenic, immune-inflammatory, proliferative, and metabolic subtypes.

Unique delivery constraints arise from kidney physiology. Very small particles or breakdown products may pass through the glomerular filtration process, while large molecules may get trapped in the liver and spleen. Kidney dysfunction would change the clearance of payloads and metabolites[18]. Therefore, a clinically translatable system would require a model that takes into consideration tumor delivery and kidney function. Variables to include are human pharmacokinetics, glomerular filtration rate, proteinuria, blood pressure, and co-medication.

The possibilities would involve specific delivery of inhibitors to kinases, nucleic acids, metabolic modulators, or immune regulators; however, there is limited clinical experience compared with breast cancer[19]. The biggest strength of this topic is biological definition of the vasculature and immunity surrounding the tumor. The weakness lies in lack of human studies in which a nanoparticle shows a better result than an optimized system therapy. In RCC, AI-based nanomedicine would be compelling only if it can reduce side effects, overcome resistance, increase intratumoral exposure, or provide a drug combination that is not tolerable otherwise.

3.4 Brain Cancers

The brain tumors represent the greatest delivery obstacle[20]. Blood-brain barrier, heterogeneous blood-tumor barrier, efflux transporters, increased interstitial pressure, diffuse infiltration, as well as vascular permeability changes as a result of treatment all limit access of drugs. Glioblastoma displays high spatial and temporal heterogeneity. Magnetic resonance imaging can recognize enhancing tumor, non-enhancing infiltration, edema, necrosis, and perfusion, but enhancement is not an adequate marker of drug delivery.

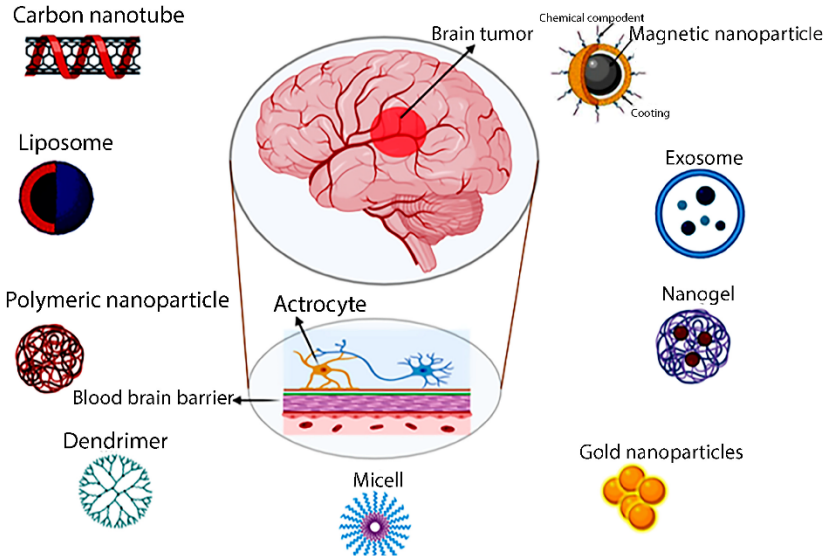

Figure 2. Nanocarrier platforms for targeted drug delivery across the blood–brain barrier in brain cancer.

This includes segmentation, radiomic phenotyping, prediction of barrier permeability, separation between progression and therapy effect, and fusion of imaging and biomarkers[21]. Nanomedicine-based approaches involve systemic carrier systems developed for receptor-mediated transcytosis, local delivery into resection cavity, convection-enhanced delivery, implantable depot formulations, and focused-ultrasound-assisted barrier modulation. These represent different solutions to different parts of the delivery problem[22]. Local delivery circumvents systemic barriers but cannot penetrate into infiltrating tumor cells; systemic delivery can target disseminated regions but suffers from low and heterogeneous penetration.

For human-centric testing of brain nanomedicines, a strategy for testing which includes direct measures like PET scanning, assessment of the concentration of drugs in tissues, and pharmacokinetics of plasma and cerebrospinal fluids needs to be used. Given that imaging results can be biased due to pseudoprogression, effects of radiation, corticosteroids, and antiangiogenic treatment, they cannot be considered alone for evaluating the effectiveness of treatment. The future should see the use of theranostics and adaptive methods combining imaging and targeted drug delivery[23].

Table 1. Comparative Human-Centered Translational Profile Across Four Cancers

Cancer	Dominant barrier	Most relevant human data	Promising nanomedicine role	AI contribution	Key translational weakness
Liver	Cirrhosis, macrophage uptake, variable perfusion	Multiphasic CT/MRI, liver function, tumor and cirrhotic	Locoregional or image-verified targeted delivery	Radiomic selection, arterial planning, toxicity	Competing liver failure and rapidly changing systemic

		organoids		prediction	therapy
Breast	Subtype and receptor heterogeneity	Pathology, HER2/HR status, multi-omics, serial biopsies	Toxicity-reducing formulations and subtype-targeted combinations	Subtype classification, target quantification, response prediction	Unselected trials and target evolution
Kidney	Renal clearance, vascular and immune biology	Renal function, CT/MRI, pathology, immune and angiogenic markers	Combination delivery and toxicity mitigation	Phenotype integration and renal safety modeling	Limited prospective clinical nanomedicine evidence
Brain	Blood–brain/blood–tumor barriers and infiltration	MRI/PET, resection tissue, CSF, microdialysis	Barrier-crossing, local delivery, theranostics	Barrier mapping, segmentation, adaptive monitoring	Delivery verification and misleading imaging endpoints

4. HUMAN-CENTERED CLINICAL TRANSLATION, EVALUATION, AND IMPLEMENTATION

The primary question regarding translation is not whether AI is able to predict some formulation property, or whether some nanoparticle is able to kill cancer cells in culture. The issue here is whether the whole system makes an improvement in clinically relevant human outcome. It requires a proper evidence hierarchy, prospective design, scalability and regulation[24].

4.1 Human Evidence Hierarchy and Clinical Trial Methodology

An evidence hierarchy starts from curated human databases and ex vivo studies, followed by patient-specific organoid and slice models, early-stage pharmacology and safety tests, proof-of-delivery test, biomarker-enabled efficacy studies, and comparison with standard therapy. At each stage, a different question is being answered[25]. Organoids provide relative sensitivity information, phase I provides safety and pharmacokinetic information, imaging and biopsy provide proof of delivery, and randomized trials provide information on the clinical benefit.

Early-stage studies need to include more than just the maximum tolerable dose. In the case of nanomedicine, a lot needs to be known about the exposure of the nanoparticle system, its association and release of the drug, immunogenicity and complement activation, and infusion reaction[26]. Organ function, lesions-level delivery, and sampling scheme should provide

knowledge about the kinetic of the carriers and payloads. If AI is being used for selection and dosing, then all of this needs to be prespecified.

An enriched adaptive trial design is an appropriate approach. Patients can be divided according to delivery predictions, target expression, and sensitivity to the payload. Interim analysis is also possible as long as allocation can be updated without compromising the validity of statistics[27]. Basket trial designs are able to test a molecule-defined target in different organs, while organ-specific trial designs can take into account different delivery hurdles. The biggest drawback of small one-arm trials is the confusion between pharmacokinetic novelty and therapeutic superiority.

4.2 Manufacturing, Quality-by-Design, and Regulatory Considerations

Quality attributes that could affect nanomedicine product performance include particle size distribution, morphology, surface chemistry, ligand density, encapsulation efficiency, free drug content, release characteristics, sterility, endotoxins, residual solvents, aggregation, and stability[28]. AI can be used to analyze data from processes, identify deviations, predict batch failure, and aid real-time release strategies. Quality by Design principles are followed because process parameters are associated with design space.

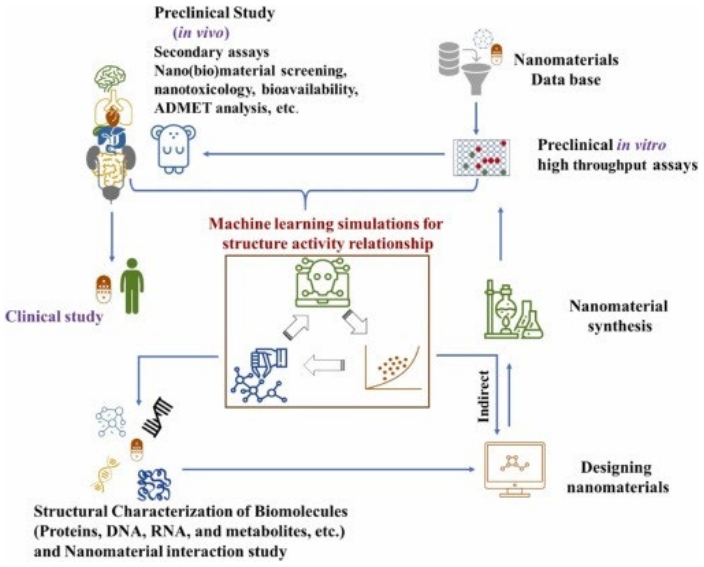

Figure 3. AI-enabled translational pipeline for nanomedicine development from computational design to clinical application.

But the algorithm developed for manufacturing becomes a component of a regulated control system. Model drift, modifications in the software, calibrations in sensors, and the integrity of the data all need regulation[29]. The importance of explainability lies not in the necessity to convert every nonlinear relationship into a simpler one, but in the need to understand what determines the decision and what conditions place the model outside the validation range.

Regulatory evaluation becomes more difficult when the product includes a nanocarrier, drug, imaging agent, companion diagnostics, and an adaptive algorithm. The solution could be in using a modular approach: analytical validation of the formulation, clinical validation of the

biomarker, confirmation of delivery, and then integration and evaluation. The harmonization of terminology and characterization techniques globally is still far from complete.

4.3 Safety, Bias, Explainability, and Real-World Implementation

The safety risks are associated with the nanomedicine itself, as well as the algorithm. They could result in complement activation, affect coagulation, lead to organ deposition, induce infusion reaction, or delayed toxicity[30]. An algorithm that works poorly on a certain group due to their demographic profile, comorbidities, location, imaging modality used, treatment history, or age/sex/ancestry discrepancy might be potentially dangerous for patients with liver cirrhosis, renal dysfunction, autoimmune diseases, or previous brain radiation therapy.

An explainability strategy has to correspond to a particular decision. If the task is to find optimal composition, the attribution of features might be an efficient way to understand what parameters are driving the predictions of stability/toxicity. For patient selection, the clinician needs to understand why certain imaging, biomolecular, and clinical features contribute to a certain prediction. For adaptive dosing, the model has to present its uncertainty and rationale[31].

Interoperability in practical implementation also needs to be maintained among radiology, pathology, genomics, pharmacy, manufacturing, and clinical systems. While federated learning might enable training of models without pooling data together, discrepancies in measurement and processes could continue to result in concealed heterogeneity. Continuous monitoring of performance, tracking of audits, and post-marketing surveillance are essential.

Table 2. Selected Literature and Its Translational Contribution

Author(s) & Year	Study Focus	Key Findings	Translational Contribution
Soltani et al. (2021)[32]	Nanoinformatics for clinical translation of cancer nanomedicine	Highlighted the role of computational modeling, nanoinformatics, and data integration in improving nanoparticle design and accelerating clinical translation.	Demonstrates how standardized nanoinformatics can bridge the gap between laboratory research and clinical implementation of nanomedicine.
Suchkov et al. (2025)[33]	Design-driven precision oncology and translational research	Emphasized personalized oncology through integration of molecular profiling, translational research, and precision therapeutic strategies.	Supports the development of patient-specific AI-assisted nanomedicine and individualized cancer treatment.
Vatta	AI and machine learning in breast	Discussed AI applications for nanoparticle optimization,	Highlights the clinical potential of AI-guided

(2025)[34]	cancer nanomedicine	targeted drug delivery, and personalized management of breast cancer.	nanomedicine for improving precision drug delivery in breast cancer.
Wang et al. (2024)[35]	AI in cancer diagnosis and tumor nanomedicine	Reviewed AI-based imaging, diagnosis, treatment planning, and optimization of nanomedicine for precision oncology.	Demonstrates the integration of AI with nanomedicine to improve cancer diagnosis, targeted therapy, and treatment monitoring.
Wang et al. (2025)[36]	Clinical application of AI in precision cancer treatment	Summarized recent clinical advances of AI in patient stratification, treatment prediction, therapeutic decision-making, and precision oncology.	Provides evidence supporting the clinical integration of AI for personalized cancer treatment and future translational nanomedicine applications.

5. DISCUSSION

There is substantial scientific basis for the integration of AI and nanomedicine from an evidenced perspective, but the level of maturation of the evidence varies at different points along the translational spectrum[37]. AI technology is currently able to detect clinically useful patterns from imaging and pathology, to optimize multidimensional design spaces, and to integrate multi-omics. Nanomedicine has already shown that reformulation via carriers can lead to increased solubility and pharmacokinetics, as well as improved select toxicity profiles. The question remains unanswered regarding whether there is a consistent advantage beyond the individual components.

5.1 Interpretation and Analysis of Findings

The study emphasizes three important aspects of the research – an effective cancer nanomedicine approach must be multi-step and include patient selection, drug delivery, cellular uptake, and response tracking using AI; organ-specific biological differences make it necessary to design an approach specifically for cancers of the liver, breast, kidney, and brain; and the clinical translation of such technology is possible only in case of solving important clinical problems and not complicating the technologies[38]. Nanomedicine usually makes cancer treatment safer, but its clinical significance should be evaluated by its ability to improve patients' results.

5.2 Implications and Significance

These results highlight the need for formulating nanomedicine, diagnostics, and their development clinically right from the start with the aid of AI in selecting patients, developing treatment plans, and monitoring their responses using imaging and molecular biomarkers[39]. Validation of nanomaterials, manufacturing process, software, and companion diagnostics is

equally critical for clinical translation. At the same time, the need for equitable implementation of AI-precision nanomedicine using multicentered studies and diagnostic technologies is crucial to avoid exacerbation of healthcare disparity issues.

5.3 Research Gaps and Limitations

Even with substantial advancements, certain issues still hinder the clinical application of AI-based nanomedicine, including the lack of prospective studies using AI, small and heterogeneous datasets, inadequacy of standardizing the human pharmacological information, organ-specific evidence, external validation of AI models, and failure to account for all aspects of human biology in the organoids[40]. The issues also include issues relating to scaling-up of manufacturing, consistency of batches, and use of narrative instead of clinical data. Importantly, this review only considers human-based information, while not considering animal research to keep the information clinically relevant, even when some of the cited literature needs bibliographic verification.

5.4 Future Research Directions

Future studies must center on the design of standardized nanoinformatics platforms incorporating formulation-related information with clinical data, imaging, pharmacokinetics, and outcomes to enhance AI-enabled precision nanomedicine. The increased incorporation of patient organoids, digital twins, federated learning, and mechanistic AI models along with biomarker-informed adaptive trials will enhance human-centric validation and personalized medicine approaches. Disease- or organ-specific needs should emphasize improved delivery platforms for cancers of the liver, breast, kidney, and brain while maintaining adequate clinical proof, data sharing, and standardized reporting for rapid clinical translation.

6. CONCLUSION

AI-based translational nanomedicine is an innovative technology that may provide new opportunities in developing precision oncology through intelligent nanoparticles and customized treatments. Clinical success of the field is based on multiple targetings, human verification, organ-based treatments for liver, breast, kidney, and brain cancers. In spite of significant advancements in drug delivery and decreased toxicity using nanomedicines, further developments of the field would depend on patient selection using AI, optimized formulations, nanoinformatics, algorithmic transparency, and clinical trials.

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