Accelerating the Adoption of Artificial Intelligence Technologies in Radiology: A Comprehensive Overview on Current Obstacles

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Abstract

Radiology has always been considered a highly technological field in medicine. Recently, a new area of radiology has emerged with the adoption of Artificial Intelligence (AI)-based health information systems due to advancements in big data, deep learning, and increased computing power. While AI elevates prevention, diagnostics, and therapy to a new level, various obstacles hinder the adoption of AI technologies in radiology. To provide an overview on these obstacles as basis for corresponding solution approaches, we identify and comprehensively outline these obstacles by conducting a structured literature review. We find 17 obstacles, which we group into six categories. Furthermore, our research discusses relevant interrelations of the obstacles, most of which we have found to be related to user attitude. Besides, these complex interrelations we expose the necessity of approaching the obstacles simultaneously.

Keywords: Artificial Intelligence, Attitude, Radiology, Obstacles.

1. Introduction

Radiology has always been considered a highly technological field in medicine; one that benefits from developments in health information systems, for example, through imaging devices and the digitization of images (Hofmann et al., 2019). A new area of radiology has emerged with the use of Artificial Intelligence (AI)-based health information systems, stemming from advancements in Big Data, Deep Learning (DL), and increased computing power (Ahmad, 2021). AI technology has the potential to elevate prevention, diagnostics, and therapy to new heights; with it, physicians can not only store individual and structural health data and retrieve it when needed but make it available for automated and accelerated analysis and decision-making (Hosny et al., 2018). Compared to traditional algorithms, AI algorithms are different as they autonomously recognize patterns, similarities, deviations, parallels, repetitions, and correlations in an unmanageable amount of digital information (Hosny et al., 2018; Yu et al., 2018). Indeed, recent advancements have seen AI algorithms able to perform comparably or beyond the performance of radiologists in specific radiological applications (Topol, 2019). For example, AI technologies in radiology are used to reduce unnecessary tests (Morey et al., 2019), prepare protocols for radiologists (Lakhani et al., 2018), reconstruct and denoise images (Hofmann et al., 2019), support radiologists by preselecting conspicuous images (Syed & Zoga, 2018), and help writing reports by speech recognition (Morey et al., 2019). While the use of AI technologies offers extensive potential to increase the efficiency and quality of medical care (Hosny et al., 2018), the use of AI technologies must be carefully considered – particularly for such a sensitive field as medicine that deals with highly personal, and privacy-preserving data (Müller-Polyzou et al., 2021).

Although it is already known that AI technology has great potential to improve patient care, especially in the field of radiology, the widespread adoption of AI technologies in radiology practice is still limited (He et al., 2019). Consequently, this study addresses the need to identify and analyze obstacles of AI technologies in radiology and therefore, provides a basis for further work to tackle these obstacles. Existing research has already partly addressed the identification of obstacles. The studies Jussupow et al. (2021) and Buck et al. (2021) demonstrate that the attitude of the radiologists strongly influence the use of AI technologies. Giansanti and Di Basilio (2022) take stock of current AI challenges in radiology and initiatives facing acceptance and consensus in the field. Hofmann et al. (2019) identified challenges and opportunities of machine learning in radiology from a managerial perspective. While research from the fields of health information systems and information systems adoption – including the literature mentioned before – analyzed challenges from specific, e.g., managerial perspectives only, literature lacks a comprehensive view on AI technology adoption obstacles in radiology. However, as we outline in this paper, only a comprehensive view can provide the basis for concurrent solutions that can overcome the complex interrelations of different obstacles regarding adopting AI technologies among radiologists.

Since research and practice need guidance for finding such solutions, our research sets out to provide a sound basis for this: to the best of our knowledge, we are the first to provide a comprehensive overview on obstacles that currently hinder the adoption of AI technologies in radiology. Therefore, this research aims to answer the following research question:

What obstacles currently hinder the widespread acceleration of AI technologies in radiology?

To answer our research question, the remainder of this paper is as follows: Following the introduction, we present relevant literature and background information on AI technology in general and its current application in radiology in Section 2. After outlining our methodological approach – including data collection and data analysis – in Section 3, we highlight the results of our research in Section 4. To structure our results, we group 17 identified obstacles into six categories. Building on this structured overview, Section 5 discusses several interrelations between the obstacles. Moreover, this section outlines our theoretical contribution and practical implications before we conclude in Section 6 with a brief summary, the limitations, and starting points for future research.

2. Artificial intelligence in radiology

Healthcare is confronted with increasing demand and expectations, increasing pressure on hospital staff and clinicians (Rubin, 2019). To adapt to the changed circumstances, digitalization and innovation are crucial. In this regard, healthcare has great potential for future developments (Houfani et al., 2022). Digitalization in healthcare offers many promising opportunities, with radiology taking a leading role in this process, as it already uses various data-driven technologies (Hosny et al., 2018). These technologies include imaging modalities such as radiography, computed tomography, magnetic resonance imaging, ultrasound, and nuclear imaging (Daffner & Hartman, 2013). Moreover, the data-intensive nature of imaging procedures makes radiology ideal for applying data-driven technologies like AI (Hosny et al., 2018).

AI has several definitions due to the many related topics and disciplines (De Felice et al., 2022). With the term 'intelligence,' we essentially comprehend any system capable of adapting its behavior to achieve objectives in diverse environments (Fogel, 1995). The term “artificial” refers to the fact of this intelligence not being human and describes the attempt to develop a system that can independently process complex problems on its own (Allen, 1998). Following Russell and Norvig (2021), we define AI as a range of technology solutions that enhance value by utilizing self-learning algorithms to accomplish cognitive tasks at a level similar to that of humans. Especially in recent years, AI technologies have gained more attention due to rapid advancements in Big Data and computing power (Jayaraman et al., 2020), resulting in numerous developments and implementation areas.

In clinical practice, AI technology is implemented through decision support systems (DSS), which support decision-making processes (Power et al., 2011). There are two types of DSS: knowledge-based systems, which use rule collections to simulate a human expert’s problem-solving behavior, requiring the formalization of rules reconstructed in a top-down approach as a series of “if-then” statements (Kaplan & Haenlein, 2019). And there are non-knowledge based systems that are usually machine learning (ML) models (Berner & La Lande, 2007) following a bottom-up approach (Kaplan & Haenlein, 2019). For image recognition-related tasks, convolutional neural networks (CNNs) are mainly used as they can take into account the spatial relations between neighboring pixels in an image (Choi et al., 2020). CNN is a network architecture of DL, which is a subfield of ML. To reduce complexity and knowing that there are differences, we refer to AI as an overarching paradigm, including ML, DL, and CNNs.

There are already several potential use cases of AI technologies along the radiology value chain that can support radiologists and improve clinical workflow.

According to Boland et al. (2014) and Enzmann (2012) the radiology value chain is as follows. First, there are preparation steps, followed by image acquisition, processing and reading, compiling reports, and post-processing steps.

The preparation step includes the selection of appropriate imaging exams (Boland et al., 2014). In this step, AI technologies can help to reduce inappropriate imaging tests and avoid duplicate testing to comply with radiation safety (Morey et al., 2019). In the next step, the image acquisition, a protocol must be drafted by the radiologist for the intended examination, which details the aim and reason for the examination and the patient’s medical history (Morey et al., 2019). This drafting process can be time-consuming, whereas AI technologies can create the protocols in advance under the supervision of the radiologist (Lakhani et al., 2018). The next sequence is image processing, which includes reconstruction, denoising, registration, and segmentation (Hofmann et al., 2019). AI technologies can augment the reconstruction by producing high-quality images from weak scanners (Morey et al., 2019). It follows the step of image reading which includes hanging protocols, interpretation, and integration. In the step of interpretation, the radiologist investigates the images for abnormalities and characterizes findings (Enzmann, 2012) – here, AI technologies can support the radiologist by preselecting conspicuous pictures and marking interesting sections (Syed & Zoga, 2018). In creating reports AI technologies can be used to help the physician write reports by using AI-based speech recognition (Morey et al., 2019). In post-processing AI technologies can provide and track follow-up information from radiology reports (Xu et al., 2012).

Although the data-driven nature of radiology offers great potential for AI technologies, their use is not yet widespread (He et al., 2019). In order to exploit the potential, the reasons for the limited adoption of AI technologies need to be identified.

3. Methodological approach

3.1. Data collection

We conduct a structured literature review to identify obstacles of AI technologies in radiology. Therefore, we orient the steps of our structured literature review according to Webster and Watson (2002). First, we form search strings by linking relevant topic search terms and include synonyms and abbreviations. We use the term "machine learning" due to its frequent use in the context of AI. In the process of search string formation, we tried several combinations of search terms to identify the most relevant articles for our context. The final search string is as follows:

(radiology) AND ((artificial intelligence) OR (AI) OR (machine learning) OR (ML)) AND ((obstacles) OR (barriers) OR (hindrance) OR (hindering))

After forming the search string, we select databases from different disciplines. We use PubMed for medical articles, and Web of Science and Science Direct for economic articles. Through the database search, we retrieve a total of 555 articles. In the next step we exclude books, non-English or German written articles, non-peer reviewed work, and remove duplicates, resulting in 510 remaining articles. When selecting the articles, we do not restrict the selection to the thematic focus or ranking of the journals and conferences and include information systems research, healthcare research as well as research on the interface of both. Following, we screen the titles of the remaining articles for relevance to the research topic. During this step, we exclude 402 articles due to irrelevance. We repeat the process for the abstracts, with another 56 articles being irrelevant and subsequently excluded. We consider articles irrelevant if their understanding of AI did not match our definition of AI as a self-learning ML model, or if they did not sufficiently connect the topics of radiology and AI technologies. In cases where the correspondence of AI understanding to our own was not evident from the abstract, we looked more closely at the article to find indications. In the next step, we acquire and screen the full texts of the articles, except one that was unavailable, and one published in Chinese only. We then exclude five additional articles due to not focusing on obstacles of AI technologies and nine articles lack a more direct focus on radiology. This results in a final study sample of 34 articles. On this basis, we conduct a backward and forward search. We search through the sources of the included studies, add relevant findings to our literature selection, and use Google Scholar during the forward search to assess previous citations of an article. We collected further 14 articles – resulting in a total of 48 relevant research papers, applying the same exclusion criteria as mentioned above.

3.2. Data analysis

When analyzing our literature, we follow an inductive approach (Bandara et al., 2015). As the use of AI technologies in radiology is relatively young, we choose an inductive approach to coding, enabling new concept developments (Gioia et al., 2013). As Wolfswinkel et al. (2013) state, the analytical step of coding is essential to label and build concepts based on the insights presented in the selected literature.

In analyzing the literature, we first attach preliminary codes and our thoughts on conspicuousness and possible connections to the positions of interest in the articles. We divide coding into two steps: In the first step, we use the auto-code function of MAXQDA - a computer-assisted qualitative data and text analysis tool to highlight specific keywords related to obstacles, with the following marked synonyms: obstacles, barriers, hindrance, hindering, challenges, hurdle, problem, difficulty, obstruction, barricade, blockade, issue, limit, limitations, uncertainty, challenge, challenging. In the second step, the author team carefully read independently from each other the relevant articles to find further obstacles which the automatic function has potentially missed. In this way, we could assign codes not only to individual words but also to entire sections. In the next step, we further examine and paraphrase the identified codes and group those with common topics into concepts (Strauss & Corbin, 1996). In the first round, each author groups the codes into concepts independently of the other co-authors. In the following rounds, the groupings of each author are constantly compared and modified. Disagreements among the author team regarding individual assignments of codes to concepts are resolved in discussion with an independent researcher who has his research focus on information technologies in healthcare. In all cases of discrepancies, a solution is found. This grouping approach aims to increase the validity of the coding results. After comparing the assignment of concepts, we group them into categories, following the same assignment approach to increase validity as mentioned above. Further, drawing from our data analysis and subsequent discussions among the authors, we observed that certain categories are interrelated. We present and elucidate a first derivation of the interrelationships between the obstacles in Figure 1 of Section 5. In this context, it is important to note that this paper does not aim for statistical verification and validation.

4. Results

Table 1 presents the identified 17 obstacles of AI technologies in radiology grouped into six categories.

Table 1. Obstacles of AI technologies in radiology.

Category	Obstacle	Frequency in studies
Data	Data Availability	24
	Data Quality	25
	Standardization	8
	Data Privacy & Security	24
Software	Accuracy	24
	Transparency	25
	Generalizability	23
	Bias	15
	Scientific Validation	21
Market	Costs	11
	Support	22
Clinical Application	Added Value	5
	Technical Infrastructure	12
User Attitude	Physicians' Attitude	26
	Patients' Attitude	8
Regulations	Insufficient Regulations	22
	Unfavorable Regulations	13

Data

The following obstacles are all data-related: *Data Availability, Data Quality, Standardization,* and *Data Privacy & Security.*

Data Availability – The reasons for the lack of data availability are manifold. On the one hand, there are no, or not enough, public databases available (Cuocolo & Imbriaco, 2021). On the other hand, many people cannot or do not know how to access public databases (Kazmierska et al., 2020). Kazmierska et al. (2020) continue that creating a culture of data sharing is a significant challenge. Institutional rivalry and other proprietary interests hinder data sharing (Thrall et al., 2018). Besides, health data is held under privacy and security regulations, which makes data sharing and database creation difficult (Liu et al., 2021).

Data Quality – The obstacle Data Quality refers to the rarity of relevant, high-quality, and properly annotated data (Habuza et al., 2021). It is a bottleneck in the development of AI technologies (Wichmann et al., 2020). Data annotation is time-consuming, labor-intensive, requires experienced radiologists, and is very costly (Pesapane et al., 2018). Another point to consider is that abnormalities in medical images are not inevitably directly linked to a specific diagnosis, which leads to further uncertainty (Wichmann et al., 2020). Defining a distinct ground truth for annotations might not be possible (Thwaites et al., 2021) as there is the issue of perception both among individuals and across different datasets (Padash et al., 2022).

Standardization – The obstacle of a lack of Standardization is strongly related to the obstacles of Data Availability and Data Quality. It features different problems, such as the standardization of reporting and processes (Lekadir et al., 2021). Radiology reports are usually unstructured in a free text format and handwritten, with images being not annotated (Lekadir et al., 2021). In the study of Hofmann et al. (2019), a radiologist stated that standardization was deemed unnecessary before the era of AI and only used to report and label data for the benefit of clinical workflow - not for training algorithms.

Data Privacy & Security – Data privacy and security is of high relevance to the medical field and form a great obstacle for AI technologies (Liu et al., 2021). Medical information that has been classified as sensitive data fall under strict regulations. For data to be used on a lawful basis, it must have been deidentified (Taylor & Fenner, 2019). This poses a barrier for AI technologies because deidentification is challenging and time-consuming (Buda et al., 2021). Moreover, consent from patients to use their data is required (Cuocolo & Imbriaco, 2021), which is an elaborate and costly exercise (Taylor & Fenner, 2019).

Software

This category includes the obstacles Accuracy, *Transparency, Generalizability, Bias,* and *Scientific Validation*.

Accuracy – Insufficient accuracy poses an obstacle to the uptake of AI technologies in radiology (Buck et al., 2021). The accuracy of AI software is a very important topic, with every error bringing potential risks and costs for the patient's health and the physician in terms of being responsible (Piotrowski et al., 2021). A performance issue that needs to be solved is the number of false-positive findings, which requires reduction (Chan & Siegel, 2019). Furthermore, the performance of the AI algorithm depends on the quality and amount of available data (Thrall et al., 2018) – as previously addressed in the category Data. From an interview study, it becomes apparent that patients and physicians fear the malfunction of AI technologies (Müller et al., 2021). However, these concerns are not without merit, as the performance of AI technologies often degrades outside of the training environment in real-world applications (Eche et al., 2021).

Transparency – The second hurdle is the lack of transparency - and thereby difficulty in the interpretability - of the decisions made by AI technologies. Whenever AI algorithms have been used, the black-box property has been perceived as a potential obstacle (Arora, 2020), with the term 'black box' alluding to this lack of transparency regarding AI algorithms. The underlying reasoning behind AI technologies' output cannot yet be accessed and revealed (Galsgaard et al., 2022). The black box property opens the door for the risk of bias, as systematic errors cannot be identified (Müller et al., 2021), while outputs and risks are challenging to foresee (Taylor & Fenner, 2019). The lack of transparency hinder physicians and patients from building trust and obstruct the potential for acceptance (Buck et al., 2021).

Generalizability – A key challenge affecting AI algorithms' performance is the phenomenon of 'generalizability' (Ahmad, 2021), with a lack of generalizability as an anticipated hurdle of adoption (Huisman et al., 2021). The term refers to the problem of a drop in performance when the algorithm is tested on data it has not been trained on – although it performs well on similar data, it fails to generalize on diverse datasets (Liu et al., 2021; Recht et al., 2020). This occurs when the algorithm is trained with data from one source or with small data samples (Willemink et al., 2020).

Bias – Bias occurs when datasets overrepresent, underrepresent, or completely miss relevant characteristics for the desired application (Recht et al., 2020). Characteristics that can be sources of bias include differences in age, gender and ethnicity, income, education, and geography (Lekadir et al., 2021). The types of bias are manifold. On the one hand, there are cases where the data sources do not reflect the true epidemiology in a population (Wichmann et al., 2020). On the other hand, there are cases where the composition of the dataset does not contain certain populations (Vayena et al., 2018). If trained on biased data, the algorithm may yield incorrect results and discriminate against minorities (Hofmann et al., 2019).

Scientific Validation – Poor reporting and subsequent inadequate reproducibility (Piotrowski et al., 2021) and insufficient or lack of validation (Cuocolo & Imbriaco, 2021) are other obstacles of AI technologies in radiology (Buda et al., 2021). To avoid risks and dangers in clinical use, extensive validation and testing of the accuracy and limitations of AI technologies are obligatory (Thwaites et al., 2021). This validation process is challenging and time-consuming and poses a major obstacle (Noguerol et al., 2019). Circumstances that complicate the validation include a lack of public qualitative databases (Cuocolo & Imbriaco, 2021) and inadequate documentation of methods and code (Haibe-Kains et al., 2020).

Market

Market contains the obstacles *Costs* and *Support*.

Costs – Costs are a decisive factor for enforcing AI technologies and can be divided into costs for the user and costs in the development process (Huisman et al., 2021). Costs arise from the need to comply with regulations, such as obtaining regulatory approvals and ongoing monitoring of software - particularly for AI technologies classified as high-risk, extensive testing (Taylor & Fenner, 2019). These costs initially fall on developers, but there are also costs for end users, such as medical institutions, which have to consider not only the cost of the AI technologies, but also the cost of the technical infrastructure (Noguerol et al., 2019).

Support – Another obstacle of AI technologies is the lack of support for implementing new technologies. Radiologists are confronted with the problem – that being a lack of a universal platform for acquirable AI technologies (Leiner et al., 2021). Radiologists have to navigate themselves through different solutions offered by vendors (Cuocolo & Imbriaco, 2021). Radiologists need more collaborative support, such as additional resources (Liew et al., 2019), help from experts (Giansanti & Di Basilio, 2022), and protected time (Taylor & Fenner, 2019) to implement AI technologies.

Clinical Application

This category contains the obstacles *Added Value* to clinical workflow and *Technical Infrastructure*.

Added Value – The obstacle of Added Value to the clinical workflow relates to the fact that the contribution of AI technologies to the workflow is often unclear and not precisely measurable. There are uncertainties and a lack of empirical evidence regarding diagnostic performance improvements, clinical efficacy gains (Fritz et al., 2022), contribution to the radiological workflow (Strohm et al., 2020), improving and guiding clinical outcomes (Qian et al., 2021). This uncertainty can cause low acceptance rates among physicians and hinder the acquisition of funding (Strohm et al., 2020).

Taylor and Fenner (2019) opine that evidence for the added value, even if it is difficult to obtain, spurs the adoption and implementation process.

Technical Infrastructure – Inadequate or insufficient digital infrastructure of the medical facility is a hurdle for the clinical implementation of AI technologies (Huisman et al., 2021). For AI technologies, the existing hardware is insufficient in most cases, with infrastructure often not in place leading to complicated implementation by extensive reconfiguration of the IT systems, as AI technologies require certain prerequisites such as real-time up- and downloads for inquiries (Kanakaraj et al., 2022). Furthermore, facilities may be bound to old technologies due to network effects, which halts the implementation of new infrastructure (Arora, 2020).

User Attitude

This category includes *Physicians' Attitude* and *Patients' Attitude*. Meaning that in our context, the user can be either the radiologist or the patient.

Physicians' Attitude – Physicians' attitude is a major obstacle to the successful adoption of AI technologies, with users playing a key role in the adoption process (Waller et al., 2022). Several articles mentioned the skeptical attitude of physicians toward AI technologies (Buck et al., 2021; Clements et al., 2022). This cynicism comes from multiple concerns - some of which have already been addressed in previous sections – regarding, for example, the accuracy, the possibility of errors, malfunction, and concerns about validation, lack of transparency, cyber security, costs, issues of responsibility, and issues around buying and implementing the technology (Galsgaard et al., 2022). Besides, a satisfactory level of AI literacy is not yet possessed by all radiologists (Recht et al., 2020), influencing their attitude.

Patients' Attitude – Patients' attitude also plays a key role in adopting AI technologies. According to Clements et al. (2022) Patients do not trust the use of AI technologies and would rather confide in the radiologist's expertise since they value in-person interaction. This lack of trust comes partly from the fact that they do not understand how AI technologies function (Habuza et al., 2021) – with the lack of transparency of the AI technologies again posing a problem regarding patient acceptance (Wichmann et al., 2020). Furthermore, patients worry malfunctions (Müller et al., 2021), biases (Hofmann et al., 2019), and data security (Clements et al., 2022).

Insufficient Regulations – Regulations are a big hurdle to the adoption of AI technologies. The regulatory situation is very unclear and, in some areas, insufficient: from approval, to use in daily clinical work, and to the open question of liability (Giansanti & Di Basilio, 2022). AI software in radiology is legally classified as a medical device and is subject to special regulations. However, there is no universal legal framework for the approval of AI technologies (Cuocolo & Imbriaco, 2021), making the approval process mostly unclear (Qian et al., 2021). Further, a significant legal problem is the question of liability. It remains open as to who is responsible for damage caused by a decision made by AI technologies (Pesapane et al., 2018).

Unfavorable Regulations – As described above, a lack of legal frameworks is a persistent problem (Cuocolo & Imbriaco, 2021). But at the same time, if an existing guideline is outdated, it can also hinder innovation (X. T. Li & Huang, 2020). There are privacy regulations that refer to the storage, custody, and sharing of medical and imaging data of patients (Noguerol et al., 2019). These personal data are held under strict privacy laws. Taylor and Fenner (2019) explain that according to European regulations, there are two ways to use personal data: Patient consent and anonymization.

5. Discussion

To provide guidance on how to tackle the obstacles of the adoption of AI technologies in radiology, we present a first derivation of the interrelationships between the obstacles in Figure 1, discuss the interrelations between the identified obstacles and present the contribution of our work.

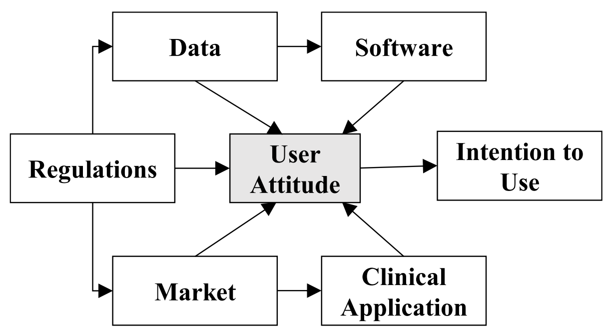

Figure 1. Interrelations of the obstacles of AI technologies in radiology.

First, *Unfavorable Regulations* (Regulations) influences *Data Privacy & Security* (Data) and *Data Availability* (Data). Since training AI technologies require a large amount of data, data availability is very important for AI technologies. We acknowledge that there is a need for very strict data protection regulations, as patient data is very personal and sensitive, which must be protected. Nevertheless strict regulations slow down the development and training of AI technologies by limiting data availability (Kazmierska et al., 2020). Consequently, policy makers have an important role to play by creating incentives for healthcare providers to improve data availability through structured and complete documentation in daily practice. The *Data Availability* itself influences the *Generalizability* (Software). Poor availability of different data sets leads to the AI application not being able to be applied in a generalist manner (Liu et al., 2021; Recht et al., 2020). For example, if AI technologies are trained only on data from a specific population because only that data is available, having an AI application diagnose a different population will produce erroneous results.

While *Unfavorable Regulations* may hinder AI technologies because they are very strict, *Insufficient Regulations* (Regulations) may hinder AI technologies because they are too unclear or non-existent, resulting in uncertainty for developers and users. For instance, the obstacle of *Insufficient Regulations* influences the obstacle *Support* (Market) as there are no or unclear regulations to support the development and adoption process of AI technologies (Giansanti & Di Basilio, 2022). Moreover, there is a lack of regulations and specific guidelines that help physicians incorporate AI technologies into clinical practice (Galsgaard et al., 2022), which will particularly discourage technology-averse physicians from using AI technologies.

Certain technical prerequisites, like real-time upload and download capabilities, are essential for AI technologies (Kanakaraj et al., 2022), which reveals the next interrelated obstacles: *Technical Infrastructure* (Clinical Application) is influenced by *Costs* (Market). Inadequate IT infrastructure that needs to be renewed increases the expenses and costs associated with implementing AI technologies (Noguerol et al., 2019). Furthermore, facilities may be bound to old technologies, which halts the implementation of new technical infrastructure (Arora, 2020); cf. the research stream of technical dept (Keller et al., 2019; Z. Li et al., 2015). Moreover, some medical facilities may be unable or unwilling to afford the AI application's costs without assistance. Thus, policy makers should consider monetary subventions in the development or adoption of AI technologies. Further, in the context of general practitioners, Buck et al. (2022) concluded that they view financial affordability as a minimum requirement for using AI technologies, influencing their attitude.

As illustrated in Figure 1, not only Costs but many of the identified obstacles influence the *Physicians' Attitude* (User Attitude), such as the obstacles *Insufficient Regulations* regarding unclear liability, *Unfavorable Regulations* in combination with *Data Privacy & Security*, as well as Accuracy, *Transparency, Bias, Added Value,* and *Technical Infrastructure*. For instance, the attitude is influenced by the obstacle *Transparency* as radiologists lack trust in AI technologies' decisions due to the black-box nature of many AI algorithms (Eche et al., 2021; Qian et al., 2021); cf. the research stream of explainable AI (XAI) (Gunning et al., 2019; Miller, 2019). Further, radiologists have concerns that AI technologies will not be accurate (Strohm et al., 2020) or might bias the physician toward an erroneous conclusion, leading to patient mistreatment (Buck et al., 2021). To minimize these concerns, the hospital/practice must establish clear best practices, e.g., guidelines mandating cross-checking AI diagnostic suggestions by a second person to mitigate bias. Further, *Data Privacy & Security* influences the *Physicians' Attitude* as they fear potential data misuse through AI technologies' internet access (Buck et al., 2022). Moreover, patients' increasing desire for involvement in treatment decisions inevitably affects physicians' attitude (Buck et al., 2022). Hence, patients' sentiment can significantly affect physicians' adoption of AI technologies. Consequently, we find – in line with, e.g., Freiesleben et al. (2021) – that the obstacles are strongly interrelated and especially the user and its attitude play a central role in the adoption of AI technology (Jussupow et al., 2022).

Following the discussion that also outlines our practical implications, we present the theoretical contributions of our study. We contribute to research by developing a model that illustrates the categories' interrelations and suggests a comprehensive simultaneous approach to overcome respective obstacles. To accelerate the adoption of AI technologies, the obstacles need to be tackled by combining different solutions in a holistic approach.

Moreover, our results contribute to acceptance and behavioral research. In contrast to well-known theories of technology acceptance research (e.g., Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2016)) or behavioral research (e.g., Theory of Reasoned Action (Ajzen & Fishbein, 1980)), our findings suggest that users' attitude plays an important role in explaining the intention to use AI technologies in the medical context. With this result, we are in line with Buck et al. (2022), who examine general practitioners' attitude toward AI technologies and conclude attitude to be a non-negligible influencing factor of the intention to use. Moreover, we extend this finding to radiologists: We reveal that most of the identified obstacles influence the radiologists' attitude by raising concerns, e.g., that lack of transparency has serious consequences for treatment outcomes. Therefore, to accelerate the adoption of AI technologies, the identified obstacles need to be addressed and resolved, which can positively influence the attitude and the intention to use AI technologies.

6. Conclusion, limitations, and future research

By performing a systematic literature review, we identify 17 obstacles of AI technologies in radiology, which we categorize into six categories: *Data, Software, Market, Clinical Application, Regulations,* and *User Attitude*. We discuss the interrelations of the categories by giving examples and highlight the need of a holistic approach to overcome the obstacles. Moreover, for the successful and widespread adoption of AI technologies in radiology, we note that research needs to elaborate on and outline approaches that address the obstacles simultaneously. Of course, such a simultaneous approach needs to base on a bouquet of solutions to account for the identified complexity of the obstacles. Furthermore, with the insight of all obstacles influencing physician's attitude, we contribute to acceptance and behavioral research.

Despite rigorously following the research methodology, this study has some limitations leading to possible directions for future research. First, since we focus on the field of radiology, our results are context specific. Further research should examine obstacles in other fields of medicine and compare obstacles across disciplines. Moreover, further research may either explore to what extent our results can be embedded into an existing framework or validate our presented model for its causal effects and for its applicability in practice by experts from the field of radiology. Besides, we recommend future research to quantitatively determine the obstacles' impact on radiologists' attitude by noting the weighting of each obstacle. Moreover, we recommend future research to be directed towards the identification of possible solutions to develop a holistic approach for accelerating the adoption of AI technologies in radiology.

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