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Research paper

## Trends in cardiology and oncology artificial intelligence publications



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### ABSTRACT

**Study objective:** To determine whether there has been growth in publications on the use of artificial intelligence in cardiology and oncology, we assessed historical trends in publications related to artificial intelligence applications in cardiology and oncology, which are the two fields studying the leading causes of death worldwide. Upward trends in publications may indicate increasing interest in the use of artificial intelligence in these crucial fields.

**Design/setting:** To evaluate evidence of increasing publications on the use of artificial intelligence in cardiology and oncology, historical trends in related publications on PubMed (the biomedical repository most frequently used by clinicians and scientists in these fields) were reviewed.

**Results:** Findings indicated that research output related to artificial intelligence (and its subcategories) generally increased over time, particularly in the last five years. With some initial degree of vacillation in publication trends, a slight qualitative inflection was noted in approximately 2015, in general publications and especially for oncology and cardiology, with subsequent consistent exponential growth. Publications predominantly focused on “machine learning” (n = 20,301), which contributed to the majority of the accelerated growth in the field, compared to “artificial intelligence” (n = 4535), “natural language processing” (n = 2608), and “deep learning” (n = 4459).

**Conclusion:** Trends in the general biomedical literature and particularly in cardiology and oncology indicated exponential growth over time. Further exponential growth is expected in future years, as awareness and cross-disciplinary collaboration and education increase. Publications specifically on machine learning will likely continue to lead the way.

## 1. Introduction

Artificial intelligence (AI) is a broad concept describing computer-performed tasks that would normally require human intelligence. AI applied to medicine has impacted several disciplines, but may have the broadest applications in cutting-edge research-oriented fields such as cardiology and oncology. Cancer and cardiovascular diseases are the leading causes of death [1,2], and may benefit from applications of AI to elucidate pathophysiology and opportunities for prevention and early diagnosis. Great evidence of growth in a field can come from acceleration in publications indicative of advancement and potential impact in the field. Yet, this has not been objectively assessed for AI publications in

the general biomedical literature, nor specifically for the prominent fields of cardiology or oncology.

AI plays a crucial role in our daily lives and our interactions with technology. There is increasing interest in the implementation of AI in healthcare. A main driver of AI in healthcare is the application of machine learning (ML) algorithms, which are a subset of AI and glean and use insights from training datasets to perform tasks and make predictions without explicit additional programming [3,4]. Deep learning (DL) is a form of ML that is also based on pattern recognition and uses layered artificial neural networks to assess data at different levels of abstraction, to automate complex cognitive tasks that may not yet be clearly delineated [5,6]. Natural language processing (NLP) is another

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subfield of AI, in which computer-based algorithms analyze, process, and transform natural language data into a form ready for computation [7–9]. All of these forms of AI have utility in healthcare, including in cardiology and oncology [10].

In healthcare, there is great hope for the potential of AI to impact data management and aid in clinical decision-making as we continue to propel clinical practice and biomedical research into the precision medicine era. Ultimately, AI promises to improve quality of care and patient outcomes in a data driven, automated, and cost-effective manner. AI already has applications in the interpretation of biomedical data, including radiographic scans, skin lesions, pathology slides, vital signs, electrocardiograms, faces, and so on, as well as in the measurement of patient data in real time using wearable biometric monitoring devices, and in the guidance of biomedical interventions. Such applications yield rapid accurate image and pathological interpretations, potential reduction of diagnostic error, systematization of treatment decisions, and prognostication [11–15] and have the potential for AI to improve healthcare globally. Growth in the use of AI in biomedicine should lead to growth in the numbers of publications on AI in medicine. Yet, there is no objective analysis of publication trends describing the overall use of AI in medicine, particularly in cardiology and in oncology.

There is literature providing the state-of-art, promises, and challenges of AI in cardiology and in oncology [11,16–18], yet their scope does not include the historical trends or any bibliometric analysis indicating the increasing use of AI use in cardiology or oncology. In this study, we hypothesized that the numbers of publications related to AI have accelerated over time in the general biomedical literature and particularly in cardiology and oncology, especially in recent years. AI publications in cardio-oncology alone are not assessed in this manuscript, given the nascence of the field and the presence of this manuscript in a series with other manuscripts describing opportunities for artificial intelligence in cardio-oncology.

## 2. Methods

### 2.1. Database

Using the MEDLINE PubMed database of the US National Library of Medicine (the biomedical repository most frequently used by clinicians and scientists in these fields), we performed a cross-sectional study to review historical trends in AI-related publications up until May 2019, which included all data available at the time of the analysis.

### 2.2. Inclusion criteria

Articles were included in the analysis if the title or abstract referred to “artificial intelligence” or its subcategories “machine learning”, “natural language processing”, or “deep learning”. Publication trends using these four terms were also considered in the context of cardiology publications alone (searching for “cardiology”, “cardiac”, “cardio”, or “heart”), or oncology publications alone (searching for “oncology”, “oncologic”, “oncological”, “cancer”, “malignancy”, “malignant tumor”, “malignant neoplasm”, “chemotherapy”, “radiation therapy”, or “radiotherapy”).

### 2.3. Exclusion criteria

Articles were excluded from the analysis if the title or abstract did not include one of the terms “artificial intelligence”, “machine learning”, “natural language processing”, or “deep learning”.

### 2.4. Data mining

The database was mined using a combination of keywords in a search strategy modeled as follows: ((artificial intelligence[Title/Abstract]) OR

(machine learning[Title/Abstract]) OR (natural language processing [Title/Abstract]) OR (deep learning[Title/Abstract])) AND (cardiology [Title/Abstract] OR cardiac[Title/Abstract] OR cardio[Title/Abstract] OR heart[Title/Abstract]); ((artificial intelligence[Title/Abstract]) OR (machine learning[Title/Abstract]) OR (natural language processing [Title/Abstract]) OR (deep learning[Title/Abstract])) AND (oncology [Title/Abstract] OR oncologic[Title/Abstract] OR oncological[Title/Abstract] OR cancer[Title/Abstract] OR malignancy[Title/Abstract] OR (malignant[Title/Abstract] AND tumor[Title/Abstract]) OR (malignant [Title/Abstract] AND neoplasm[Title/Abstract]) OR chemotherapy [Title/Abstract] OR (radiation therapy[Title/Abstract]) OR radiotherapy[Title/Abstract]).

### 2.5. Trends analysis

We obtained the total number of publications related to the field of AI for cardiology, oncology, and general biomedical publications to evaluate historical trends. In addition, we normalized the numbers of AI-related publications in cardiology or oncology in a given year to the total number of cardiology or oncology publications, respectively, for that year.

### 2.6. Data adjudication

SAB manually reviewed the titles and abstracts of 50 randomly selected abstracts for appropriateness, as well as subsequently several additional abstracts specifically on “deep learning” to determine whether a high frequency of irrelevant abstracts was inappropriately included in our analysis. Overall, the only substantial frequency of irrelevant abstracts was noted for “deep learning” and these were removed from the analysis. Of note, in initial publications, “deep learning” referred to an individual style of assimilating information by students. In later publications, “deep learning” referred to a machine learning technique that relies on multi-layered artificial neural networks. This difference in meaning was taken into account when selecting appropriate publications and quantifying “deep learning” publications for this study; therefore, the difference contributed negligibly to the overall analyses. For the rest of the manuscript, “deep learning” refers to the definition specifically relevant to machine learning.

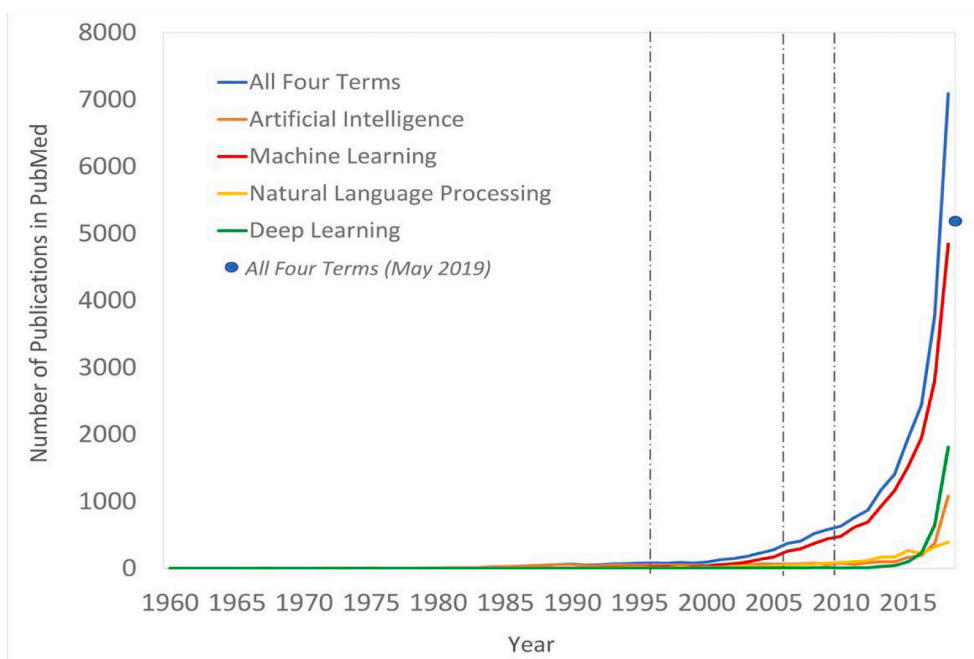
### 2.7. Statistics

Descriptive statistics were used to catalog AI publications over time, especially in oncology and cardiology. A regression analysis was performed to assess the goodness-of-fit of the number of AI publications in cardiology, oncology, and the general biomedical literature to an exponential growth model. The correlation coefficient  $R^2$  was computed for each exponential fit. Microsoft Excel software was used for basic statistical analysis and data plots.

## 3. Results

Publications using the term “artificial intelligence” in the title or abstract were first noted in 1963, “machine learning” in 1964, “natural language processing” in 1978, “deep learning” in general in 1989, and “deep learning” relevant to machine learning in 2011. In the last two decades, publications using all four terms related to AI showed remarkable growth (Fig. 1). Most publications used the term “machine learning” ( $n = 20,301$ ) with a notable predominance (Fig. 1) compared to the other three distinct terms “artificial intelligence” ( $n = 4535$ ), “natural language processing” ( $n = 2608$ ), and “deep learning” ( $n = 4459$ ) (Table 1). Consequently, the acceleration of publications in AI overall appeared to be due almost entirely to publications on “machine learning”.

Cardiology publications in PubMed are associated with publication



**Fig. 1.** Publication trends in artificial intelligence (AI). Trends for AI-related publications in PubMed from 1960 to May 2019 showing increases for all terms, with publications on “machine learning” as major contributors to this remarkable growth. Dashed lines approximate points of growth acceleration for various AI-related terms.

**Table 1**

Number of publications using terms related to artificial intelligence and its subgroups in the title or abstract in PubMed from 1960 to May 2019.

	Artificial intelligence	Machine learning	Deep learning	Natural language processing	All four terms
All publications	4535	20,301	4459	2608	31,903
Cardiology publications	172	725	190	85	1172
Oncology publications	449	2070	634	238	3391

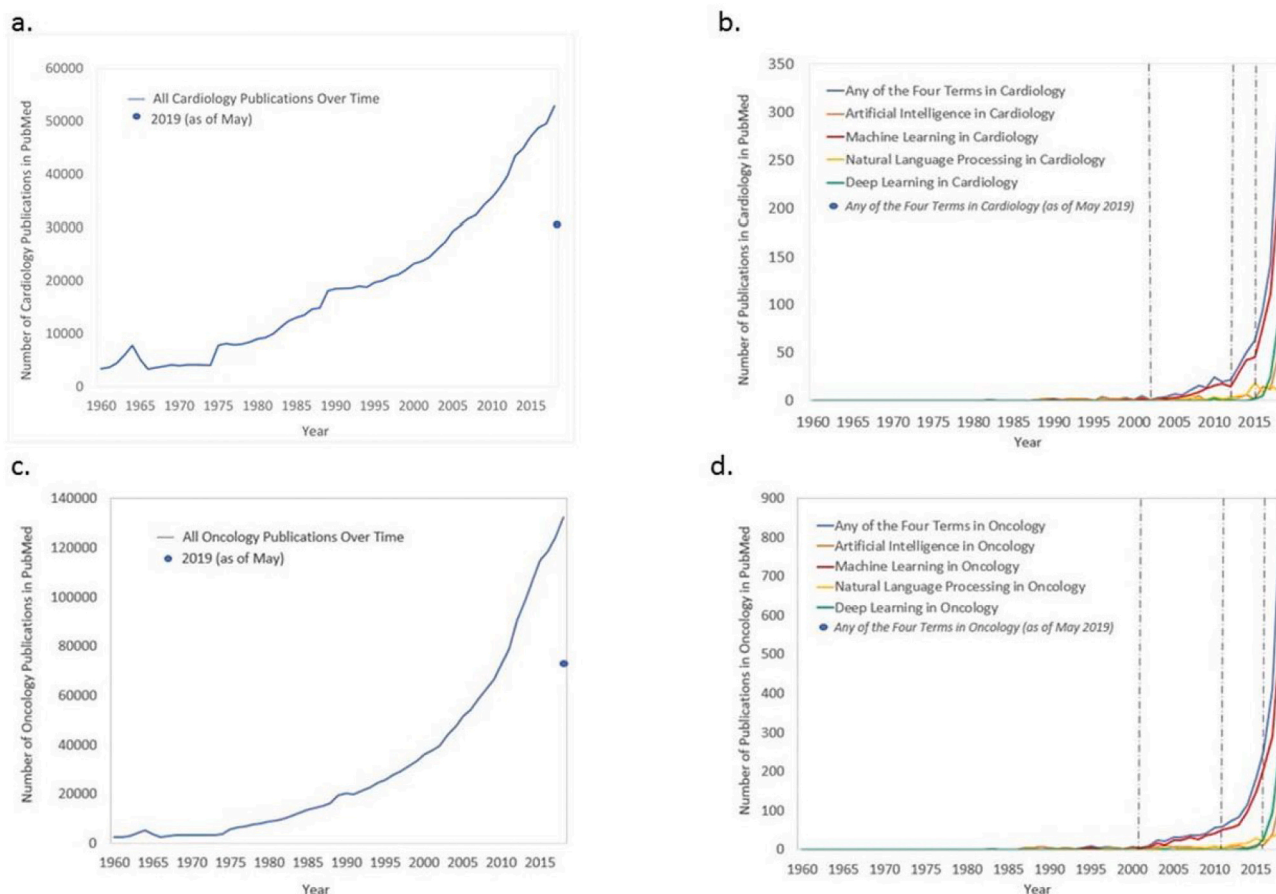
  

All publications by year		
	Steepest curve	Shallowest curve
2008	372	68
2009	441	77
2010	479	86
2011	615	96
2012	690	118
2013	929	170
2014	1161	171
2015	1518	265
2016	1950	222
2017	2809	323
2018	4842	391
2019	3215	251

dates as early as 1985, with a growth trend over time shown in Fig. 2a. Cardiology publications had an impressive total of 1,164,685 as of May 2019 with as many as 53,752 in any given year (particularly in the year 2018). Cardiology publications using the term “artificial intelligence” in the title or abstract were first noted in 1982, “machine learning” in 1990, “natural language processing” in 1983, and “deep learning” in 2012. Fig. 2b illustrates the general uptrend of cardiology publications related to AI. Cardiology publications used “machine learning” (n = 725) more frequently than any of the other three terms, “artificial intelligence” (n = 172), “natural language processing” (n = 85) or “deep learning” (n = 190) (Table 1). Oncology publications were first noted in 1987, with a steep uptrend over time (Fig. 2c). There were as many as 132,389 oncology publications in any given year (particularly in the year 2018) and a total of 2,015,637 over time as of May 2019. Table 2

shows a sample of the top journals publishing these manuscripts in January to May 2019, with a qualitative depiction of the relative distribution of article and study types for the manuscripts in this time frame on artificial intelligence in cardiology. A snapshot of the bibliographic search results from that time period displays the article name, authors, journal, and citation for these artificial intelligence manuscripts in cardiology (Supplemental material 1).

Oncology publications using the term “artificial intelligence” were first noted in 1983, “machine learning” in 1994, “natural language processing” in 1997, and “deep learning” in 2004. Similar to cardiology and general biomedical publications, oncology publications using all AI-related terms showed remarkable growth over time (Fig. 2d). Most oncology publications used “machine learning” (n = 2070) with higher frequency than any of the other three terms: “artificial intelligence” (n



**Fig. 2.** Publication trends in cardiology and oncology. a, Trends for all publications in PubMed from 1960 to May 2019 for cardiology (a) and oncology (b); trends for AI-related publications in PubMed from 1960 to May 2019 for cardiology (c) and oncology (d) depicting remarkable growth and a predominance for publications using the term “machine learning”. Dashed lines approximate points of growth acceleration for various AI-related terms. AI = artificial intelligence.

= 449), “natural language processing” ( $n = 238$ ), and “deep learning” ( $n = 634$ ) (Table 1). Table 2 shows a sample of the top journals publishing these manuscripts in January to May 2019, with a qualitative depiction of the relative distribution of article and study types for the manuscripts in this time frame on artificial intelligence in oncology. A snapshot of the bibliographic search results from that time period displays the article name, authors, journal, and citation for these artificial intelligence manuscripts in oncology (Supplemental material 2).

The number of cardiology publications with any of the four terms normalized to all AI publications in PubMed was ten times higher than the number of cardiology publications with any of the terms in PubMed normalized to all cardiology publications in PubMed. Similarly, the number of oncology publications with any of the four terms in PubMed normalized to all AI publications in PubMed was ten times higher than the number of oncology publications with any of the four terms in PubMed normalized to all oncology publications in PubMed. These data suggested that cardiology and oncology publications might have more prominence in AI publications than vice versa. Interestingly, the overall number of AI-related publications for all four terms over time was greater for oncology ( $n = 3391$ ) than for cardiology ( $n = 1172$ ). In fact, the total publication in oncology ( $n = 2,015,637$ ) was almost double the number of cardiology publications ( $n = 1,164,685$ ) over time, which was accounted for with normalization as described.

Most publications in cardiology, oncology, and the general biomedical literature used “machine learning”, far exceeding the frequency of any of the other three terms, including “artificial intelligence”. Consequently, the acceleration of publications in AI overall appeared to be due almost entirely to publications on “machine

learning”. This differentiation was first noted in the early 2000s (circa 2004) and persisted with the gap widening rapidly over time. Nevertheless, publications on “artificial intelligence” and “deep learning” started to increase in later years, even more so than publications on “natural language processing”. Interestingly, “deep learning” (with the relevant definition) as the newest “kid on the block” of the four terms in this field, started rising more quickly in the number of publications than “artificial intelligence” as of 2015.

While in the late 2000s into early 2010s the increase in the number of AI publications overall started to slow down, a tremendous acceleration was then noted circa 2011–2015. Indeed, a slight qualitative inflection point was seen in 2015 for AI publications in cardiology, oncology, and the general biomedical literature, with a steep take-off in publications on all four terms (Figs. 1, 2b, d, and 3). There were 519 publications for all terms combined (AI, ML, NLP, and DL) in 2008, 578 publications in 2009, 632 in 2010, 739 in 2011, 868 in 2012, 1173 in 2013, 1406 in 2014, 1939 in 2015, 2441 in 2016, 3778 in 2017, 7086 in 2018, and 5021 in 2019 as of May (Fig. 1). Interestingly, publications with “machine learning” were steepest; with 372 publications in 2008, 441 in 2009, 479 in 2010, 615 in 2011, 690 in 2012, 929 in 2013, 1161 in 2014, 1518 in 2015, 1950 in 2016, 2809 in 2017, 4842 in 2018, and 3215 in 2019 as of May (Table 1). Conversely, publications with “natural language processing” were the shallowest with 68 publications in 2008, 77 in 2009, 86 in 2010, 96 in 2011, 118 in 2012, 170 in 2013, 171 in 2014, 265 in 2015, 222 in 2016, 323 in 2017, 391 in 2018, and 251 in 2019, as of May (Table 1).

The qualitative inflection point was more remarkable when considering AI publications in cardiology or oncology particularly as

**Table 2**

Types of journals, articles, and studies in publications using terms related to artificial intelligence and its subgroups in the title or abstract in PubMed from 1960 to May 2019.

Specialty	Cardiology	Oncology
Top journals	Nat Med Nat Rev Cardiol Nat Mach Intell NPJ Digit Med Sci Rep Lancet Oncol J Am Coll Cardiol JACC Clin Electrophysiol JACC Cardiovasc Imaging Circulation Circ Arrhythm Electrophysiol Circ Cardiovasc Qual Outcomes J Am Heart Assoc Cancers Eur Heart J Eur J Heart Fail Eur Heart J Qual Care Clin Outcomes Eur Heart J Cardiovasc Imaging Eur J Radiol Eur J Hybrid Imaging Eur J Med Chem ESC Heart Fail J Am Med Inform Assoc JAMIA Open J Nucl Med J Clin Med J Physiol J Invasive Cardiol J Thorac Imaging J Electrocardiol J Cardiovasc Electrophysiol J Am Soc Echocardiogr J Heart Lung Transplant Genet Med Radiology Bioinformatics JMIR Cardio JMIR Ment Health JMIR Med Inform J Med Internet Res JMIR Res Protoc J Med Syst Int J Med Inform Front Physiol Front Neurol Med Phys PLoS One Curr Treat Options Cardiovasc Med Curr Cardiol Rep Curr Opin Cardiol Curr Opin Biomed Eng Am J Cardiol BMJ Open BMC Med Inform Decis Mak BMC Med Res Methodol BMC Bioinformatics BMC Psychiatry Open Heart Cardiovasc Toxicol Biosci Trends Radiol Artif Intell AMIA Jt Summits Transl Sci Proc IEEE EMBS Int Conf Biomed Health Inform. IEEE J Transl Eng Health Med IEEE Trans Biomed Eng IEEE Trans Med Imaging IEEE Rev. Biomed Eng IEEE Trans Biomed Circuits Syst	Nat Genet Nat Commun Nat Protoc Nat Biomed Eng NPJ Digit Med NPJ Precis Oncol Sci Rep Lancet Oncol Cancers Genome Med CA Cancer J Clin Eur J Radiol Eur J Cancer Am Soc Clin Oncol Educ Book JCO Precis Oncol JCO Clin Cancer Inform JAMA Oncol JAMIA Open JAMA Netw Open AMIA Jt Summits Transl Sci Proc Oncol Lett JMIR Med Inform JMIR Cancer JMIR Hum Factors Am J Health Behav BMC Bioinformatics BMC Biol BMC Cancer BMC Med Genomics BMC Genomics BMC Med Imaging BMC Syst Biol BMJ Open Gastroenterol BMC Med Inform Decis Mak Gene J Biomed Inform J Digit Imaging J Am Coll Radiol J Med Syst J Transl Med J Clin Med Cancer Inform Curr Oncol PLoS One PLoS Med PLoS Biol PLoS Comput Biol J Am Chem Soc Cell Cell Commun Signal Front Mol Biosci Front Bioeng Biotechnol Front Endocrinol Front Genet Front Oncol Front Pharmacol Front Neurosci Proc Natl Acad Sci Int J Med Inform Int J Mol Sci JMIR Cancer Oncogene Oncology Molecules IEEE J Biomed Health Inform IEEE Trans Med Imaging IEEE Trans Image Process Bioinformatics AMA J Ethics. J Med Ethics Trends Cancer Systematic review
Article type	Systematic review ++	Systematic review +++

(continued on next page)



Table 2 (continued)

Specialty	Cardiology	Oncology
	Meta-analysis	Meta-analysis
	+	++
	Randomized controlled trial	Randomized controlled trial
	++	++
	Original research	Original research
	+++++	+++++
	Review	Review
	+++++	+++++
Study type	Assessment of outcomes of interventions	Assessment of outcomes of interventions
	++	+++
	Diagnostics/predictive analytics	Diagnostics/predictive analytics
	+++++	+++++
	Epidemiology	Epidemiology
	++++	++++

+ Relative prevalence of article/study type.

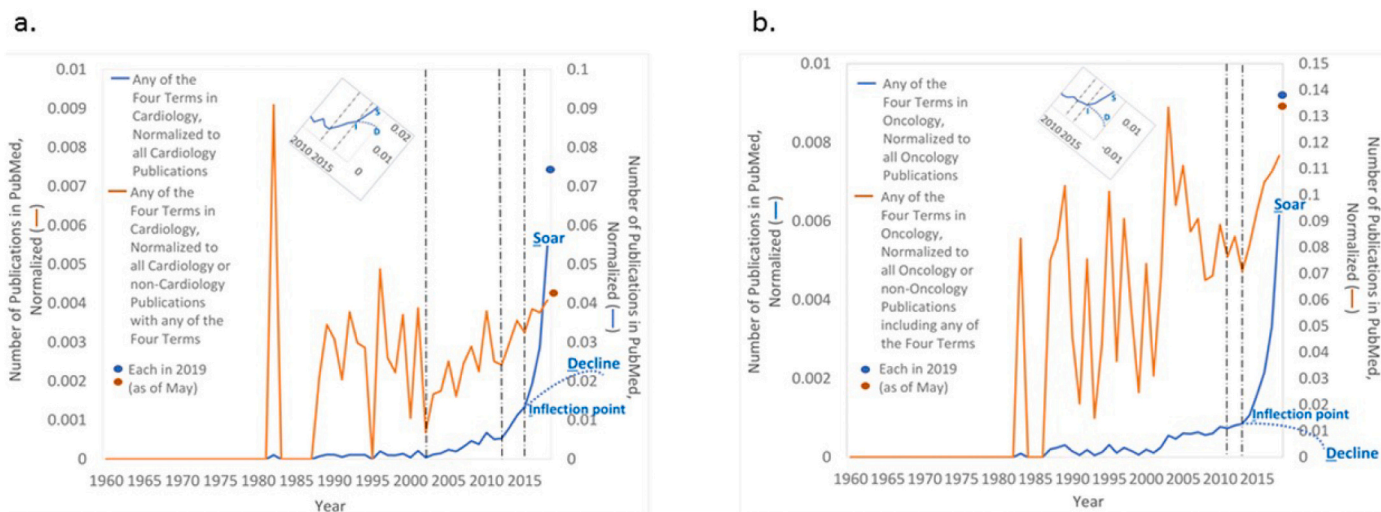


Fig. 3. AI-related publication trends for cardiology and oncology. Trends for AI-related publications in PubMed from 1960 to May 2019 for cardiology (a) and oncology (b) normalized to all cardiology and oncology publications, respectively, each with an associated qualitative inflection point. Dashed lines approximate points of growth acceleration for various AI-related terms. AI = artificial intelligence; S = soar; D = decline; I = qualitative inflection point.

proportions of all cardiology or oncology publications in PubMed, respectively (Fig. 3a ad b). The qualitative inflection point for the growth of AI-related publications in cardiology as a proportion of all cardiology publications was the most notable. While just prior to 2015 the increase in the number of publications started to slow down, tremendous acceleration was then noted after 2015. Consistent with this, a regression analysis showed an excellent fit of the publication data after the proposed qualitative inflection point to an exponential growth model for all four AI-related terms in cardiology ( $R^2 > 0.98$ ), oncology ( $R^2 > 0.98$ ), and the general biomedical literature ( $R^2 > 0.96$ ) (data not shown). In fact, at just under halfway through 2019 (in May), the number of cardiology publications on “machine learning” had already reached 60 % of the total for 2018, with 53 % for “artificial intelligence”, 100 % for deep learning, and 40 % for “natural language processing”, illustrating a growing interest in the critical role that AI will likely play in precision cardiovascular medicine.

#### 4. Discussion

Our results from this review of >50 years of AI-related publications confirmed the historical increase in research in AI and its qualitative inflection point and exponential growth in the last approximately five years. We found a predominance of publications using the term “machine learning” as a major contributor to this remarkable growth. The predominance was maintained when compared to the related terms

“artificial intelligence”, “natural language processing”, and “deep learning” for publications in cardiology, oncology, and the general biomedical literature. The presence of prior publications predominantly on “machine learning” in PubMed may have helped its spread more than “artificial intelligence” or other terms. Additionally, in certain publications these terms may have been used interchangeably.

This remarkable rise over the past five years is noteworthy and it is expected to grow, as AI gains recognition for its potential to solve some of healthcare's biggest challenges. AI is still in its early stages, and there is much ground to be covered in AI-related research and practical applications. Nevertheless, its promise to help advance precision medicine, improve accuracy of clinical decision-making, and enhance patient care is unquestionable. AI-based technology in healthcare is rapidly being incorporated into research endeavors, yet it still faces many challenges regarding its translation into real-world, clinically meaningful applications [19,20]. To this end, there are concerns about unstructured datasets, generalization of the collected data, large-scale security and privacy data breaches, and the potential for harm to patients from flawed algorithms [14,21]. This highlights the need for systematic extensive validation and rigorous regulations of AI-based technologies prior to their adoption in clinical practice.

Our study is not without limitations. The analysis was not intended to be exhaustive, but specific and reasonably comprehensive and representative of AI publications in cardiology, oncology, and the general biomedical literature. The database query for cardiology did not

include the terms “cardiovascular”, “atherosclerosis”, or “atherosclerotic cardiovascular disease” (ASCVD), as these frequently yielded studies more specific to Vascular Medicine, Cerebrovascular Medicine, Endocrinology, and so on. The database query for oncology did not include the terms “hematology”, “hematologic”, or “hematology-oncology”, as several non-cancerous conditions were obtained for all three terms. In addition, the database search relied on the identification of keywords only in the title or abstract of each publication. Despite these limitations, our study demonstrated the large volume of, accelerating increase in, and qualitative inflection point in AI-related publications in cardiology, oncology, and the general biomedical literature.

The deep learning models are a type of artificial neural networks with a number of layers processing data. These additional layers may correspond to hundreds of thousands or millions of parameters that are being learned during model training. Such a high number of model parameters require very large training datasets. Consequently, training a deep learning model on very large datasets, especially image datasets, require high performance processors and memory. Despite the fact that deep learning models were introduced decades ago, their widespread use had to wait for technological advancement and data availability. A technological breakthrough was the introduction of advanced programmable Graphical Processing Units (GPU) at consumer level in the early 2000s, which partially explains the increased machine learning literature in the last two decades. However, because deep learning models require very large datasets for training, the real jump on deep learning occurred around 2015, following AlexNet [22,23], which is a deep learning model trained on a subset of the ImageNet visual database (a manually annotated database of over 1.2 million images from over 1000 categories). This inspired other deep learning models such as ResNet [24] and DenseNet [25], which are now forming baseline models for transfer learning on many disciplines including cardiology [26] and oncology [27,28]. Such a transfer learning approach helps reduce computation time needed to train deep learning models and also enables obtaining robust deep learning models with smaller sample sizes. These trends in feasibility of deep learning applications in large part explain the major increment in deep learning literature in 2015 and its exponential growth over the recent years as illustrated in our study particularly in the cardiology, oncology, and general biomedical literature. As technologies that enable deep learning and other forms of machine learning continue to advance, these terms will continue to rise above those related to natural language processing or other forms of artificial intelligence.

It is important to recognize that increasing publications in a field can reflect increasing interest, with combinations of original research papers, as well as reviews, editorials, and commentaries. Consequently, increase publications does not equate to increased original impactful studies. As a result, our findings suggest a higher frequency of discussion and conversation in biomedical literature and especially in cardiology and oncology in the realms of AI and its subgroups. For example, a study was published in 2017 describing the results of training a deep convolutional neural network to classify skin cancers using 129,450 clinical images of skin lesions [29]. The algorithm that was developed can classify lesions in photographs that are not very different from pictures taken with a mobile phone. The system's accuracy in detecting malignant melanomas and carcinomas was comparable to that of trained skin cancer doctors. This article has been subsequently cited by >7000 publications. If this article is mentioned in the abstract of these publications using AI or AI subgroup terms along with “oncology”, these citing abstracts may be counted as ones relevant to AI in oncology. Yet, while these abstracts may not be directly studying AI in oncology, they may be applying insight and findings from applications of AI in oncology to other fields. This also contributes to the overall conversation and can be informative for considerations in both oncology and the fields driving the citing manuscripts.

Future bibliometric studies should delve more deeply into the content and characteristics of these publications, differentiating quantity

and quality, to determine which are original articles and how to gauge impact over time. In addition, a literature logic growth curve model could be used to detect the inflection point. We hope that our preliminary findings indicating exponential growth can be useful to the field, as we advance in the digital era. It will be key for the cardiology, oncology, and AI research communities to come together to establish standards, processes, tools, and best practices that can help further accelerate advancement of science while ensuring meaningful, high caliber research methods. These methods will need to be founded on the traditional ones that encourage reproducibility and validation using external cohort datasets to ensure that AI models are transferable, generalizable, and reliable.

In summary, the frequency of AI publications has been accelerating, with a slight qualitative inflection point noted circa 2015 in the cardiology, oncology, and general biomedical literature, with publications specifically on “machine learning” leading the way. Based on these historical trends, continued exponential growth is forecasted in the powerhouse research fields of cardiology and oncology, and in biomedicine in general. The prospective for AI to process big data in an efficient manner is the future for data-driven, high-performance medicine, where data interpretation, workflow and access to information by patients are improved. Moreover, the progress of AI will hopefully aid in selecting the best treatment options and predicting patient outcomes. Consequently, AI will likely play a crucial role in enhancing many aspects of science and healthcare delivery in the era of digital and precision medicine.

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ahjo.2022.100162>.

#### Data availability

The data used in this study is publicly available in the PubMed database.

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#### CRediT authorship contribution statement

SAB: Study design, data analysis.

SAB, GASA, AH, OA: Result interpretation, manuscript preparation and paper revisions.

All authors approved the completed version.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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