Quality improvement in radiology reporting by imaging informatics and machine learning

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GENERAL DISCUSSION AND FUTURE PERSPECTIVES

General discussion and future perspectives

This thesis presented studies covering the intersection of quality management, radiology, and imaging informatics. The overarching framework was the radiology workflow, wherein tools were applied at distinct levels to improve or assess quality. The approach was broad, starting with an inquiry, implementing a feedback system and structured reporting, developing natural language processing pipelines, and, finally, forming a systematic technographic review on artificial intelligence.

This study's projects applied to subdomains of radiology, such as oncologic imaging, chest imaging, and neuroradiology. The methodology can be applied to all other subspecialties as well. The projects demonstrated that, in clinical practice, radiologists can use imaging informatics and AI tools in the radiology workflow to improve radiology reporting. Scientific methods can assess the impact of quality improvement projects, which subsequently generate data that can also be used for scientific purposes.

Although widely used in other industries, the application of the plan-do-check-act (PDCA) cycle in healthcare still needs methodological improvement [1, 2]. Regarding quality management in radiology, it can help to structure phases of quality assurance [3]. In this chapter, we used the PDCA cycle to organize the topics in a logical manner that corresponded to the consecutive steps that have to be taken in continuous quality improvement.

How the results of this thesis can be generalized and implemented in radiology is discussed in the following section. Together with topics for future research, the recommendations based on this thesis represented in the PDCA cycle are as follows:

Plan

1. Assess referral physician satisfaction.
    - **Chapter 2** proved that referring physicians are skilled professionals who can provide valuable feedback to radiologists. This feedback gives insight into areas of radiology reporting that can be improved. Also, radiology reports are only valuable when the information in the report is used by the referring physician during patient care. Therefore, the reports should be actionable and tailored to the needs of the referring physician.
    - Future research can be directed to more specific enquiries to referring physicians and to the development of EPD/PACS integrated feedback systems to monitor the quality and usefulness of radiology reports, not only at a general level, but also at the levels of subspecialty, modality, and

specific radiologist.

2. Assess guidelines.
    - In general, guidelines are the result of multidisciplinary efforts and are based on scientific evidence. Consulting guidelines in the planning phase is therefore essential. This was done for the projects of **Chapter 3** and **Chapter 4**, which resulted in improved guideline adherence.
    - Guideline authors, especially representatives of the radiology community, should incorporate implementation advice in their work to improve the chance of successful application [4].
3. Foster support in radiologists' groups.
    - In **Chapter 3**, the primary focus was on the technical implementation of the study, whereas in **Chapter 4** and **Chapter 5**, attention was also paid to good decision making before implementation. Evaluation of these studies demonstrated a greater participation among radiologists in the latter two studies compared to the former, indicating the value of involving all stakeholders in a timely manner.
    - The commitment to base reporting practice on guidelines and on the needs of the referring physician can facilitate further implementation steps. It is a precondition to agree on functional requirements of the information technology tools to be implemented and allow clearer assessments of the results of quality improvement projects.
4. Make working agreements among radiologists and referrers.
    - In **Chapter 4**, the project started with a working agreement among the radiologists and oncologists that described the content and workflow of requests and reports. Subsequent post-implementation evaluation demonstrated good participation and improved quality of both requests and reports.
    - Sub-specialization contributes to better radiology reporting (**Chapters 2** and **4**) and should therefore be included in working agreements among radiologists.

Do

5. Adapt a radiology information system and PACS to support sub-specialization.
    - Improved requests helped radiologists make better reports (**Chapter 4**). Decision support and targeted questions for referring physicians in the request workflow optimize the information available for radiology technicians and radiologists.
    - Subspecialty reporting can be facilitated by dedicated worklists in the PACS to ensure that specific examinations are reported by specific

radiologists (**Chapter 4**).

6. Implement a structured reporting program.
    - **Chapters 4** and **5** contributed to the evidence that structured reporting improves radiology reporting and, additionally, extended the concept of structured reporting by regarding it as an integral part of a multifactorial quality improvement project.
    - To ensure a consistent reporting practice, it is important to centralize the management of departmental structured reporting efforts. Close collaboration between PACS technicians and subspecialty radiologists is needed for adequate content, structure, and technical implementation of structured reporting.
    - A data scientist can complete the quality improvement team to ensure that the recorded data in the reports is usable for evaluation and scientific purposes [5].
7. Implement AI tools to improve radiology reporting.
    - **Chapter 9** demonstrated that current AI applications in neuroradiology can support radiologists in analyzing radiological examinations and extend the possibilities of radiology reporting by extracting quantitative information from images.
    - **Chapter 9** also demonstrated that the scientific evidence of the clinical impact of these AI tools is limited. Therefore, implementation studies should follow to provide evidence on the impact of these AI tools on workflow and quality. It is recommended to embed AI projects in the broader quality management strategy of the radiology department.
8. Extract information from radiology reports by NLP for usage in dashboards and algorithms for personalized medicine.
    - Deep learning NLP can extract information from radiology requests and reports (**Chapter 8**).
    - The extracted information has great potential for diverse purposes, for example, in dashboards that notify referring physicians in case certain image findings are described in the radiology report.
    - Another potential application is the combination of NLP with computer vision tools [6]. Image analysis algorithms are usually applied to imaging data of a single examination. However, this is not the same approach that radiologists use; they not only look at the image data, but also take into account the request data and previous examinations. Input from NLP of requests and previous radiology reports may improve the performance of image processing algorithms, as this approach resembles the more

personalized reporting strategy of a radiologist. Future research should elucidate this hypothesis.

Check

9. Evaluate radiology reporting by NLP tools.
   - o NLP not only has applications that broaden the use of radiology report content, but it can also evaluate the radiology report itself. **Chapters 4** and **5** demonstrated that the impact of structured reporting can be assessed by classifying radiology reports pre- and post-implementation. The NLP algorithms described in this thesis (**Chapters 6**–**8**) are suitable for classifying radiology reports and can therefore also be used to monitor the impact of a structured reporting quality improvement program. Training of the NLP algorithms with other datasets makes them suitable for application to other subspecialties.
10. Provide feedback to and collect feedback from radiologists.
    - o In **Chapter 5**, the retrospective post-implementation assessment demonstrated better results in the long term compared with the short-term evaluation. Monitoring by NLP allows prospective evaluation that can be used as feedback for the radiologist. Earlier insight into the reporting practice might contribute to faster improved compliance.
    - o Usability is important to optimize the usage of structured reporting, AI applications, and other information technology tools. Feedback from radiologists is a good source for evaluating usability [7, 8].
11. Provide feedback to and collect feedback from referring physicians.
    - o **Chapter 8** provided insight into referral patterns and the diagnostic yield of chest imaging. This type of data can be included in feedback to referring clinicians because the referral pattern feedback contributes to cost-effective imaging utilization [9].
    - o Future research can be directed at assessing the value of this type of information in clinical practice and determining if this information contributes to reducing variations in referral patterns and diagnostic yields among different providers.

Act

12. Prioritize and schedule improvements based on data from previous phases.
    - o The collected data from the previous phases is a valuable source of information meant to improve the impact and usability of quality projects. Good performance promotes further extension of the program, while the identification of less successful features encourages the adaption of the program.

Using these steps not only contributes to improved departmental quality management but also generates data for new research projects in implementation science [10]. The scale can vary from the application of a single subspeciality-structured reporting template to an extensive program with the development of NLP and computer vision algorithms, which improve quality in many subspecialties, including domains of quality, such as optimizing turn-around times, the content of radiology reports, and the impact on patient management. In conclusion, radiology professionals should embrace imaging informatics and machine learning to ensure evidence-based, data-driven, efficient, and improved patient care for the mission of quality assurance.

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