Nazmun Nisat Ontika, Sheree May Sassmannshausen, Aparecido Fabiano Pinatti de Carvalho, and Volkmar Pipek, (2023): Embedding Artificial Intelligence into Healthcare Infrastructure for Prostate Cancer Diagnosis. 9th International Conference on Infrastructures in Healthcare. DOI: 10.48340/ihc2023_pd027

Embedding Artificial Intelligence into Healthcare Infrastructure for Prostate Cancer Diagnosis

Nazmun Nisat Ontika[1*], Sheree May Sassmannshausen[1*], Aparecido Fabiano Pinatti de Carvalho[2] and Volkmar Pipek[1]
[1] Institute for Information Systems, University of Siegen, Germany
[2] Department of Informatics, University of Oslo, Norway
{nazmun.ontika,sheree.sassmannshausen,volkmar.pipek}@uni-siegen.de, fabiano.pinatti@ifi.uio.no

Abstract. Early detection and diagnosis of prostate cancer are of utmost significance for effective treatment, and artificial intelligence (AI) has the potential to assist radiologists in this area by analyzing medical images and improving diagnostic accuracy, especially given the scarcity of radiologists. This article outlines our ongoing research, focusing on designing a human-centered AI system to aid radiologists in detecting and diagnosing prostate cancer and integrating it into the existing infrastructure. Through qualitative field research involving observations, contextual inquiries, and interviews, we examined current practices, workflows, and usage contexts in German radiology centers. Our study reveals inconsistencies, barriers, and communication gaps among specialists in the diagnostic process. Based on this, we explore the potential benefits and obstacles of incorporating AI into prostate cancer diagnosis while emphasizing human-AI interaction.

Introduction and Background

Artificial Intelligence (AI) has made its way to a diverse range of healthcare sectors and is driving a technological shift in medical infrastructures. It has been

[*] Nazmun Nisat Ontika and Sheree May Saßmannshausen contributed equally.

progressively developed, and its adoption is becoming the standard in many healthcare sectors, including primary care, unique and severe illnesses, emergency care, biomedical research, and public health (Lekadir et al., 2022).

AI has the potential to revolutionize prostate cancer diagnosis by assisting radiologists in improving the accuracy, consistency, and efficiency. It can be integrated into healthcare infrastructure, especially through medical imaging, where it plays a crucial role in enhancing the precision and competency of image analysis and interpretation. By analyzing medical images such as the magnetic resonance images (MRIs) used for prostate examinations, AI has the prospect to assist radiologists in detecting abnormalities and diagnosing diseases more accurately (Bardis et. al, 2020). We are currently working on the design of an AI-powered demonstrator that assists radiologists in analyzing multiparametric MRIs (mpMRIs). This technology aims to detect patterns and anomalies in prostate images that may be challenging for human eyes to detect without AI assistance, leading to improved early detection of health conditions like prostate cancer.

Although healthcare practitioners are open to incorporating AI technology in their practices, its availability is still limited to specific team members and departments. Previous research has shown that different parts of an organization's structure are connected through standard connections, enabling employees to benefit from reflexivity and versatility (Pipek and Wulf, 2009). Understanding how these connections are made and how the interactions between social and technical aspects contributes towards the establishment and use of infrastructures is key for the design of technologies that can indeed support the practitioners.

Here we argue that AI can serve as a unifying force, bringing together various components within healthcare infrastructures to contribute to the early detection and diagnosis of prostate cancer. AI technologies can help seamlessly integrate disparate systems, data sources, and processes, supporting teams of physicians, including radiologists, in their work. In particular, AI can play a pivotal role in optimizing healthcare infrastructure, enhancing efficiency, interoperability, and decision-making, ultimately improving the delivery of healthcare services.

Developing any new technology can be challenging, especially in a robust infrastructure like healthcare, where physicians must make immediate decisions with potentially far-reaching implications (Ontika et al., 2022). Furthermore, there exist several barriers that may hinder the widespread adoption of AI in healthcare, including the lack of a practice-centered approaches for the design of such technologies, the complexity and unpredictability of the final applications, the limited involvement of humans in the development process, and the lack of explainability for professionals (Abdul et al., 2018). Hence, despite notable advancements in AI for healthcare, only a few AI systems have effectively transitioned into medical practice due to the lack of human involvement during development (Ontika et al., 2022). This highlights the need for a more human-centered approach to AI, one that combines technological capabilities with humanistic considerations (Shneiderman, 2022). Successful adoption of AI in the healthcare sector and by practitioners heavily relies on its seamless integration into existing infrastructure. If the implementation of AI is not smooth, it can introduce additional complexities and significant challenges can arise.

Additionally, the healthcare sector, with its established infrastructure, poses difficulties in the development and acceptance of new technologies. We argue that a practice-centered approach combined with a human-centered AI (HCAI) focus can help designers to identify opportunities for the integration of AI in current practices of medical teams and avoid barriers to medical acceptability to foster a transformative human-AI collaboration. Practice-centered computing take into consideration not only users, technologies, and the interactions in place, but also the practices that users engage in and the extent to what such technologies can really support them with their work (Wulf et al., 2018).

In our ongoing project, we are dedicated to designing a HCAI solution specifically tailored for radiology. Considering that HCAI systems can be effective and that, in our context, sensitive medical data is used, an extensive assessment of ethical and responsible design is necessary to develop technologies that accurately reflect human intellect. Our focus is on understanding human practices and identifying opportunities for the effective integration of AI in medical settings, with the aim of fostering a collaborative environment between humans and AI. Moreover, we don’t want to add just another tool to the market; rather, we'll be focusing on how our system can be embedded into the current infrastructure of the diagnosis process, ensuring a seamless transition.

Methodology

Over a period of five months, we conducted extensive qualitative field research, immersing ourselves in the environment of four distinct radiology centers (RC) across Germany. To gather comprehensive data, we employed contextual inquiry (Beyer and Holtzblatt, 1997) as one of our research methods. This approach involved eight inquiry sessions accompanied by in-depth interviews with five experienced radiologists who work with prostate cancer patients. Each observation session spanned three to five hours, while the semi-structured interviews lasted between 40 and 80 minutes.

Our primary objective throughout this research endeavor was to gain a profound understanding of the radiologists' existing practices. We aimed to delve into their professional experiences, workflows, interactions with various tools and stakeholders, as well as the challenges they encounter in their daily work. Moreover, we sought to explore their perspectives on working with AI for cancer diagnosis. We conducted thematic data analysis (Braun and Clarke, 2006) to extract meaningful insights from our data. In the following section, we will highlight some of the noteworthy observations that emerged from our research.

Results and Discussion

During our field research, we have comprehended that, although the exact steps and processes may vary depending on the institution, radiologists typically follow three significant blocks of action in their daily diagnosis of prostate cancer: patient data and image acquisition, image interpretation, and reporting. This diagnosis process can be seen in Figure 1. The radiologist begins by examining the patient's data, including clinical history, symptoms, laboratory results (such as prostate-specific antigen (PSA) values), previous and/or relevant medical records, and images obtained through imaging modalities such as mpMRI. All this information provides important context for the interpretation of the imaging findings to the radiologist for the next step, where s/he carefully analyzes the images to identify any suspicious lesions or abnormalities within the prostate gland. This process involves assessing the shape, size, and signal characteristics of the lesions, as well as their location within the gland, to determine the likelihood of cancer, its aggressiveness, and then classify them according to the PI-RADS scheme, which is a standardized classification system used for interpreting and reporting prostate MRI findings, aiding in the detection and characterization of prostate cancer (Leitlinienprogramm Onkologie - Oncology Guideline Program, 2021). Finally, the radiologist prepares a comprehensive report summarizing the findings, including the description of any detected lesions, their characteristics, and the overall assessment of the likelihood of malignancy, and clinical recommendations for further diagnostic steps, such as targeted biopsies or additional imaging studies.

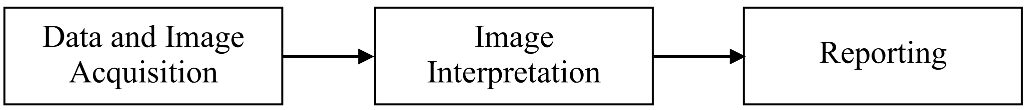

Figure 1. Main phases of the diagnosis process of prostate MRIs by radiologists.

Considering the challenges, including the image quality coming from the image provider artifacts and the heterogeneity of the prostate and prostate cancer, the diagnosis process is very complex. It is also very time-consuming, especially considering the limited number of radiologists in Germany, accounting for only 2.29% of all doctors (Bundesärztekammer - German Medical Association, 2021). We have also noticed that the interpretation of imaging findings can vary among radiologists due to differences in expertise, experience, and subjective judgment. Different radiologists may have varying levels of familiarity with prostate imaging, leading to discrepancies in lesion detection and characterization.

Our observations also revealed significant variations in the practices and utilized artifacts among different RCs. A critical distinction emerged in terms of whether the diagnostic process was conducted individually or through double analysis. Notably, RCs with two radiologists faced time constraints, leading to the first radiologist providing a summary to the second. This practice introduced bias as the second radiologist may not thoroughly analyze the images. Compounding this issue, limited resources often resulted in a single radiologist handling the entire prostate diagnosis, disregarding the recommended double analysis (PI-RADS, 2019). Decision conflicts among radiologists further prolonged examination times as they strived to reach a consensus. Furthermore, we observed that different RCs yielded divergent results for the same patient, highlighting decision discrepancies stemming from subjective interpretations of imaging findings. Such variability in diagnosis and treatment recommendations raised concerns about the reliability of the process.

Our investigation also unveiled numerous manual tasks and redundancies inherent in current practice. These tasks included manual calculations of prostate size, volume, and PSA density, as well as redundant work steps in reporting and data transfer. Apart from consuming additional time, these manual processes raised valid concerns about human errors, data loss, and inaccurate diagnoses. Interestingly, when queried about the potential for an AI system within their workflow and its trustworthiness, the radiologists responded positively. They acknowledged the scope for automation and expressed that such a system would enhance their daily work, provided it could demonstrate accuracy and efficiency.

Communication among the involved doctors is essential not only for discussing cases but also for validating their previous work. However, we discovered a communication gap in the process. Although radiologists request additional tests to confirm their findings, they rarely receive feedback from patients or referral doctors such as pathologists, and urologists.

Based on our empirical findings and our combined HCAI and practice-centered approach, we identified real user needs and gained a lot of insights about the doctors' current practice, workflow, and existing infrastructure. It is evident that radiologists can benefit from the integration of AI to assist in their diagnoses. Such a system would provide supplementary information and analysis of medical images, addressing the issues identified in the current practice. Our envisioned tool, PAIRADS, aims to mitigate the aforementioned challenges through the utilization of AI. By reducing the risk of human error and ensuring consistency in diagnoses across different radiologists, PAIRADS becomes particularly valuable in the realm of prostate cancer, where the interpretation of imaging data is subject to individual interpretation. By leveraging AI into their existing infrastructure, radiologists can make more accurate and prompt diagnoses, ultimately leading to improved patient outcomes. Our overarching goal is to enable humans to comprehend and interpret AI-generated outputs through Explainable AI, supported by visualization techniques. This approach ensures that human intelligence remains central to the decision-making process, resulting in the realization of hybrid intelligence (Jarrahi et al., 2022).

AI has the potential to be integrated into the diagnosis procedure in all the three steps that we mentioned before. However, in our current project we are primarily focusing on the middle phase, namely image analysis, as shown in Figure 2. Our system focuses on several key functionalities, including the accurate localization and segmentation of the prostate in MRI images, automated detection of abnormalities within the prostate, automatic calculations of relevant parameters, and the provision of a comprehensive result to end users. By presenting visual representations of the results as part of explainable AI, users can potentially identify patterns, trends, and anomalies in the data easily and quickly, enabling them to make informed decisions based on the algorithm's output.

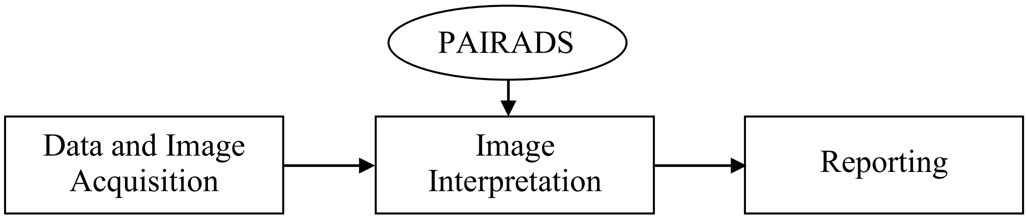

Figure 2. Embedment of PAIRADS into the diagnosis process of prostate MRIs by radiologists.

Our preliminary findings demonstrate the importance of adopting a human-in-the-loop approach to actively involve radiologists in the AI's learning process. This approach ensures that the model learns from real and relevant data, corrects errors, identifies biases, leverages domain expertise, and builds trust with users. By incorporating human intelligence into the process, the AI model can improve its performance and effectiveness. It is important to note that while AI can bring numerous benefits to healthcare infrastructure, it should primarily be used as a support for healthcare professionals and adhere to ethical and regulatory guidelines to ensure patient safety and privacy. However, addressing critical trade-offs involving accuracy, explainability, and trust in AI is essential to foster a transformative human-AI collaboration embedded within the existing healthcare infrastructure, a perspective widely supported in the current literature.

Acknowledgments

The authors would like to acknowledge the financial support from the Bundesministerium für Bildung und Forschung - BMBF through the PAIRADS project (funding code: 16SV8651; https://pairads.ai) as well as the financial support through the German Research Foundation (DFG) – Project no: 262513311 – SFB 1187 Media of Cooperation.

References

Abdul, A., Vermeulen, J., Wang, D., Lim, B. Y., & Kankanhalli, M. (2018). Trends and trajectories for explainable, accountable and intelligible systems: An HCI research agenda. Conference on Human Factors in Computing Systems - Proceedings, 2018-April. https://doi.org/10.1145/3173574.3174156.

Bardis, M. D., Houshyar, R., Chang, P. D., Ushinsky, A., Glavis-Bloom, J., Chahine, C., Bui, T. L., Rupasinghe, M., Filippi, C. G., & Chow, D. S. (2020). Applications of Artificial Intelligence to Prostate Multiparametric MRI (mpMRI): Current and Emerging Trends. Cancers, 12(5), 1204. https://doi.org/10.3390/cancers12051204

Beyer H, Holtzblatt K. (1997). Contextual Design: Defining Customer-Centered Systems. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

Braun V, Clarke V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology. 3(2):77-101.

Bundesärztekammer - German Medical Association. (2021). Ärztestatistik zum 31. Dezember 2021.

Jarrahi MH, Lutz C, Newlands G. (2022) Artificial intelligence, human intelligence and hybrid intelligence based on mutual augmentation. Big Data Soc. 2022 Jul;9(2):205395172211428.

Leitlinienprogramm Onkologie - Oncology Guideline Program. (2021). S3-Leitlinie Prostatakarzinom (Version 6.2); October. Last accessed 3 February 2023. Available from: https://www.leitlinienprogramm-onkologie.de/leitlinien/prostatakarzinom/.

Lekadir, K., Osuala, R., Gallin, C., Lazrak, N., Kushibar, K., Tsakou, G., Aussó, S., Alberich, L. C., Marias, K., Tsiknakis, M., Colantonio, S., Papanikolaou, N., Salahuddin, Z., Woodruff, H. C., Lambin, P., & Martí-Bonmatí, L. (2021). FUTURE-AI: Guiding Principles and Consensus Recommendations for Trustworthy Artificial Intelligence in Medical Imaging.

Ontika, N., Syed, H., Saßmannshausen, S., Hr Harper, R., Chen, Y., Park, S., Grisot, M., Chow, A.,Blaumer, N., Fabiano, A., De Carvalho, P., & Pipek, V. (2022). Exploring Human-CenteredAI in Healthcare: Diagnosis, Explainability, and Trust. In: Proceedings of the 20th European Conference on Computer Supported Cooperative Work. DOI: 10.48340/ecscw2022_ws06.

Pipek, V., & Wulf, V. (2009). Infrastructuring: Toward an integrated perspective on the design and use of information technology. Journal of the Association for Information Systems, 10(5). https://doi.org/10.17705/1jais.00195.

PI-RADS v2 1. (2019). Prostate Imaging Reporting Data System. Last accessed 3 February 2023. Available from: https://www.acr.org/Clinical-Resources/Reporting-and-Data-Systems/PI-RADS.

Shneiderman B. (2022) Human-Centered AI. Oxford University Press. Available from: https://books.google.de/books?id=YS9VEAAAQBAJ.

Wulf, V., Pipek, V., Randall, D., Rohde, M., Schmidt, K., & Stevens, G. (eds.) (2018): Socio Informatics - A Practice-based Perspective on the Design and Use of IT Artefacts, Oxford University Press, Oxford.