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MINI-REVIEW

Artificial Intelligence to Improve Patient Understanding of Radiology Reports

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Diagnostic imaging reports are generally written with a target audience of other providers. As a result, the reports are written with medical jargon and technical detail to ensure accurate communication. With implementation of the 21st Century Cures Act, patients have greater and quicker access to their imaging reports, but these reports are still written above the comprehension level of the average patient. Consequently, many patients have requested reports to be conveyed in language accessible to them. Numerous studies have shown that improving patient understanding of their condition results in better outcomes, so driving comprehension of imaging reports is essential. Summary statements, second reports, and the inclusion of the radiologist's phone number have been proposed, but these solutions have implications for radiologist workflow. Artificial intelligence (AI) has the potential to simplify imaging reports without significant disruptions. Many AI technologies have been applied to radiology reports in the past for various clinical and research purposes, but patient focused solutions have largely been ignored. New natural language processing technologies and large language models (LLMs) have the potential to improve patient understanding of their imaging reports. However, LLMs are a nascent technology and significant research is required before LLM-driven report simplification is used in patient care.

INTRODUCTION

Artificial intelligence (AI) is increasingly applied to the field of radiology. Since 2017, the number of radiology related AI papers has drastically increased (Figure 1). The current applications of AI are centered around interpreting medical images and improving workflow, driven by deep learning such as convolutional neural networks trained on large data sets [1]. Computer aided detection has found application in breast imaging and chest radiographs, among other modalities [2]. During this recent boom, AI has transformed the radiology experience for radiologists, but the use of AI and big data to improve the patient experience has largely been unexplored (Figure 1). New generative AI technology, based off of natural language processing (NLP), has the potential to drastically improve patient health literacy [3].

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Abbreviations: AI, Artificial Intelligence; NLP, Natural Language Processing; LLM, Large Language Model; EHI, Electronic Health Information.

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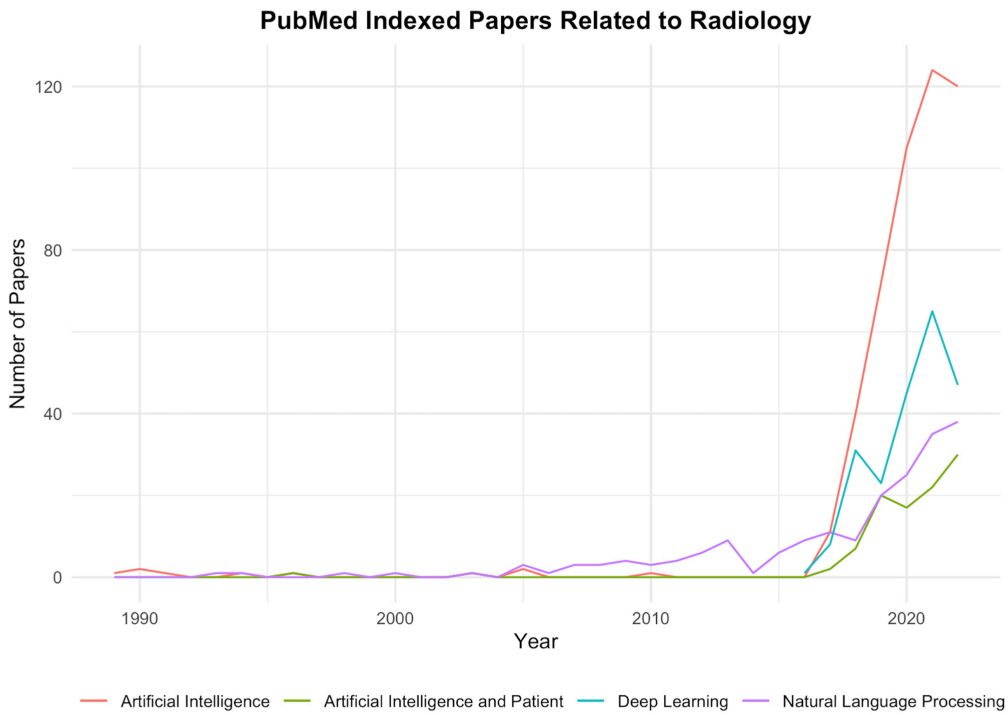

Figure 1. **Graph of PubMed Indexed radiology publications between 1989 and 2022 related to artificial intelligence, both artificial intelligence and the patient, deep learning, and natural language processing**.

PATIENT HEALTH LITERACY

Imaging Reports

Imaging reports have historically been written with a target audience of other physicians and healthcare professionals. Until the 1970s, radiology reports were predominately a form of communication between the radiologist and the referring provider, earning radiologists the nickname “the doctor’s doctor.” In the late 20th century, legal pressures forced radiologists to increasingly become the patient’s doctor as well [4]. Notably, the Mammography Quality Standards Act (MQSA) passed in 1992 legislated that radiologists send a lay summary directly to patients.

21st Century Cures Act

Today, with the 21st Century Cures Act [5], imaging reports are increasingly and immediately available to patients. Unfortunately, they remain incomprehensible by the average patient in the United States [6]. The Health Insurance Portability and Accountability Act’s Privacy Rule (1996), with adjustment by the Health Information Technology for Economic and Clinical Health Act of 2009, established the patient’s right to access their medical records [7]. However, many barriers to access remained, as patients would have to request providers to receive their health information [8]. The 21st Century Cures Act, signed into law in December 2016, significantly changed the way patients interact with their health information. While the act is known for its provisions designed to accelerate drug and device approvals, lesser-known provisions improved patient access to their electronic health information (EHI). The Cures Act Final Rule requires that patients can electronically access their EHI – whether unstructured or structured – for free [9]. Further, the Information Blocking Provision necessitated that patients have access to segments (including imaging reports) of their EHI, defined by the United States Core Data for Interoperability (USCDI), by April 5, 2021 and all of their EHI by October 6, 2022, with certain exceptions [9].

Before the information blocking provision, many practices participated in time-delayed responses to allow the referring provider time to review the report and facilitate future care before patients became aware of abnormal or anxiety-inducing images [10-12]. The effect of the Information Blocking Provision on time-delayed responses is ambiguous, but many providers have already stopped this practice [10-12]. Practices dropping time-delayed responses have reported increased call volume, which may contribute to physician workflow disruptions and provider burnout [10,11]. At the same time, the information blocking provision has many ramifications for patient privacy. Notably, parents or caregivers with proxy-access to an adolescent’s or older adult’s EHI may inadvertently see information that was requested to be withheld [9]. Immediate release creates an opportunity to further patient-centered care and allows for greater patient participation in their care decisions, but many hurdles remain. Here, issues related to patient health literacy are addressed.

Patient Engagement

Even prior to the Cures Act, patients engaged with radiology web portals with 51.2% of patients viewing their radiology reports [13]. In another study, 85% of patients wished to view their radiological images while 64% of patients wished to receive access to their reports [14]. Additionally, a study looking at requests on web portals found that 33% of patients sent messages asking for the results of a recent scan [8]. Demographically, women, English speakers, those with commercial insurance, and patients 25-39 were the most likely to view their reports; compared to whites, Asian Americans were significantly more and African Americans were significantly less likely to view their reports [13]. For content of radiology reports, patients wish to receive very detailed reports of their radiology findings: 81.6% for abnormal findings and 46.4% for normal findings [15].

Limitations to Patient Health Literacy

As radiology moves to a value-based and patient-centered practice, access is only the first step: patients must understand their imaging reports. The American Medical Association (AMA) and National Institutes of Health (NIH) recommend that patient education materials are written between the 3rd- and 7th-grade levels, given that the average American reads at the 8th-grade level [4,16,17]. However, a study by Martin-Carreras found when analyzing 97,052 radiology reports, the mean reading grade level (± standard deviation) was 13.0 ± 2.4 and only 4.2% of reports were at or below the 8th-grade reading level [6].

The average reading level of reports may reflect the fact that the patient's ability to understand these reports is often not considered [18]. A scoping review of English language diagnostic imaging reporting guidelines found that only two out of six international guidelines (The Royal College of Radiologists and the Royal Australian and New Zealand College of Radiologists) explicitly note that imaging reports should consider the patient. Instead, the guidelines from international radiology professional bodies emphasize structure and technical detail in reports [18].

Some authors have also written about making radiology reports more understandable for both patients and their referring providers [19-21]. These authors recognize that the report must be clear, concise, and specific while balancing the preferences of different readers of the report. Though, authors suggest reports can strike a greater balance between the patient, referring provider, and radiologist without losing medical sophistication by using medical language from medical school over residency specific jargon [19].

Currently, the greatest limitations preventing patient literacy of reports are polysyllabic terms and intricate concepts unknown to the layperson. A pilot study by Gunn et al. asked 104 patients to review CT, X-Ray, ultrasound, and MRI reports and rate their comprehension level, identify any issues with the report, and provide free-text feedback [22]. They found that the median comprehension was 2.5/5, and the most common issue impacting comprehension was "unclear or technical language" (59.6% of the evaluations). In the free text portion, the most common request was an explanation in lay terms (20.1% of evaluations). These findings are despite the fact that 63% of the respondents had at least a college degree, which is much higher than the national average of 32.5% [22,23]. Many other studies extensively show that patients have a poor understanding of their radiology findings, often due to the technical language [24-28].

Importance of Patient Health Literacy

A systematic review by Nickel et al. found that the use of medical jargon contributes to greater patient anxiety, perceptions of increased severity of the ailment, and increases inclination for more aggressive treatments [29], creating concern for many referring providers [30]. This concern is amplified given the increasingly immediate access to imaging reports.

Immediate access to readable imaging reports has the potential to tremendously benefit patients, as patients with a greater understanding of their disease are more likely to adhere to treatment plans [31]. For mammograms, decreasing the grade level of the wording for "recall" letters following an abnormal finding has been shown to significantly improve timely patient follow-up [32]. In general, a systematic review by Berman et al. found improved health literacy is associated with decreased hospitalizations and emergency care, improved use of health care services, improved health status and lower mortality in older patients, and diminished racial disparities [33]. Improving the comprehension of imaging reports has the potential to tremendously improve patient outcomes while also improving the visibility of radiologists [32].

Potential Solutions

There are many potential solutions to bridging the gap in patient health literacy. Early efforts in clinical informatics by the Canon Group sought to bring structure and standard lexicon to radiology reports in the 1990s

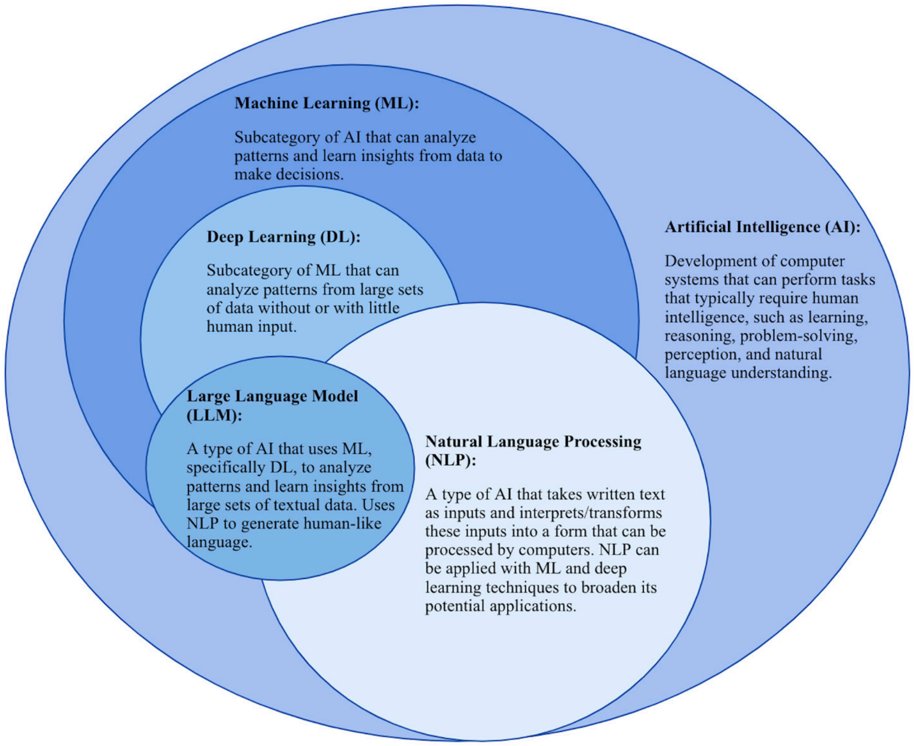

Figure 2. **Concepts in Computer Science and Artificial Intelligence**.

to aid future computer-assisted analyses [34,35]. Today, standard lexicon, such as RadLex by the Radiological Society of North America, and structured reports have the potential to improve patient comprehension of their radiology reports [4].

Decreasing the reading level of imaging reports has also been proposed, but communication with other providers may be impacted and the chance for medical errors may increase [22]. Instead, radiologists could generate a second report in lay terms for each examination, in addition to the report directed toward other healthcare professionals. However, a second report would increase the administrative burden on radiologists and may lead to lower job satisfaction [22]. Others have suggested the inclusion of the radiologist's contact information in the reports [36] or an immediate result consultation with a radiologist [37]. Some articles have also suggested the inclusion of a single summarizing statement in layman's terms at the end of the report [22,38].

Authors have also suggested using AI to mine the report to create these simple summary sentences, representing one of the many AI-driven solutions [10]. Many have also suggested providing annotated reports with definitions or including hyperlinks on medical terms to receive more information and or images. [11,22,39,40]. These suggestions are implementable with software that can recognize medical and radiological terms and then link to medical databases [41].

NEW ARTIFICIAL INTELLIGENCE METHODS TO BRIDGE THE GAP

Background

AI driven computer-aided diagnosis systems have long been incorporated into radiology workflow [2]. However, NLP, a subset of AI, is now being used to create many patient-experience tools (Figure 2). NLP has shown effectiveness in summarizing text, translating text, and answering questions [42]. NLP is divided into symbolic and statistical NLP [43]. While symbolic NLP uses a rules-based architecture, statistical NLP learns from large amounts of data [43]. Symbolic systems allow a programmer to know exactly why a certain output was generated and allow programmers to add additional rules to incorporate greater information. Meanwhile, statistical NLP produces greater variation in output but does not require the inclusion of as many linguistic rules to generate the desired output [44]. Statistical approaches are particularly useful in analyzing imaging reports, as there are large variations due to modality, indication, preferences, and culture [45,46]. The earliest initiatives involved in processing radiology reports were based on symbolic approaches, but with advances in NLP, most paradigms are combinations of symbolic and statistical approaches [44].

These initial efforts related to imaging reports include noting critical findings [47]; identifying diseases such as urinary tract calculi [48], pneumonia [49], peripheral arterial disease [50], and thromboembolism [51]; creating follow-up recommendations [52]; describing the change in radiology findings over time [53]; categorizing oncologic responses [54]; and extracting information such as measurements [55] and Breast Imaging-Reporting and Data System (BI-RADS) classification [56]. Further, using conventional methods of machine learning Goff and Loehfelm explored the use of NLP in summarizing imaging reports [57].

Deep Learning NLP (DL-NLP) can be considered a type of statistical NLP, but DL-NLP is often used to differentiate earlier simple statistical methods and modern neural-network architecture [58]. Large Language Models (LLMs) such as OpenAI's ChatGPT are examples of DL-NLP. These DL-NLP approaches have also been applied to imaging reports for similar purposes: identifying critical findings [59], categorizing oncologic responses [60], finding follow-up recommendations [61], identifying pulmonary emboli [62,63], detecting complications of stroke [64], and classifying epilepsy brain MRIs [65] among others.

AI to Simplify Imaging Reports

DL-NLP and LLMs have the potential to generate impressions, simplify radiology reports for a patient, and improve patient engagement [66]. A host of publications have recently explored this possibility [67-76]. The most common LLM studied thus far for radiology report simplification and generation is ChatGPT [67-70,75], but authors have also studied other mass market LLMs such as Google Bard and Microsoft Bing [70] while others have trained their own models [73,74].

To simplify radiology reports, authors have tested various prompts – with different levels of context – in mass market LLMs; the authors suggest greater context leads to improved simplification [67,69,70]. To measure the degree of simplification, few papers have measured the reading grade level of raw reports and LLM produced outputs using well established metrices such as Flesch-Kincaid, Coleman-Liau, Automated Readability Index, and Gunning Fog [68,70]. In line with Martin-Carreras's study, the reading grade level of raw reports was found to be above the recommended 8th-grade reading level. For certain prompts and LLM combinations, the LLMs were able to simplify the radiology reports to below the 8th-grade reading level [68,70]. Though, the accuracy of simplified reports verifiably beneath a certain grade level is yet to be sufficiently tested.

Some studies have measured the accuracy of simplified reports [67,69]. In Jeblick et al.'s study, most radiologists agreed that the simplified reports were factually correct and complete. Though, factual errors were discovered: misinterpretation of medical terms, imprecise/odd language, and grammatical errors. Further, some key medical information was often skipped in the simplified report [67]. Overall, the radiologists recognized that there are many statements in the simplified report that may lead to the wrong conclusion and consequently psychological harm, but generally believed that direct harm to patients would be averted [67]. In Lyu et al.'s study, an evaluation by two radiologists found that ChatGPT output for CT scans (MRIs) had on average missing information every 10.3 (12.5) outputs and incorrect information every 31.3 (15.4) outputs. The radiologists gave an overall quality score of 4.268/5.0, with 52% of all outputs receiving a full score.

Limitations

These results suggest that LLMs have the potential to simplify radiology reports. Automatically generated second reports could be sent to patients along with their original report after verification by experts. Though, as of now, verification is necessary because LLMs have the potential to hallucinate and provide false information. LLMs may also not have the full picture of a patient's history and may provide incorrect recommendations. Over time, the LLMs may improve in their ability to accurately simplify radiology reports as GPT-4 has been shown to perform better than GPT-3.5 in certain tasks [69,70].

CONCLUSION

Due to the Cures Act, patients have greater access to their imaging reports. However, these reports are often not comprehensible by the median patient. As medicine and radiology evolve to a more patient-centered practice, improving the ability of patients to understand their radiology outcomes is warranted, given that patient understanding of their medical information has been shown to improve outcomes [33]. Many solutions such as summary statements or second reports have been proposed, but these may impact a radiologist's workflow. AI, which already has many applications in radiology, has the potential to drive the simplification of imaging reports without significant disruptions to clinical workflow. However, LLMs are nascent technology and rigorous research is required prior to the implementation of LLM-driven report simplification in patient care.

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