AI-Driven Prognostication and Treatment Simulation in Interventional Oncology.

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Purpose

- There is an exponential growth in novel therapeutics for cancer and an increased understanding of the tumor environment.
- Expanded availability of oncologic interventions allows improved patient-centered care by customization of therapy to increase efficacy while minimizing side effects.
- Artificial Intelligence (AI) is a revolutionary technology that has the capabilities to analyze extensive amounts of information.
- AI models can be trained to prognosticate diseases and identify optimal treatments by integrating radiomics, genetic profiles, and clinical presentation.

Methods

We conduct a comprehensive review of the latest literature featuring AI models that have been incorporated into treatment prognostication. Data is collected from the latest published narrative reviews, retrospective studies, and clinical trials. Findings are presented in text and figure format covering current technology trends, future directions, and limitations.

The Process

- The workflow of AI in prognostication and optimal choice of treatment involves the preprocessing of medical images to reduce noise. Thereafter, images are processed to segment tumors and extract radiomic data, which can be combined with clinical, genetic, and histopathological data to identify optimal treatment. These models require thorough external and cross-validation to achieve accurate and reliable results[1].

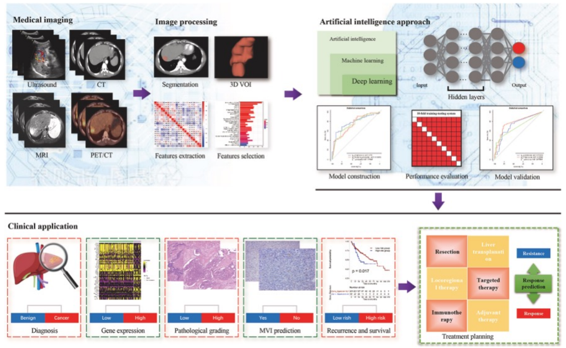

Fig. 1[1]. Schematic adopted from Bo. et al. depicting the workflow of AI model training and validation as well as its use in clinical settings. Models multiple modalities of data to identify optimal therapy.

Results

- Literature analysis of 18 studies covering 4861 cases showed that AI models trained in prognostication of non-small cell and small lung cancer achieved area under the curve (AUC) values ranging from 0.73 to 0.92, while the tumor, node, metastasis framework achieved an AUC of 0.61[2].
- The response of hepatocellular carcinoma (HCC) to transarterial chemoembolization (TACE), radiomics-based AI models have achieved AUCs of 0.79 (95% CI: 0.75–0.82) while non-radiomics counterparts have AUCs of 0.73 (95% CI: 0.61–0.77). Models combining clinical and radiomic features outperformed models using solely clinical data to predict treatment response[3].
- Plachouris et al. trained a deep learning model to predict the distribution of Yttrium-90 microspheres across liver parenchyma through radioembolization. The model achieved an average absorbed dose of 5.42% ± 19.31% and 0.44% ± 1.64% for the tumor and healthy liver tissue, respectively[4].
- Neural network models can predict recurrence after radiofrequency ablation in liver cancer, achieving a C-index of 0.855[5]

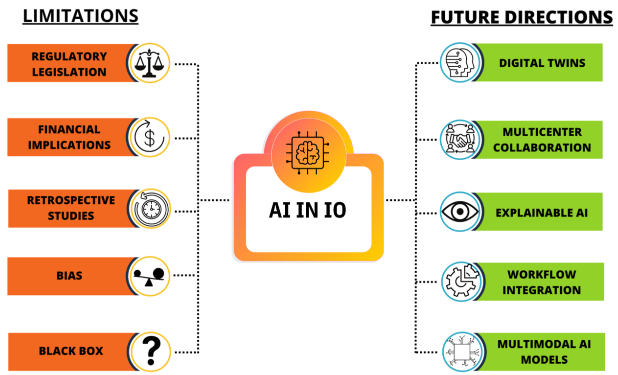

Fig. 2. Visual representation of the discussed Limitations and Future Directions of AI in Interventional Oncology.

Limitations and Barriers to Clinical Implementation

- Lack of standardized regulatory legislation and frameworks pertaining to the use of AI in medicine, compounded with data privacy concerns.
- Significant financial capital for technological upgrades required for the operation of AI models, as well as expert personnel for implementation and maintenance[7].
- An expansive range of studies present, however, most are retrospective in nature.
- Bias in datasets and models.
- "Black Box"- Lack of transparency and interpretability raises skepticism among clinicians[8].

Future of AI in IO

- Creation of digital twins for patients, integrating multi-modal data for treatment simulation[9].
- Multicenter collaboration and validation to allow for higher-quality datasets and better-trained models[10].
- Explainable AI to bridge trust between clinicians and AI models[11].
- Integration into clinical workflow.
- More expansive multi-modal data integration as input to AI models.

Conclusion

- AI has shown strong potential in prognostication, prediction of recurrence, and simulation of treatment for multiple therapies and cancers in Interventional Oncology.
- AI models have been found to outperform conventional prognostication methods, particularly when AI models are trained with multimodal data.
- Many factors have hindered the full Implementation of AI models into clinical settings
- Interinstitutional collaboration is essential to improve the training of models and increase accuracy.

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