Review Article GU J Sci, Part A, 12(3): 894-917 (2025) 10.54287/gujsa.1768020

Gazi University
Journal of Science
PART A: ENGINEERING AND INNOVATION
http://dergipark.org.tr/gujsa

The Application of AI in Oncology Research in Türkiye: Impact and Future Directions

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Keywords

Artificial Intelligence
Machine Learning
Cancer
Turkey
Türkiye
Review

Abstract

Artificial Intelligence (AI) techniques such as machine learning and deep learning have seen increasing application in medical diagnosis. The field of oncology has seen the application of AI in cancer detection and diagnosis, treatment selection and survival prediction for patients. This study evaluates recent research in the application of AI in oncology and its potential impact on the Turkish health and medical sectors through a review-based study. We identified 41 research studies from 2020 to 2024 applying AI in oncology utilizing datasets curated from Turkish medical data. Our analysis showed that all studies were retrospective, with the majority being diagnosis studies. Patient datasets were unicentric, relatively small and not publicly available. Thus, most of the reported results cannot be generalized until the models are validated in larger, more diverse studies. The majority of studies concentrated on model accuracy, with limited evidence of model integration in clinical settings or within the health industry. Our findings indicate that more work is required in order to develop more advanced approaches for human-AI collaboration, i.e., clinician–in-the-loop or patient-in-the-loop approaches. An important step toward achieving this is to create and maintain a national dataset for AI in oncology research in Türkiye. Although this study is specific to Türkiye, we anticipate that its findings may be relevant to countries with similar research environments.

Cite

Osman, R., & Arslan, H. (2025). The Application of AI in Oncology Research in Türkiye: Impact and Future Directions. *GU J Sci, Part A*, *12*(3), 894-917. doi:10.54287/gujsa.1768020

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Article Process

Submission Date	19.08.2025
Revision Date	07.09.2025
Accepted Date	22.09.2025
Published Date	30.09.2025

1. INTRODUCTION

Artificial Intelligence (AI) has the potential to revolutionize cancer diagnosis and patient survival rates by analyzing a multitude of factors - including tumor biology, treatment response, and patient health records - that influence a patient's prognosis. Furthermore, AI techniques can be used to detect gene mutations and genetic markers associated with specific cancer types. Early and timely detection of any cancer is crucial in improving patient outcomes, survival rates, and effective treatments. The application of AI and its sub-fields - machine learning (ML) and deep learning (DL) - in cancer diagnosis from medical images, and radiometric and clinical features has enhanced prediction accuracy by 15% to 20% (Mazhar et al., 2023). The impact of AI on the field of oncology, particularly in cancer related diagnosis, has been profound, e.g., the US Federal Drug Administration (FDA) has approved more than 70 AI-augmented clinical devices in oncology between 2015 and 2021 (Luchini et al., 2022), most of which are used in lung, prostate and breast cancer diagnostics.

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Given the potential of AI in oncology, extensive research has been conducted investigating various application scenarios for ML and DL models and methods. Several authors have conducted literature reviews on the application of AI in specific sub-fields of oncology (e.g., head and neck cancer (Mahmood et al., 2021)) and AI-based devices in healthcare (Luchini et al., 2022). There is limited work that investigates the application of AI in the Turkish health sector in general and in diagnosis and prognosis in oncology in particular. Orman and Sebetci (2022) reviewed Turkish articles on AI and ML from 2010 to 2020, finding that over 50% of the publications were authored by researchers from the Engineering discipline and only 7% were from Medical researchers. In a 2021 survey of Turkish health care professionals in breast cancer treatment (Emiroglu et al., 2022), 80% stated that they had never used AI in practice and 70% believed that AI would be most beneficial for early diagnosis. Some Turkish researchers provided general guidelines for mitigating the risks associated with the application of AI in the medical field (Uygun İlikhan et al., 2024). In contrast to previous work, the objective of our study is to gauge the maturity of the application of AI in oncology in Türkiye and to assess both the current and potential impact of such research on the Turkish healthcare system.

1.1. Motivation

International research has shown that AI-enhanced devices have had the largest impact in the area of cancer diagnosis (Luchini et al., 2022). However, the accuracy of AI models and their generalizability is directly related to the quality of training data, which directly influences accuracy and may introduce bias in results. In addition, the promise of individualized, AI-supported medical diagnosis and treatment cannot be fulfilled without validated models tailored to the target populations. Both of these aspects require local medical and health data that is representative of the target population. Furthermore, investigating the application of AI in the medical field across different countries exposes any challenges that are specific to those countries.

Another aspect is that the adoption of AI is constrained by the ability to verify the accuracy of the models and *trust* their results. This is particularly important for medical and health applications. The application of AI in healthcare is a multidisciplinary endeavor requiring collaboration among various entities, which - depending on the academic, research and health system frameworks - may not be straightforward in different countries. An evaluation of the success of such collaborations is important for policy makers and researchers to fully utilize limited resources.

We chose to investigate the application of AI in oncology due to its successful integration in cancer treatment (Luchini et al., 2022) and because of the steady increase in cancer diagnosis in Türkiye (Yılmaz et al., 2011). Similar studies conducted in other countries utilized publicly available data, e.g., government databases as in (Luchini et al., 2022). Unfortunately, such data is not publicly available in Türkiye. Moreover, information relating to public research funding, and research project objectives and results are not publicly available. Consequently, it is difficult to identify and assess industry-academic partnerships and commercially viable research outputs. To overcome this obstacle, we propose conducting a review of recent research articles applying AI in oncology, with a focus on the models used, the dataset characteristics and their clinical applications. Our proposition is that an analysis of Turkish research applying AI in oncology can provide insights into the current and future impact of AI on oncology practice within Türkiye.

1.2. Contributions

In this study, we adopted a literature review approach to examine existing academic research publications in the application of AI in oncology. To achieve the objectives of this study, we focused on publications from Türkiye from 2020 to 2024 that utilize Turkish patient data. Our emphasis on studies using only local patient data stems from the fact that Turkish patient data is the key differentiating factor between studies – even when the same AI models are used – since the local application of AI in oncology necessitates research grounded in country-specific data. The main contributions of this paper are as follows:

- We analyze 41 research articles that apply AI in oncology using Turkish patient data focusing on their impact on clinical practice. The analysis focuses on (1) the types of AI models, (2) patient dataset characteristics, and (3) evidence of clinical or industrial application.
- Our analysis showed that the majority of the research studies were retrospective patient diagnosis studies using relatively small datasets. Thus, the reported results cannot be generalized without being validated in larger-scale studies. Moreover, the majority of the studies lacked evidence of real-world applicability in clinical settings or within the health industry.
- We present recommendations for future research directions in AI in oncology targeting both academic researchers and policy makers in Türkiye.

The remainder of this paper is organized as follows. Section 2 summarizes the methodology used in the systematic literature review and describes how the articles were selected. Section 03 presents the analysis of the articles in terms of study type, model types and dataset characteristics. In addition, we evaluate the applicability of the studies in clinical and industrial settings. In Section 04, we discuss these findings in light of current international recommendations for AI research in oncology and examine their implications for academia and policy makers. Finally, we conclude the paper in Section 05.

2. METHODOLOGY

To achieve the goals of this study, our literature search has to cover multiple disciplines, i.e., medical, engineering, computer science, etc., as the articles targeted in this study can be from any discipline. Furthermore, Türkiye has its own national database for Turkish scholarly publications which may mean that we may find duplicates across different databases. We opted to use Google Scholar to search for relevant articles due to its wide coverage and high recall (Bramer et al., 2013), and its indexing of multiple disciplines from other scientific databases such as PubMed and IEEE Xplore. Furthermore, Google Scholar indexes grey literature, i.e., theses, dissertations, posters and conference papers which can give a general indication of the extent of the research based on local patient data. After determining the articles to be included in this study, we searched for the articles in relevant scientific databases, e.g., PubMed, to give an indication of the quality of the articles included in our study.

Our search objective was to retrieve Turkish articles in the research area with a publication date between 2020 and 2024 inclusive. We limited our study to recent articles as that would give a better indication of the current and future impact of AI in comparison to a more historical search. For the search strategy we used a custom range for the date (i.e., we searched each year individually) using all the following search terms together: cancer Turkey Türkiye "artificial intelligence" OR "machine learning" and chose *sorting by relevance* and *include citations*. For each year, we considered the first 80 results produced by Google Scholar and manually screened all the results, i.e., we screened 400 results for all the years combined. Figure 1 details the search, inclusion and exclusion process. We note that we conducted a parallel Google Scholar search for each year using the same search terms but in the Turkish language. This produced mostly review articles or irrelevant results and only three research studies that would eventually be excluded (two used non-Turkish data and one was a thesis). Thus we opted not to include the Turkish language results in this study.

During the initial screening, we excluded all articles from non-Turkish institutions, articles using patient data for mathematical proofs, and review articles; this resulted in 196 articles. Then, we excluded all studies that utilized datasets of non-Turkish origin, i.e., publically available datasets or proprietary patient data from international institutions. This exclusion criterion would give a better indication of the application of AI research within the Turkish health care sector. Thus, we excluded 120 articles, i.e., 61% of the total articles. The majority of these excluded articles relied on public datasets, e.g., the UCI Breast Cancer Coimbra and Wisconsin datasets (Kelly et al., 2024). Utilizing public datasets is expected in early research and for initial model validation or for researchers outside of the health sector. Unfortunately, these studies represented a large majority of the identified research output, and may indicate a need for accessible research datasets from within Türkiye.

We further excluded another 20 articles: abstracts, theses, conference papers, pre-prints and papers that were inaccessible. Upon further detailed review of the studies, we excluded another 15 articles which included duplicates and articles with ambiguous models or data. This resulted in a total of 41 articles for inclusion.

Table **1** summarizes the included and excluded articles by publication year. The 41 included articles were distributed over a large range of journals, specifically 35 journals. To give a general indication of the quality of the journals and articles, we searched for all 41 articles in PubMed, followed by Scopus, then the TR-Index and DergiPark. The TR-Index (TR Dizin) (2025) is the Turkish national database indexing Turkish scholarly publications and DergiPark (2025) is a publicly funded hosting service provided for Turkish academic publications independent of the TR-Index. If an article is not indexed in PubMed, we continued the search in Scopus and so on until DergiPark. Table 2 gives the distribution of the included journals and articles by indexing database.

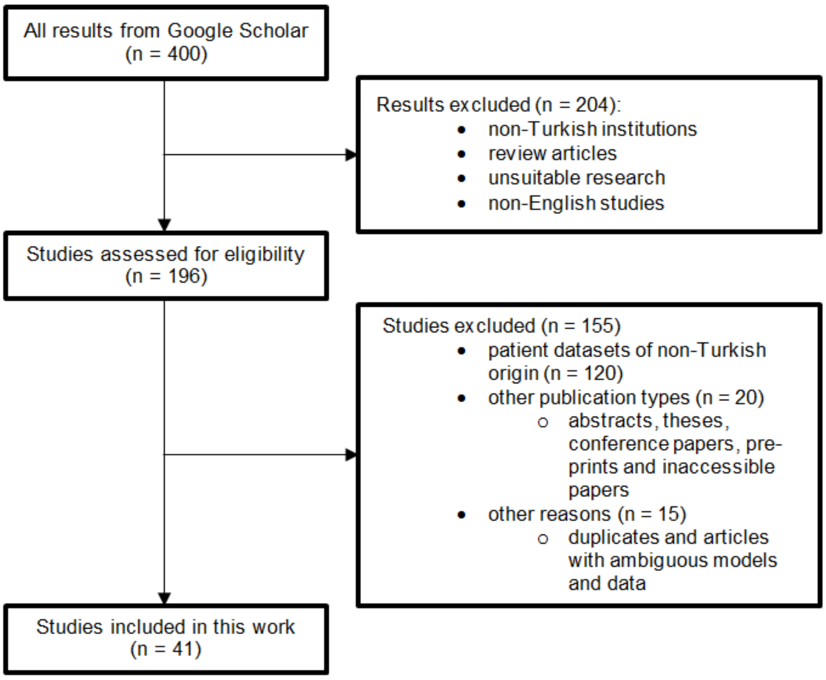

Figure 1. *Search and exclusion process*

Table 1. *Result of article search and the number of excluded and included articles*

Year	Turkish articles	Exclusion				Total included
		Non-Turkish data	Unsuitable article type	Duplicates, ambiguous data	Total excluded	
2020	31	22	2	2	26	5
2021	37	27	0	2	29	8
2022	45	31	1	5	37	8
2023	43	23	3	4	30	13
2024	40	17	14	2	33	7
Total	196	120	20	15	155	41

Table 2. *Indexing databases of included articles*

	# of journals indexed	# of papers
PubMed	21	24
Scopus	9	10
TR-Index	4	6
DergiPark	1	1
Total	35	41

3. RESULTS

Table 3 and Table 4 summarize the studies included in this review. Due to space limitations we give a general summary of the goal of each study and provide the AI model that was reported to give the best performance in each study. For each AI model we provided the reported accuracy (or other performance metrics, i.e., AUC (Area Under the Curve) if the accuracy is not provided). We only provided the general class of the AI models, e.g., Karagoz et al. (2023) adapted the nnU-Net (Isensee et al., 2021), a convolutional neural network-based (CNN) self-configuring medical image segmentation model. However, in the table we only state that the model is CNN. In the following, we analyze the studies and focus on indications of their expected impact on the Turkish health and medical sectors.

3.1. Study Type

All studies were retrospective studies; with approximately a third of the articles (29%) investigating breast cancer, followed by studies investigating brain, lung, or prostate cancer each representing 12% of the studies. This distribution is in line with international trends in the application of AI in oncology (Luchini et al., 2022). Figure 2 details the distribution of all the cancer types investigated in the articles. The studies stated that their main objectives for the application of AI were for diagnosis prediction (63%) and only 23% investigated applications in prognosis prediction. In addition, we note that one study investigated augmenting a diagnosis device with AI (Özsandikcioğlu & Atasoy, 2023), another two studies investigated the prediction of treatment plans for brain (Sümer et al., 2022) and prostate cancers (Alataş et al., 2023), one study examined patients' predisposition to colorectal cancers (Cakmak et al., 2023), and two studies explored the ability of AI to determine the primary cancer based on the type of secondary cancer (Gultekin et al., 2023; Özgül et al., 2023).

In regards to the diversity of the disciplines involved in the research work, we classified the articles into five broad disciplines based on author affiliations. Figure 3 shows the distribution of disciplines within single and multidiscipline research studies. We found that researchers from the *Medical and Health Sciences* collaborated on all (98%) the studies except one. Researchers from the *Engineering and Technology* and *Information Technology and Informatics* areas were authors in 51% and 29% of the papers respectively. When investigating multidisciplinary work, the majority of work (65%) was a collaboration of researchers from multiple disciplines which always included researchers from the *Medical and Health Sciences*. All single-disciplinary studies (35%) were for researchers from the *Medical and Health Sciences*, except for one study – (Arslan et al., 2024) – which had researchers from the *Engineering and Technology* area only.

***Table 3**. Summary of studies (2020-2022) applying AI in ontology using Turkish datasets*

Year	Study	Objective	Best Model	Reported Accuracy
2020	Bicakci et al. (2020)	differentiating ADC and SqCC in lung cancer	CNN	AUC 69%
	Yurttakal et al. (2020)	detection of breast cancer	CNN	98.33%.
	Yazici et al. (2020)	identifying BRCA1/2 gene mutations in breast cancer	DT	92.88%.
	Ayyıldız et al. (2020)	differentiating ADC and SqCC in lung cancer	SEM	AUC 69.63%
	Alis et al. (2020)	the IDH1 status of HGG in brain cancer	RF	86.94%
2021	Kabakçı et al. (2021)	determine the CerbB2/HER2 scores in breast cancer	EBT	90.19%
	Dirican and Akkus (2021)	invasive ductal carcinoma	SVM	AUC 89%
	Ikizceli et al. (2021)	differentiate malignant and benign breast masses	DT	95.2%
	Şimşek et al. (2021)	predicting disease-free survival and overall survival in pancreatic cancer	LGBM	AUC 73% & 78%
	Ekşi et al. (2021)	predict biochemical recurrence after prostatectomy	RF	AUC 95%
	Doğaner et al. (2021)	predict renal cell carcinoma	SEM	90.6%
	Şen et al. (2021)	survival of esophageal cancer patients	1-year: DT 5-year: NB	DT: 64.29% NB: 82.66%
	Turk et al. (2021)	detect malign cases from thyroid nodules	ANN	recall 98% sens. 100%
2022	Hamyoon et al. (2022)	classification of breast lesions	SVC	AUC 88.5%
	Yildirim et al. (2022)	detect prostate cancer	KNN	96.09%
	Seven et al. (2022a)	detection of gastrointestinal stromal tumours	CNN	86.98%
	Yirgin et al. (2022)	diagnose breast cancer	CNN	AUC 8.53%
	Seven et al. (2022b)	predict malignant gastrointestinal tumours	CNN	99.6%
	Baysal et al. (2022)	breast cancer molecular subtypes	ANN	AUC 90%
	Çayır et al. (2022)	mitosis recognition in breast cancer tissue	CNN	prec. 88% recall 34.9%
	Sümer et al. (2022)	predict dose plan based brain tumours shape	GBT	89.36%

ANN: Artificial Neural Network, CNN : Convolutional Neural Network, DT: Decision Tree, EBT: Ensemble-boosted trees, GBT: Gradient Boosting Trees, KNN : k-nearest neighbour, LGBM: Light Gradient Boosting Machine, LR: Logistic Regression, NB: Naïve Bayes, RF: Random Forest, RR: Ridge Regression, SEM: Stacked Ensemble method, SVC: Support Vector Classifier, SVM : Support Vector Machine, XGB: XGBoost

Table 4. *Summary of studies (2023-2024) applying AI in ontology using Turkish datasets*

Year	Study	Objective	Best Model	Reported Accuracy
2023	Ozer et al. (2023)	diagnosis of brain tumours	Deep ANN	97%
	Özsandıkcıoğlu and Atasoy (2023)	enhancing e-nose detection of lung cancer	SVM	95.36%
	Sacli-Bilmez et al. (2023)	predict progression and overall survival from brain tumours	1 year: SVM 0.5 yr: KNN	SVM: 81.71% KNN: 77.41%
	Gultekin et al. (2023)	identifying the primary cancer in brain metastases	CNN	AUC 85 %
	Bulut et al. (2023)	predict pCR after NAC in breast cancer	Deep CNN	84.79%
	Etiz et al. (2023)	predict the response to SBRT in lung cancer	LR	80%
	Alataş et al. (2023)	treatment prediction in prostate cancer patients	XGB	89%
	Yardimci et al. (2023)	prediction of the response to NAC in rectal cancer	RF	81.13%
	Özgül et al. (2023)	differentiating multiple myeloma from osteolytic metastatic bone lesions in the peripheral skeleton	KNN	92.3%
	Cakmak et al. (2023)	identify predisposition to colorectal cancer	KNN	96%
	Karagoz et al. (2023)	detecting prostate cancer	CNN	AUC 86%
	Erturk et al. (2023)	predict lymphoma types	ANN	81%
	Mese et al. (2023)	detect thyroid cancer from nodules	CNN	81%.
2024	Arslan et al. (2024)	predict liver fibrosis/cirrhosis	RF	88.83%,
	Karagöz et al. (2024)	diagnose breast cancer	CNN	95.05%
	Seker et al. (2024)	diagnose breast cancer	CNN AI system	AUC 89.6%.
	Demir et al. (2024)	diagnosis of bladder cancer	CNN	blood: 97.3% urine: 95.3%
	Ozbozduman et al. (2024)	Gleason grade group upgrade prediction in prostate cancer	all: SVM GG>:RR	SVM: 85.6% RR: 90.4%
	Öztürk et al. (2024)	Predict bone metastasis in head and neck squamous cell carcinoma	SVM	AUC 99%
	Canayaz et al. (2024)	detect malign cases from thyroid nodules	XGB	97.98%

ANN: Artificial Neural Network, CNN : Convolutional Neural Network, DT: Decision Tree, EBT: Ensemble-boosted trees, GBT: Gradient Boosting Trees, KNN : k-nearest neighbour, LGBM: Light Gradient Boosting Machine, LR: Logistic Regression, NB: Naïve Bayes, RF: Random Forest, RR: Ridge Regression, SEM: Stacked Ensemble method, SVC: Support Vector Classifier, SVM : Support Vector Machine, XGB: XGBoost

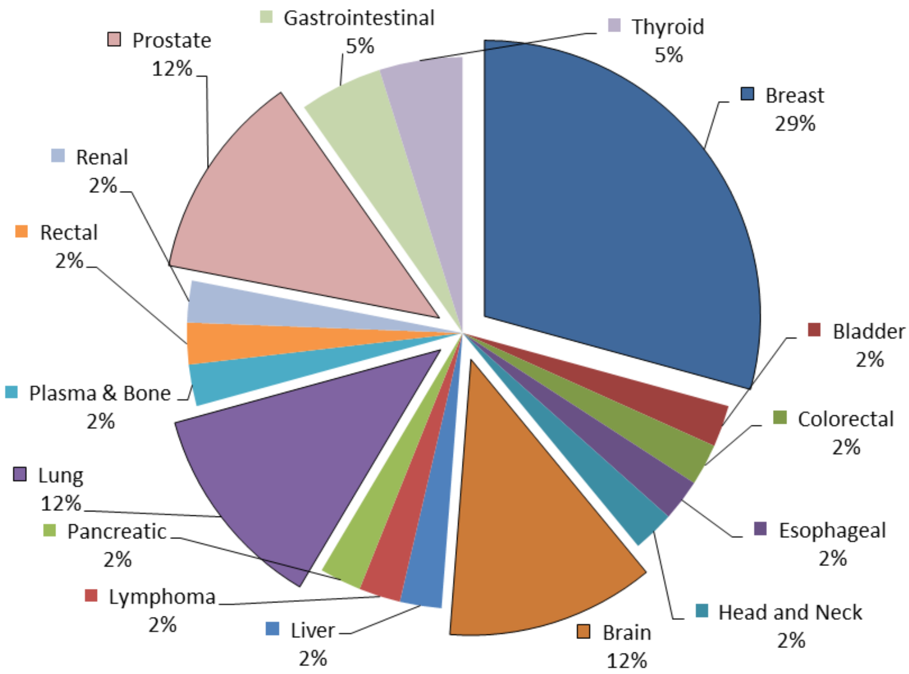

Figure 2. *Distribution of cancer types in the identified studies*

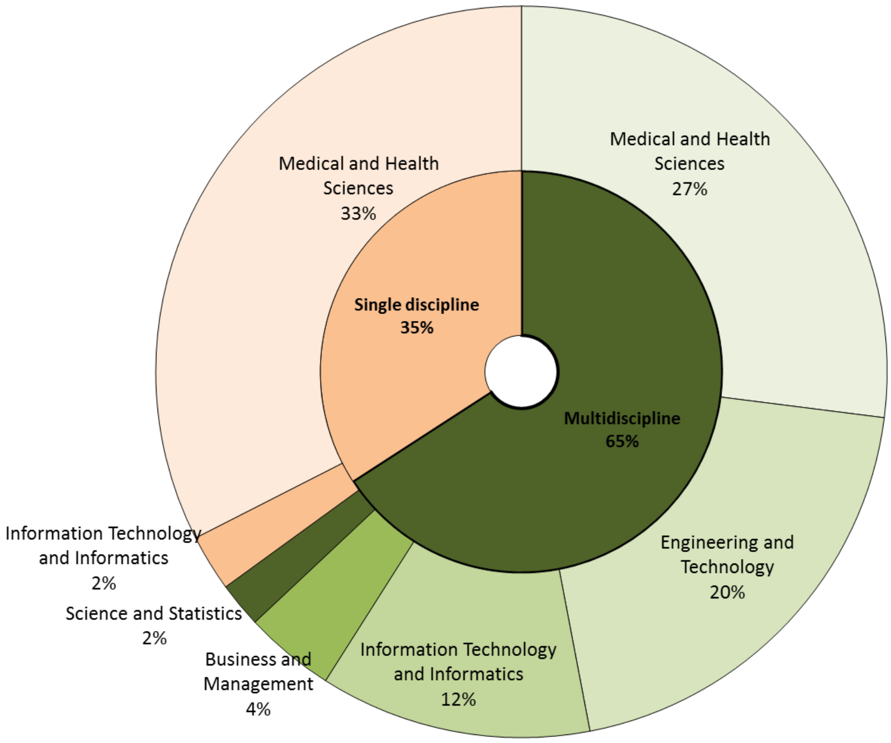

Figure 3. *Distribution of disciplines in the identified studies*

3.2. AI Models

The studies implemented a diverse set of ML models which include k-nearest neighbor (KNN), support vector machine (SVM), decision tree (DT), random forest (RF), multilayer perceptron (MLP), logistic regression (LR), ensemble techniques, and Adaboost. Deep learning techniques included convolutional neural network (CNN), SqueezeNet, VGG11, VGG16, VGG19, ResNet, GoogleNet, and Xception. Both DL and ML models were used for preprocessing the datasets, feature selection and for predicting the result. The choice of model type in each step depended on the objectives of the study and the medical data used for training and validating the model.

Most studies compared the accuracy of DL and ML methods, e.g., Dirican and Akkus (2021) compared the performance of SVM, RF, and artificial neural networks (ANN) in predicting the survival of patients with invasive ductal carcinoma. Other researchers used different models for feature selection and for classification. For example, Canayaz et al. (2024) evaluated the CNN-based models: IncetionV3, DenseNet121, and SeResNet101 for deep feature extraction from chest CT lung images. Then the ML methods: KNN, SVM, Ridge classifier, and XGBoost were compared for their ability to identify benign and malignant nodules. Figure 4 details the distribution of the AI models based on the best performing models reported in the studies. Deep learning models are implemented for prediction in 40% of the studies. This corresponds to the percentage of studies that use medical images for training and validating their models (see Figure 7).

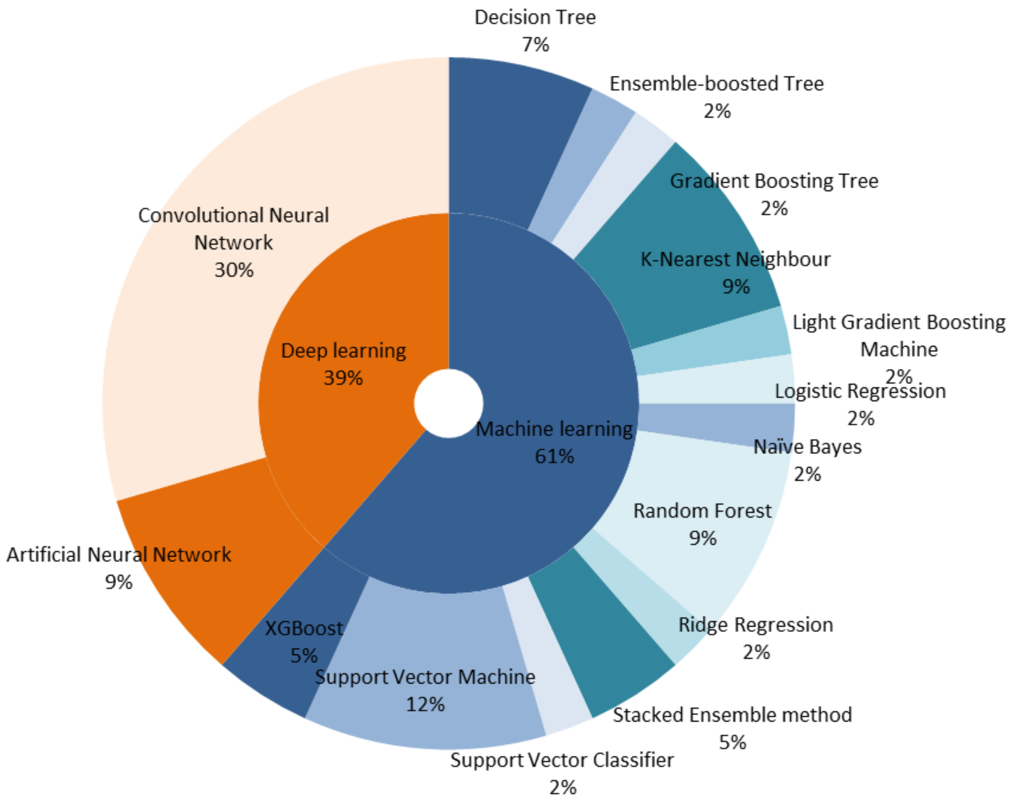

Figure 4. *Distribution of DL and ML models in the identified studies*

3.3. Evidence of Clinical Application

The majority of studies concentrated on model accuracy and did not show any evidence of the incorporation of the models in clinical practice. Two studies compared their modeling results with known diagnosis software applications. Kabakçı et al. (2021) compared their ML augmented CerbB2/HER2 breast tissue image scoring method to that of the ImmunoMembrane (Tuominen et al., 2012) HER2 image analysis grading software. Cakmak et al. (2023) attempted to predict the predisposition of patients to colorectal cancer based on genetic markers. The authors showed that their ML classifiers outperformed ColonFlag (Kinar et al., 2017); the current state-of-the-art commercially available approach.

Two breast cancer studies, (Yirgin et al., 2022) and (Seker et al., 2024) both from the same institutions, provided results that may have the potential to be extended into clinical practice. First, an initial study was conducted with a relatively small patient cohort (221 mammograms) (Yirgin et al., 2022) and then a more comprehensive study was conducted with 4282 patients and 5136 mammograms (Seker et al., 2024). The authors evaluated the Lunit INSIGHT MMG (Lunit Inc., 2024) application which is an internationally developed AI diagnostic support software which detects and diagnosis breast cancer from mammograms. Both studies showed an improved cancer detection rate when radiologists are assisted by the AI system as a second reader and when the AI system is used as a triage mechanism (Seker et al., 2024). In addition to improved diagnosis accuracy, results showed that the assisting AI system offered the potential of decreased staff workloads in breast cancer screening programs.

3.4. Evidence of Health İndustry Application

The majority of the surveyed studies followed the trend of using AI for diagnosis purposes. However, only five studies presented research that can be perceived as indicative of future device or health application implementations. A 2021 study by Şimşek et al. (2021) that evaluated the prediction accuracy of deep learning models for the prognosis of pancreatic cancer patients was funded by an AI medical company, in which one of the authors was a shareholder. In another study, by Sacli-Bilmez et al. (2023), one author was affiliated with a biotechnology company, however, we did not find any online presence for that company.

Çayır et al. (2022) presented MITNET, a tool implementing a two-stage deep learning approach to determine the prognosis of breast cancer patients based on detecting mitosis in breast cancer tissue. The majority of authors were from an AI pathology solutions company and the research was funded by the teaching hospital in which some of the authors were affiliated. The source code of the MITNET tool is provided on GitHub under the company’s account. Özsandıkcıoğlu and Atasoy (2023) presented an ML enhanced breath analyzer for the detection of lung cancer, however, we did not find any evidence that the device was ever produced. Karagoz et al. (2023) investigated the accuracy of a deep learning biomedical image segmentation method in detecting prostate cancer. The majority of authors were affiliated (co-founders, CEO and employees) with an AI-based medical imaging company. The source code for their method is shared on GitHub under the first author’s account.

3.5. Datasets

3.5.1. Dataset Diversity

The majority of studies (93%) used unicentric data procured from their respective institutions. This may affect the generalization of the results of these studies, as the models may be biased towards the specific cohort of patients in each study. Furthermore, diversity in patient lifestyles, socioeconomic status, geographic region and genetic disposition are important factors that must be considered when developing AI solutions for the public health system (Uygun İlikhan et al., 2024).

Three studies only used data from multiple centers. In one study, Karagöz et al. (2024), incorporated a large diverse cohort of patient data collected from the cancer early detection, scanning, and education centers (KETEM) of the Turkish Ministry of Health in Kayseri Province. The dataset had a cohort of 23,258 women that provided 92,938 mammography images. However, due to the (natural) imbalance in the dataset the authors reported further work was required to increase the accuracy of their proposed models. In another study, Karagoz et al. (2023) used the MRI scans from a cohort of 1236 prostate patients' from 9 centers. Another study evaluated a breast cancer ML classifier on three patient cohorts, two cohorts from two international centers and one Turkish cohort from one center (Hamyoon et al., 2022). The Turkish data was used for external validation of the proposed model.

3.5.2. Dataset Availability

Given the nature of the data, all studies did not provide public access to their data. Only the study by Kabakçı et al. (2021) indicated that their dataset was publicly available. However, access to the data via the provided web link required author permission. Nonetheless, given the number of studies in this survey, more cooperation between different research groups can facilitate conducting larger studies by combining the currently available data. This would significantly enhance the robustness and reliability of the findings of future studies.

3.5.3.Dataset Size

Figure 5 details the distribution of the number of patients per study. More than 50% of the studies had a cohort of less than 150 patients. For the majority of studies (63%) the dataset size was similar to the number of patients, i.e., one data item per patient. For the remaining studies, researchers collected more than one data item per patient; this ranged from a slight increase in the dataset size, e.g., 224 images from 221 patients in (Baysal et al., 2022); to a much higher increase in dataset size, e.g., a lung cancer study collected 1457 PET/CT images from 94 patients (Bicakci et al., 2020) and one breast cancer study extracted 7565 patches and cell images from 329 patients and, as stated above, the Kayseri Province study collected 92,938 mammography images from 23,258 women. Figure 6 shows the distribution of dataset sizes for these studies.

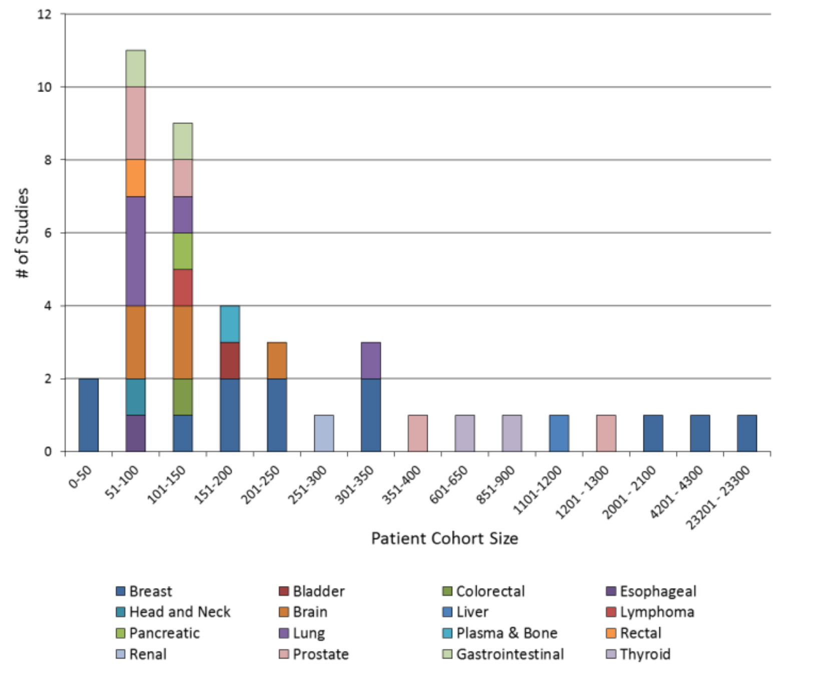

Figure 5. *Distribution of the studies based on patient cohort sizes*

As illustrated by Figure 5, most of the datasets in the studies are relatively small, which may lead to overfitting and thus impacting the reliability of the models. To overcome the limitations of these small datasets, some studies oversampled the minority class in the training dataset (e.g., (Seven et al., 2022a; Etiz et al., 2023; Sacli-Bilmez et al., 2023; Yardimci et al., 2023)), other studies (e.g., (Gultekin et al., 2023; Ozer et al., 2023; Demir et al., 2024)) utilized models pre-trained on the ImageNet dataset (Deng et al., 2009) and a few studies (e.g., (Çayır et al., 2022; Karagoz et al., 2023)) utilized publicly available cancer datasets to train their models.

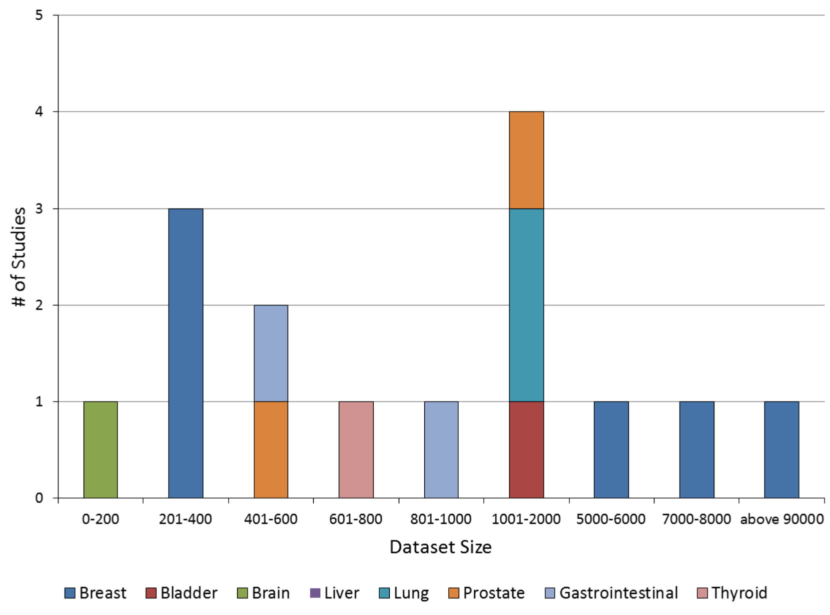

Figure 6. *Dataset sizes for studies that had more than one data item per patient*

3.5.4. Dataset Data Types

Most studies used a single type of data for training and validating the AI models. Image data – such as CT, MRI, mpMRI, PET/CT, mammograms, and ultrasound – was the most commonly used. This was followed by clinical, pathological, and histological data, either alone or combined with demographic features. Figure 7 illustrates the distribution of data types used within these studies. The relationship between the cancer types and the data types in the studies is detailed in Figure 8. The dominance of some cancer types, i.e., breast, brain, lung and prostate, has most likely influenced the distribution of data types seen in Figure 7.

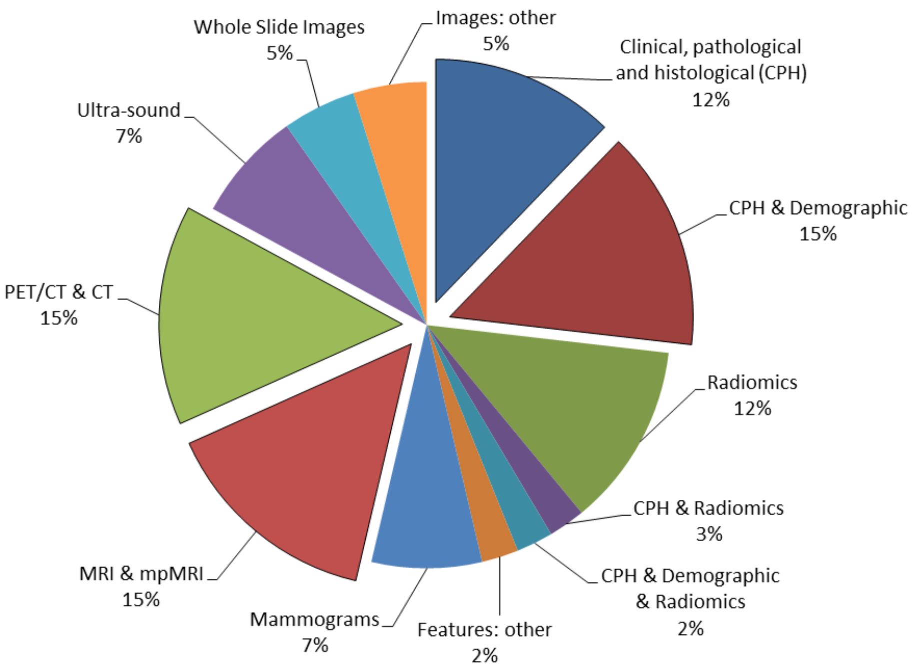

Figure 7. *Distribution of data types used in the studies*

3.6. Funding

The majority (68%) of articles stated that their research was not funded. The remaining (32%) studies reported diverse sources of funding: six articles (Ayyildiz et al., 2020; Bicakci et al., 2020; Karagoz et al., 2023; Özsandikcioğlu & Atasoy, 2023; Sacli-Bilmez et al., 2023; Demir et al., 2024) stated that the Scientific and Technological Research Council of Türkiye (TÜBİTAK) funded their research, five studies (Yazici et al., 2020; Çayır et al., 2022; Sümer et al., 2022; Alataş et al., 2023; Cakmak et al., 2023) were funded by their respective institutions, one study (Şimşek et al., 2021) as funded by an industrial partner and one study (Turk et al., 2021) received international funding.

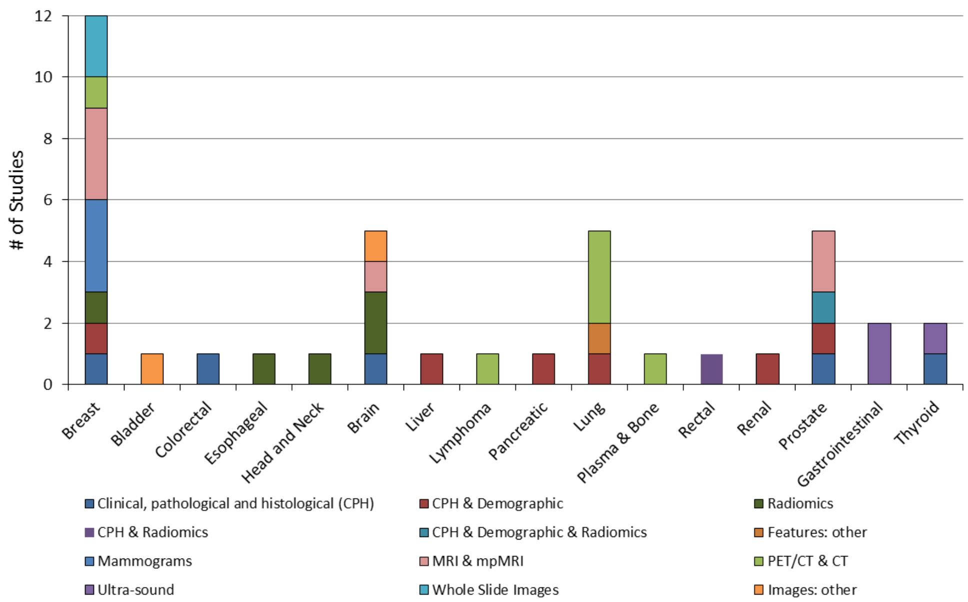

Figure 8. *Distribution of data types based on cancer type*

4. DISCUSSION

Rajpurkar et al. (2022) outlined key research directions to enable the full potential of AI implementation within the medical field. These research directions include: (1) the curation of improved datasets, i.e., realistic heterogeneous datasets with multimodal data; (2) moving beyond labelled data and supervised models towards self-supervised and semi-supervised methods; (3) placing more emphasis on clinical deployment and on AI and human collaboration; and (4) increasing trust in AI medical systems. We further analyze our findings in light of these research directions.

Based on our results and the guidelines identified in (Rajpurkar et al., 2022), it is clear that further work is required in the application of AI in oncology research in Türkiye. Researchers must expand the field beyond conventional retrospective and validation studies. In addition, there is a need for studies that utilize heterogeneous patient data and multiple data types that are collected from multiple centers. The current trend, as observed in our study, of focusing on single data type studies – particularly the prevalence of medical images – should be re-evaluated in order to develop more realistic and generalizable AI models. Research that integrates multiple data types with medical images will require more investigations exploring self-supervised and semi-supervised learning approaches.

For AI to have a meaningful impact on oncology practice in Türkiye, more studies are required that utilize multi-centric data, that are prospective, and are evaluated in clinical settings with the objective of realistic clinical AI applications. This entails increased collaboration with industry and a stronger focus on research with practical, translational potential. Clinician–in-the-loop or patient-in-the-loop investigations such as (Seker et al., 2024) should be prioritized. Multidisciplinary research efforts should be further encouraged and actively funded in order for clinical practitioners to fully leverage AI, understand its limitations, and improve its accuracy.

For ethical and regulatory requirements, *trustable* AI systems are essential. One facet of trustable AI models is *explainability* in which models are *white boxes* clearly explaining how they arrived at their predictions. Another facet is model accuracy, i.e., models that can be proven to produce accurate results. Our findings illustrated that the current studies have an overall focus on model accuracy. However, given the critical role of AI in healthcare, demonstrating the accuracy of models is not sufficient (Charilaou & Battat, 2022). Further research is required to develop explainable models that clinicians can trust and interpret and thereby ensuring safe and effective integration into clinical practice.

Trustable models require reproducible research and results; which in turn require public (or semi-public) datasets, models and code. Datasets must be heterogeneous, multi-centric and of sufficient size to support result generalization and prevent model overfitting (Charilaou & Battat, 2022). As this paper illustrates, collecting suitable datasets - in terms of size and heterogeneity - is a significant challenge for researchers. Given the inevitable incorporation of AI into medicine and into health services, a national dataset for AI in oncology research in Türkiye should be created and maintained. This would not only empower researchers in the field to advance the current state-of-the-art in AI in oncology, but also contribute valuable new datasets to the international AI and medical communities. This Turkish medical dataset should aim to mitigate the biases currently reported in international medical datasets (e.g., see (Cirillo et al., 2020; Larrazabal et al., 2020)). Another important consideration is the timeliness and relevance of the data, given that disease management and treatment regimens evolve over time (Naqa et al., 2023). Therefore, the collected data may need to be augmented with clinical context and an associated validity period.

4.1. Implications for Academia

The application of AI in oncology requires a multi-disciplinary effort and our results have shown that this is the case among Turkish researchers. However, the limited impact of current research indicates that greater national-level collaboration is required, especially in regard to datasets and patient data. Such collaborations will help to avoid repetitive and wasteful research that more or less replicates similar methods and findings. Clearly, there is limited funding available; therefore, research should be more strategically focused and clearly defined in order to achieve broader impact on the medical and health services. This is essential to fully leverage AI models, understand their limitations and enhance their accuracy and explainability. Moreover, achieving this goal requires a new perspective to the teaching of AI in medical education, one which incorporates the latest advancements in AI modelling and its application within the medical field. The limited impact of the studies signifies some deficiencies in the teaching of AI in Turkish medical departments. This issue has also been raised by Turkish researchers (Civaner et al., 2022; Gencer & Gencer, 2024).

4.2. Implications for Policy Makers

For AI research to effectively impact the health sector in Türkiye, more targeted funding is required to support the transition of AI applications to the clinical and implementation stages. This, in turn, will facilitate the development of an AI-driven medical industry. Comprehensive national policies will be necessary to guide the integration of AI in clinical practice, medical devices and health applications, especially to support the anticipated clinician–in-the-loop and patient-in-the-loop applications.

In the *Government AI Readiness Index 2024 Report* (Nettel et al., 2024), Türkiye ranked 53rd out of 188 countries, with a total score of 60.63, improving on its ranking in 2020. While the country ranked 2nd in the *South and Central Asia* region, it fell below the average score (69.56) for the *Western Europe* region. One of the priorities outlined in the Turkish *National Artificial Intelligence Strategy 2021-2025* (Digital Transformation Office, 2021) was *facilitating access to quality data* – a goal, which for the health sector, was to be supported by the *Türkiye Health Data Research and Artificial Intelligence Applications Institute* (Türkiye Health Data Research and Artificial Intelligence Applications Institute, 2025) established in 2022. However, based on our findings, more effort is required in the area of medical and health datasets, especially in regard to creating and maintaining a national dataset for AI in oncology research in Türkiye.

5. CONCLUSION

In this study, we focused on research articles published between 2020 and 2024 that applied AI in oncology utilizing data from Turkish patients. Our proposition is that analyzing the research in these articles provides insight into the current impact of AI on oncology practice in Türkiye. Our results showed that the majority of studies were retrospective with the aim of predicting patient diagnosis using relatively small, unicentric datasets. This limits the generalization of the reported results as the implemented models require validation in larger, more diverse studies. Moreover, the majority of the studies did not show evidence of applicability in clinical settings or within the health industry.

One limitation of this study is that it is specific to Türkiye, and thus the results may not be directly generalizable to other countries. However, in contexts where access to public data is limited, a systematic review can serve as a proxy for assessing the current state and impact of AI research. Another limitation is that some relevant publications may have been missed. Nonetheless, given the goals of our study, we believe we have reviewed a sufficient number of articles to present a realistic indication of the impact of AI in oncology research on the medical and health sectors.

For AI to have a meaningful impact on oncology practice in Türkiye, more studies are required that are multidisciplinary, that utilize multi-centric and multimodal patient data, that are prospective and that are evaluated in clinical settings. Increasing funding is necessary to fully leverage AI models, better understand their limitations and enhance their accuracy and explainability. In addition, further work is required to develop approaches that foster human and AI collaboration, i.e., clinician–in-the-loop or patient-in-the-loop approaches. Due to the sensitive nature of medical and health data, robust public policies are required to facilitate and coordinate AI research in oncology, ensuring the development of tools and methods that can be effectively implemented across the medical and health sectors. Therefore, establishing a strong national research agenda is essential for the successful adoption and application of AI in oncology.

AUTHOR CONTRIBUTIONS

Conceptualization, H.A. and R.O.; methodology, R.O.; title, R.O.; formal analysis, R.O.; research, R.O. and H.A.; sources, R.O. and H.A.; manuscript-original draft, R.O. and H.A.; manuscript-review and editing, R.O.; visualization, R.O.;. All authors have read and legally accepted the final version of the article published in the journal.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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