From Potential to Practice:
Promoting the Adoption of Artificial Intelligence in Medical Diagnosis

Dissertation

zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft
der Rechts- und Wirtschaftswissenschaftlichen Fakultät
der Universität Bayreuth

Vorgelegt

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Tag der mündlichen Prüfung:	*02.10.2024*

Copyright Statement

The following sections are partly comprised of content taken from research articles included in this thesis. To improve the readability of the text, I omit the standard labeling of citations of these points.

Abstract

Artificial intelligence (AI) applications offer great potential to enhance healthcare. With capabilities that surpass those of humans, AI applications are particularly promising in assisting physicians in medical diagnosis, increasing accuracy and processing speed, thereby tackling the growing challenges in healthcare. Despite various studies demonstrating the promising potential of AI applications, their widespread practical adoption has progressed slower than expected. Thus, to fully leverage the potential of AI in healthcare, (1) a detailed analysis and comprehensive overview of the various obstacles to the adoption of AI applications in medical diagnosis is necessary. With the user playing a central role in determining technology adoption, (2) an in-depth analysis of the physicians' perspectives regarding AI applications in medical diagnosis is needed to identify context-specific factors influencing adoption from individual user perspective. To promote the adoption of AI applications in medical diagnosis, not only the influencing factors must be identified, but in a second step, (3) measures addressing the hindering factors are required, always mindful that technology should not be used merely for its own sake.

This thesis addresses the three research imperatives through seven research articles. One article provides a comprehensive overview of the current obstacles to the adoption of AI applications in medical diagnosis, four articles deepen the understanding of the factors influencing the adoption of health information technologies (HIT) from an individual user perspective, and two articles focus on measures promoting the adoption of AI applications. Methodologically, this thesis is grounded in a qualitative and predominantly exploratory research approach. It comprises one structured literature review and six interview-based studies incorporating a total of 107 interviews to gain in-depth information necessary to address the thesis' aims.

Overall, this thesis makes valuable contributions to the technology adoption research stream. It contextualizes well-known influencing factors and adds new context-specific factors influencing the adoption of AI applications in medical diagnosis from an individual user perspective. Further, it contributes by emphasizing the importance of physicians' prior experience with and knowledge of the respective technology in understanding and explaining HIT adoption. This thesis encourages researchers in technology adoption not only to focus on investigating initial adoption, but also on the continuous usage of the technology. Finally, this thesis proposes practical implications in the form of specific measures to promote AI application adoption, focusing on enabling physicians to make an informed adoption decision, whereby demonstrating the added value of the HIT in clinical use appears highly relevant.

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List of Abbreviations

AI	Artificial Intelligence
GTM	Grounded Theory Methodology
RG	Research Goal
RO	Research Objective
HIT	Health Information Technologies
HIS	Hospital Information Systems
VR	Virtual Reality
TAM	Technology Adoption Model
UTAUT	Unified Theory of Acceptance and Use of Technology
GP	General Practitioners
DOI	Diffusion of Innovations
TPB	Theory of Planned Behavior

1 Introduction

Artificial intelligence (AI) has the potential to revolutionize healthcare (Fogel & Kvedar, 2018; Jiang et al., 2017; Yu et al., 2018) as it offers promising benefits due to its capabilities to improve accuracy, objectivity, rapidity, data processing, and automation (Jiang et al., 2017; Yu et al., 2018). Moreover, AI applications can improve the quality of patient care by compensating for human limitations and weaknesses such as processing speed and fatigue (Yu et al., 2018). In some cases AI applications even outperform humans (Topol, 2019). AI capabilities are also promising, considering the increasing challenges of the healthcare industry. The shortage of qualified specialists (Rimmer, 2017), coupled with an increasing medical demand (McDonald et al., 2015), puts healthcare professionals (e.g., physicians, nurses, etc.) under considerable pressure and increases the need for new (technological) solutions to guarantee high-quality care.

There are various AI application areas considered to create value in healthcare, including medical diagnosis (e.g., Bonekamp et al., 2018), biomedical research (e.g., Kadurin et al., 2017), clinical administration (e.g., Rezazade Mehrizi et al., 2020), therapy (e.g., Dankwa-Mullan et al., 2019), and intelligent robotics (e.g., Yip et al., 2023). AI applications are receiving particular attention as a helpful solution to tackle the increasing workload, especially in medical diagnosis, where imaging-based diagnosis is at the forefront. Imaging-based diagnosis has become a prominent area for the integration of AI applications, as there is already a very large amount of structured data available (Hosny et al., 2018). Using AI applications on medical images has demonstrated remarkable results in recognizing complex patterns and features that are not visible to the human eye (Hosny et al., 2018). For example, an AI application has improved breast cancer detection, achieving more accurate results by significantly reducing the rate of false positives and false negatives (Killock, 2020). Another AI application has delivered promising results in prostate cancer diagnosis, with more accurate diagnoses avoiding unnecessary procedures such as biopsies (Bonekamp et al., 2018). Thus, AI applications, not only offer medical value by minimizing patient discomfort and risks, but also business value by streamlining the diagnosis process and potentially reducing healthcare costs. It is estimated that AI applications could address 20 % of unmet clinical needs, with the industry saving up to USD 150 billion annually following the adoption of AI applications (Khanijahani et al., 2022).

However, retrospectively, the widespread practical adoption of AI applications has progressed slower than expected (Allen et al., 2021; Pagallo et al., 2024), as implementing and adopting AI applications in real-world settings have presented significant challenges (e.g., Char et al., 2020; Torous et al., 2021). This is amplified by the circumstance that physicians are generally more resistant to the adoption of new technologies, as identified in research on the adoption of health information technologies (HIT) (Bhattacherjee & Hikmet, 2007). The user's acceptance of the technology plays a key role in this regard, as known from the technology adoption research stream (e.g., Davis, 1989; Venkatesh et al., 2003). It is therefore important to gain detailed insights into the individual user's perspective on AI applications in medical diagnosis in order to identify and address remaining challenges and thus exploit the potential of AI for the respective context (in this thesis, by the user the healthcare professional is meant, not the patient). Thus, this thesis addresses the following overarching research objective (RO):

Overarching RO: Enhance the understanding of obstacles in the adoption of AI applications in medical diagnosis with a special focus on the factors influencing the adoption of HIT from an individual user perspective and on measures to promote the adoption of AI applications in medical diagnosis.

As a first step, the reasons for the discrepancy between the recognized potential and the adoption of AI applications must be understood. Creating a comprehensive overview of AI application adoption obstacles provides a crucial foundation for addressing these in subsequent steps (Chapter 3.1). Consequently, the first research goal (RG) states:

RG1: Identifying obstacles hindering the adoption of AI applications in medical diagnosis.

The obstacles can be attributed to four key areas: macro-economic, organizational, technological, and user-related (Roppelt et al., 2024). Macro-economic obstacles include strict data protection laws limiting data sharing between organizations and thus slowing down AI applications from entering the healthcare market. Organizational obstacles include the lack of technical infrastructure to implement AI applications effectively. Technological obstacles include the need for further refinement of AI applications to meet the stringent standards of accuracy and reliability required for medical applications (e.g., Article 1). User-related are all those obstacles that hinder the adoption of HIT from an individual user perspective (e.g., Articles 2-4). Thus, to better understand the adoption of HIT, a deep dive into healthcare professionals' perspectives on the regarded technology is crucial (Chapter 3.2). While researchers have already identified factors that significantly influence technology adoption from an individual user perspective, their explanatory power is context dependent. Therefore, researchers argue for contextualization, to enhance the understanding of technology adoption within specific contexts (Benbasat & Barki, 2007; Holden & Karsh, 2010; Venkatesh et al., 2011). Thus, the second RG states:

RG2: Deepening the understanding of the factors influencing HIT adoption from an individual user perspective.

Considering AI applications in medical diagnosis, this thesis argues that physicians have various expectations, including improved diagnostic quality and time efficiency, and concerns such as being replaceable and losing professional autonomy (e.g., Articles 2 and 3). Some of these concerns stem from the special characteristics of AI applications such as their capabilities to make autonomous decisions, their precision, which has already been shown to exceed that of human experts, and the non-transparency of some AI algorithms (Fan et al., 2020; Prakash & Das, 2021). Other concerns can be attributed to the lack of prior experiences with AI applications and the insufficient knowledge about AI applications (Article 3). Experience with and knowledge about the technology have already been shown to influence healthcare professionals' expectations and concerns regarding the adoption of less complex HIT (e.g., Articles 4 and 5). For instance, healthcare professionals with experience in virtual reality (VR) technology have no concerns to be replaceable contrary to those without prior experience (Article 4). Negative experience, on the other hand, reinforces healthcare professionals' concerns. For example, healthcare professionals have experienced the integration of hospital information systems (HIS) as very time-consuming, which reinforces their concerns that the HIS is more of a hindrance than a support and leads them to the implementation of workarounds (Article 5).

Learning from negative examples and promoting the successful adoption of AI applications requires measures that address the influencing factors outlined in Chapter 3.2. However, as technology should never be used just for its own sake, measures must be directed at enabling physicians to make an informed decision about adoption in a particular use case, rather than promoting the general adoption of AI applications (Chapter 3.3). Accordingly, RG 3 states:

RG3: Providing measures to enable physicians to make an informed decision about the adoption of AI applications in medical diagnosis.

To address the aforementioned research goals, this thesis comprises seven research articles contributing to the research stream of technology adoption in the specific context of healthcare. Five articles specifically provide valuable insights on the topic of AI adoption and four deepen the understanding of the factors influencing the adoption of HIT from an individual user perspective. Methodologically, this thesis comprises one structured literature review and six interview-based studies with a total of 107 interviews. The interviews capture in-depth information on healthcare professionals' perspectives on and experiences with specific HIT (Schultze & Avital, 2011), which is particularly important when conducting social, health, and information systems research (Myers & Newman, 2007; Ryan et al., 2009). Furthermore, face-to-face interviews can contribute to create an atmosphere of trust, encouraging interviewees to talk in more detail about their concerns and fears (Creswell, 2009). In this way, further information can be obtained that may remain undiscovered in more structured research approaches (Schultze & Avital, 2011). The qualitative research approach chosen does not allow for generalization of the information gained or the measurement of relationships, but the detailed information obtained on healthcare professionals' perspectives allows for contextualizing known theoretical constructs or, according to Schultze and Avital (2011), even for developing new theories.

The structure of this thesis is as follows: first, the context of medical diagnosis is explained, and exemplary AI use cases are presented. Second, an understanding of the research stream of technology adoption is provided as a basis for the theoretical embedding of the main results of this thesis. Chapter 3 presents the thesis' main findings, including one research article that provides a comprehensive overview of obstacles to the adoption of AI applications in medical diagnosis, four research articles that focus on the influencing factors in the adoption of HIT from an individual user perspective, and two research articles that are aimed at promoting AI applications adoption. Chapter 4 includes an overarching discussion, and the thesis' theoretical contributions, practical implications, limitations, and future research directions. This is followed by Chapter 5 where a conclusion to the thesis is provided.

2 Previous and Relevant Work

2.1 Artificial Intelligence Applications in Medical Diagnosis

As a central element of healthcare, medical diagnosis aims to find a precise explanation for the patient's medical problems. This task usually begins with a thorough examination of the patient's clinical symptoms and medical history, and can be supplemented by a variety of tests such as blood, imaging, and other diagnostic tests (Dreher et al., 2019; Yazdani et al., 2017). The physician's main task in medical diagnosis is to recognize patterns based on their medical expertise, experiences, and observations (Stanley, 2019). Based on the diagnosis, the physician decides whether to treat the patient or get a further diagnostic test (Müller et al., 2020). The diagnosis made by the physician thus sets an important direction for the subsequent steps and contributes significantly to the course of action.

Medical diagnosis is susceptible to errors that can cause significant harm to patients (Singh et al., 2017). In 10 % of cases, misdiagnoses even contribute to patient deaths (van Such et al., 2017). Diagnostic errors stem primarily from two factors: cognitive and system-related factors. Cognitive factors include bias and knowledge deficits (Royce et al., 2019), flawed information synthesis, premature case closure (Graber, 2005), and issues like incorrect patient positioning and physician fatigue (Brady, 2017). On the other hand, system-related factors encompass organizational challenges such as insufficient access to specialists (Singh et al., 2016), technical issues with equipment, and procedural inadequacies (Graber, 2005). Misdiagnosis is intensified by increasing time pressure due to the increasing shortage of skilled workers (Rimmer, 2017).

Considering medical imaging diagnosis, radiologists must interpret a medical image within 3 to 4 seconds to meet the demand (McDonald et al., 2015). The time pressure on physicians is exacerbated by technological advancements that make it possible to capture a greater number of medical images, all of which need to be analyzed (McDonald et al., 2015). These developments increase the workload per specialist, making diagnostic errors more likely. The average diagnostic error rate in medical imaging diagnosis lays around 30 % (Pinto Dos Santos et al., 2019). The rate varies from 3 to 5 % for routine examinations (Brady, 2017), 31 to 37 % for oncological computer tomography scans (Siewert et al., 2008), and up to 61 % for mammography screenings (Nelson et al., 2016). The time and cost pressure during diagnosis drive physicians to constantly look for new (technological) solutions to maintain high-quality care.

Technologies were utilized early on in imaging diagnosis. The first medical X-rays were taken in 1895 (Babic et al., 2016). Over the years, more advanced procedures have been used, such as computed tomography and magnetic resonance imaging (Schulz et al., 2021). In addition to these technologies, which are directed at generating better medical images, in the 1960s, radiology also began using systems supporting the diagnosis decision-making process by specific recommendations (Pesapane et al., 2018). While these first systems were limited in their capability to learn from experiences as humans do, the integration of AI algorithms opened up new possibilities for medical diagnosis (Stivaros et al., 2010). Following the definition of Rai et al. (2019), this thesis defines AI as a machine's capability to perform cognitive tasks usually associated with human intelligence, such as perceiving, problem-solving, and interacting with the environment. Furthermore, AI can be characterized by its capabilities to make autonomous decisions, to learn by itself, its precision, which sometimes exceeds that of human experts (Fan et al., 2020; Prakash & Das, 2021), and the rapid processing of large amounts of data (Obermeyer & Emanuel, 2016). In addition, AI can compensate for human weaknesses and limitations such as fatigue (Topol, 2019; Yu et al., 2018). These characteristics pave the way for a collaborative relationship between physicians and AI applications. For instance, the AI application can recognize anomalies which the physician interprets (e.g., Chilamkurthy et al., 2018). This complementarity of AI applications and humans aims to create a synergistic effect that leverages the strengths of both to improve outcome and the efficiency of healthcare (Hemmer et al., 2024).

AI applications' capabilities in imaging diagnosis have been demonstrated in previous research. For example, AI applications have been shown to be supportive in preselecting images that display potential abnormalities and highlighting areas of interest for further examination (Syed & Zoga, 2018). AI applications have also been researched in pre-screening, such as in mammography to identify high-priority cases (Lamb et al., 2022), and in assessing the severity of brain hemorrhages to prioritize patient care (Chilamkurthy et al., 2018). Another AI application increased the sensitivity in diagnosing wrist fractures and reduced misinterpretation (Topol, 2019). Besides, Gulshan et al. (2016) made evident that AI applications promise to increase the accuracy and speed of retinopathy screening, while Esteva et al. (2017) indicated that AI applications' performance in detecting skin cancer is comparable to dermatologists. Moreover, AI applications significantly reduced false positives and negatives in breast cancer screening (Killock, 2020) and improved the accuracy of prostate cancer diagnoses, thereby reducing the need for invasive biopsies (Bonekamp et al., 2018).

2.2 Theoretical Embedding of Technology Adoption

Research into technology adoption at an individual user level is a central area of information systems research (e.g., Davis, 1989; Venkatesh et al., 2003). Adoption is primarily about the individual user's intention to use technology, as highlighted by Davis (1989) and Venkatesh et al. (2003), focusing on user acceptance and usage decisions. Rogers (2003) extends the adoption concept by placing the individual perspective within the broader framework of diffusion of innovations (DOI) in a social system. In this context, the decision to adopt a technology is seen as a micro-level view that reflects individual and immediate interpersonal dynamics, while diffusion is a macro perspective that looks at how an innovation becomes established in a population over time. This relationship implies a sequential flow in which initial adoption by individuals or small groups can catalyze broader social acceptance, potentially triggering a chain reaction leading to widespread diffusion of the innovation (Rogers, 2003).

While the technology adoption research stream in the context of HIT mainly focuses on explaining initial technology acceptance, only a few studies emphasize continuous usage of the technology (Abouzahra et al., 2024). Continuous usage refers to the sustainable utilization of technology by adopters over an extended period following their initial usage decision (Kim et al., 2007). Thus, continuous usage behavior extends the initial use of technology (Al-Sharafi et al., 2017). Continuous use is critical to the sustainability of information technologies and its ultimate success relies on ongoing use rather than initial usage (Bhattacherjee, 2001). Healthcare professionals often resist new technologies (Bhattacherjee & Hikmet, 2007), which leads to them either not being continuously used over time (Blijleven et al., 2022) or not being implemented into the clinical setting at all (Bhattacherjee & Hikmet, 2007).

To explain the adoption of technology from individual perspectives, the technology adoption research stream offers well-known theories such as the Technology Adoption Model (TAM) (Davis et al., 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). While UTAUT is known to be quite frequently used to explain technology acceptance in healthcare (e.g., Diel et al., 2023; Venkatesh et al., 2011; Weeger & Gewald, 2015), the TAM is criticized for being insufficient for explaining acceptance in healthcare as it cannot explain the qualitative, emotional, and cultural aspects unique this specific context (e.g., Holden & Karsh, 2010; McCoy et al., 2007; Rahimi et al., 2018). UTAUT, in its original version, uses four factors to explain technology acceptance: *Performance Expectancy, Effort Expectancy, Social Influence,* and *Facilitating Conditions*. *Performance Expectancy* refers to the extent to which a person believes technology will improve their work performance. *Effort Expectancy* refers to the degree of ease of use associated with using the system. *Social Influence* is the extent to which a person perceives that their close social environment believes they should use the technology. *Facilitating Conditions* are defined as the extent to which a person believes that a technical and organizational infrastructure is in place to support the use of the technology. UTAUT uses four key moderating variables (*Gender*, *Age*, *Experience, Voluntariness*), which moderate the strength of the relationships between each of the four influencing factors and an individuals' intention to use a technology (Venkatesh et al., 2003).

UTAUT has been used to explain physicians' acceptance of electronic medical records (Venkatesh et al., 2011; Weeger & Gewald, 2015), physicians' acceptance of telemedicine (Diel et al., 2023), and healthcare professionals' acceptance of AI applications for venous thromboembolism (Zha et al., 2022). However, all these studies adapted UTAUT by adding further factors such as self-efficacy or emotions (Weeger & Gewald, 2015) or by contextualizing the existing factors to the research phenomenon to improve the explanatory power of the technology adoption in the specific context (Diel et al., 2023; Venkatesh et al., 2011; Weeger & Gewald, 2015;

Zha et al., 2022). Contextualizing the known influencing factors of technology adoption is crucial, as previous research has pointed out that technology acceptance theories leave room for additional contextual elements (Benbasat & Barki, 2007; Holden & Karsh, 2010; Venkatesh et al., 2011). In healthcare, with its unique characteristics, there is a critical need to adapt existing theoretical constructs or develop new theories that are tailored to fit the specific context of the healthcare sector (Holden & Karsh, 2010; Weeger & Gewald, 2015).

Articles 2 and 3 addressed the need for contextualizing technology adoption research by conducting qualitative explorative interviews to gain in-depth information on physicians' perspectives on AI applications in medical diagnosis. Columns 1 and 2 of Table 1 present the identified factors influencing physicians' perspectives. Column 3 gives short definitions of the identified influencing factors. This is followed by Column 4, which assigns the factors of UTAUT with a similar meaning to the factors of Articles 2 and 3, thereby giving first indications for contextualization, which this thesis further discusses in Chapter 4.2.2.

Table 1 Factors influencing the adoption of AI applications in medical diagnosis

Article 2	**Article 3**	**Definition**	**UTAUT**
▪ Additional Effort	▪ Time Expenditure	*Capture a physician's perception of the effort that comes with implementing and using AI applications.*	Effort Expectancy
▪ Diagnostic Accuracy ▪ Process Acceleration ▪ Objective Decision Support ▪ Workload Reduction	▪ Diagnostic Quality ▪ Diagnostic Efficiency	*Capture a physician's perception of the value AI applications come along.*	Performance Expectancy
	▪ Stakeholder Influence ▪ Change of Doctor-Patient-Relationship ▪ Lack of Human Competencies	*Captures a physician's opinion on the importance of others' opinions when considering the use of AI applications.*	Social Influence
▪ IT infrastructure	▪	*Captures a physician's perception on how sufficient the IT infrastructure is to use AI applications.*	Facilitating Conditions
▪ Job Loss ▪ Loss of Autonomy	▪ Existential Anxiety ▪ Autonomy	*Captures a physician's perception of how AI applications threaten their professional role.*	

▪ Unclear Responsibility	▪ Legal Liability	*Captures a physician's opinion on how important it is to determine responsibility and liability when using AI applications.*	
	▪ Misuse of Data	*Captures a physician's perception on how AI applications threaten data security and privacy.*	
	▪ Changing Working Conditions	*Captures a physicians' perception on how rising demands and lack of skilled workers affect the need to use AI applications.*	
	▪ Economic Viability	*Captures a physician's perception on the costs that come along with AI applications.*	
▪ Loss of Control	▪ Transparency ▪ Diagnostic Bias	*Captures a physician's perception on how AI applications are safe and dependable for use.*	
	▪ Technology Affinity	*Captures a physician's willingness to try out AI applications.*	

Articles 2 and 3 conducted interviews with physicians without prior experience using AI applications in daily practice. Article 3 assumes that all answers given are based on the physicians' knowledge of AI, regardless of whether this is right or wrong. When interpreting the identified influencing factors, the timing of any study (prospective or retrospective) is an important factor that must be considered (Hua et al., 2024). In prospective studies, participants have no prior experience with the technology in a professional context (e.g., Articles 2 and 3), resulting in potentially biased, either positive or negative perspectives. In retrospective studies, participants have already interacted with the specific technology under consideration (e.g., Articles 4 and 5). The reported perspectives of the healthcare professionals are, therefore, influenced by the users' actual experiences and their contextualized understanding of how the technology works in real or simulated medical practice (Hua et al., 2024).

2.3 Research Agenda

Given the growing interest in AI applications in medical diagnosis, driven by their benefits, this thesis aims to enhance the understanding of the topic of AI adoption in medical diagnosis by identifying factors influencing the adoption, and designing measures that enable physicians to make an informed adoption decision on AI applications. Figure 1 presents the connections of the seven research articles included in this thesis.

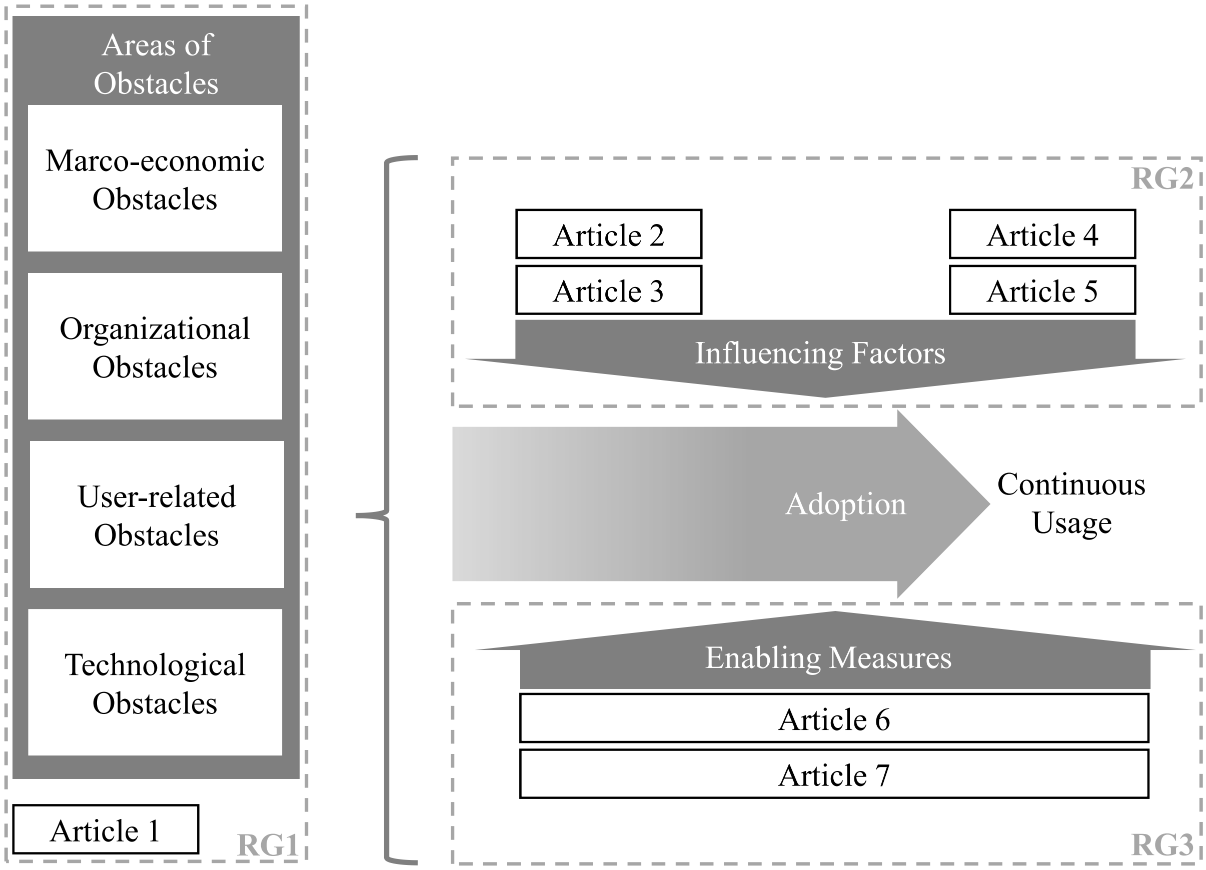

Figure 1 Connection of the seven research articles

Starting with addressing RG1 – *Identifying obstacles hindering the adoption of AI applications in medical diagnosis* – Article 1 assists research and practice in shedding light on the reasons for the discrepancy between the recognized potential of AI applications in healthcare and its actual adoption (Chapter 3.1). Article 1 offers an overview of the current obstacles that hinder the adoption of AI applications in medical imaging diagnosis, which can be attributed to four key areas: macro-economic, organizational, technological, and user-related (Roppelt et al., 2024). This thesis focuses on the user, a core element in technology adoption, and on factors influencing the adoption from an individual user perspective. This is addressed in RG2 – *Deepening the understanding of the factors influencing the adoption of HIT from an individual user* *perspective.* Article 2 explicitly analyzes radiologists' perspectives on AI applications, a user group experienced with technologies in medical diagnosis. In contrast, research article 3 examines the perspective of general practitioners (GPs), who traditionally use less technology in daily practice. Both articles reveal various factors shaping physicians' perspectives on AI applications, providing useful insights for contextualizing technology adoption. While Articles 2 and 3 derive influencing factors from interviews with physicians without prior professional experience with AI applications in medical diagnosis, Articles 4 and 5 derive influencing factors on technology adoption from interviews with healthcare professionals with prior experience with the specific technology. Article 4 investigates how prior experiences affect the healthcare professionals' perspective on VR technology in medical rehabilitation by comparing healthcare professionals' responses with and without prior experience. Article 5 derives antecedents of HIS-related workarounds by interviewing healthcare professionals who are supposed to work with the already implemented HIS in daily practice. Thus, implementing the technology does not necessarily represent success if the continuous usage of the technology is not achieved.

In aiming for the successful adoption and continuous usage of AI applications in medical diagnosis, measures are needed to address physicians' concerns. However, as technologies should never be used for their own sake, it is crucial to enable physicians to make an informed adoption decision, resulting in RG 3 – *Providing measures to enable physicians to make an informed decision about the adoption of AI applications in medical diagnosis.* Article 6 identifies and discusses enabling measures contributing to realizing AI applications' potential in medical diagnosis. Providing information about added value being important in this context, Article 7 outlines how AI applications can create value in healthcare.

Table 2 summarizes the seven research articles organized according to the three defined RGs.

Table 2 The seven research articles of this thesis and their publication status

Research Goal	**Research Article**			
	No	**Title**	**Publication Outlet**	**Publication Status**
RG1: Identifying obstacles hindering the adoption of AI applications in medical diagnosis.	1	Accelerating the Adoption of Artificial Intelligence Technologies in Radiology: A Comprehensive Overview on Current Obstacles	Proceedings of the 57th Hawaii International Conference on Systems Sciences (HICSS 2024)	Published
RG2: Deepening the understanding	2	Artificial Intelligence in Radiology: A Qualitative	Proceedings of the 42nd International	Published

of the factors influencing the adoption of HIT from an individual user perspective.		Study on Imaging Specialists' Perspectives	Conference on Information Systems (ICIS 2021)	
	3	General Practitioners' Attitudes toward Artificial Intelligence-Enabled Systems: Interview Study	Journal of Medical Internet Research (JMIR 2022)	Published
	4	Overcoming a Knowledge Gap of Healthcare Professionals: The Influence of Previous Experience on the (Non-)Adoption of VR in Medical Rehabilitation	Journal of Medical Internet Research - Working Paper	In Review
	5	Antecedents of Workarounds related to Information Systems in Hospitals: Interview Study	Journal of Medical Internet Research - Working Paper	In Revision
RG3: Providing measures to enable physicians to make an informed decision about the adoption of AI applications in medical diagnosis.	6	Enabling Physicians to Make an Informed Adoption Decision on Artificial Intelligence Applications in Medical Imaging Diagnosis: A Qualitative Approach	Journal of Medical Internet Research - Working Paper	In Review
	7	Capturing Artificial Intelligence Applications’ Value Proposition in Healthcare – A Qualitative Research Study	BMC Health Service Research (BMC 2024)	Published

3 Main Results

This chapter is divided into three main areas. Chapter 3.1 identifies current obstacles hindering the adoption of AI applications in medical diagnosis. This is followed by Chapter 3.2, which focuses on factors influencing the adoption of HIT from individual user perspective. After giving detailed information about obstacles hindering the adoption and continuous usage of HIT, Chapter 3.3 presents measures to enable physicians to make an informed adoption decision, to promote the adoption of AI applications in medical diagnosis.

3.1 Accelerating the Adoption of Artificial Intelligence Technologies in Radiology: A Comprehensive Overview on Current Obstacles (Hennrich, Fuhrmann, and Eymann, 2024a)

This study examined the current obstacles to the widespread adoption of AI applications in radiology. The potential of AI applications to improve patient care is particularly notable in radiology due to its data-intensive nature and imaging techniques (Hosny et al., 2018). There are various use cases of AI applications along the imaging diagnosis process. According to Boland et al. (2014) and Enzmann (2012), imaging diagnosis can be subdivided into preparation, image acquisition, processing and reading, compiling reports, and post-processing. During the preparation step, AI applications can assist in selecting the appropriate imaging exams, effectively reducing unnecessary tests and ensuring compliance with radiation safety standards (Morey et al., 2019). In the image acquisition step, AI applications can streamline the protocol drafting process, which is usually time-consuming. It generates these protocols in advance, detailing the examination's goals and incorporating patient history, all under the supervision of radiologists (Lakhani et al., 2018). The image processing step involves reconstruction, denoising, registration, and segmentation (Hofmann et al., 2019), where AI applications enhance image quality, even from lower quality scanners (Morey et al., 2019). This is followed by the image reading step in which AI applications can be used to preselect images and mark relevant sections on the image (Syed & Zoga, 2018). Further, AI applications can be used to write reports through speech recognition technologies (Morey et al., 2019) and to track follow-up information in the post-processing step (Xu et al., 2012). Despite the various use cases of AI applications in radiology promising significant value, its widespread adoption is limited (He et al., 2019). Thus, this study aimed to identify obstacles hindering the adoption of AI applications.

We conducted a structured literature review to identify obstacles to the adoption of AI applications in radiology, following Webster and Watson (2002). We searched PubMed, Web of Science, and Science Direct, retrieving 555 articles. After excluding non-English, non-German articles, non-peer-reviewed work, and duplicates, 510 articles remained. We screened titles and abstracts for relevance and excluded articles that did not align with our definition of AI or did not research AI in radiology, resulting in 34 articles. Further, we conducted backward and forward searches, adding 14 more articles, resulting in 48 relevant research articles.

When analyzing the literature, we followed an inductive approach to identify new obstacles to the adoption of AI applications in radiology (Bandara et al., 2015; Gioia et al., 2013). First, we used the auto-code function of MAXQDA to mark relevant keywords. Then, the authors read the articles independently to identify additional obstacles. The identified codes were paraphrased and grouped into concepts (Strauss & Corbin, 1996). Ultimately, we identified 17 obstacles, which we grouped into six overarching categories: *Data, Software, Market, Clinical Application, Regulations,* and *User Attitude* (Table 3).

Table 3 Obstacles of AI applications in radiology (Hennrich et al. 2024a)

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

Furthermore, during data analysis, we found that some categories are interrelated. A first derivation of the relationships between the obstacles is presented in Figure 2. However, this article is not aimed at statistically verifying and validating these relationships.

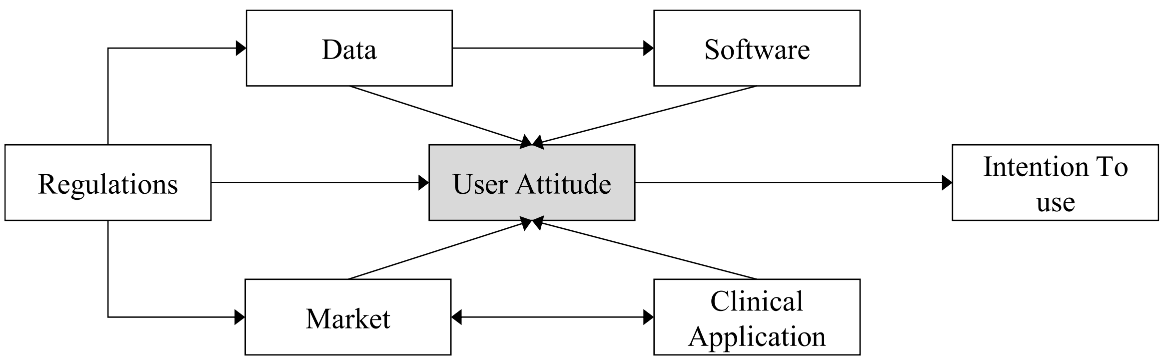

Figure 2 Interrelations of the obstacles of AI applications in radiology (Hennrich et al. 2024a)

Revealing 17 obstacles and by discovering potential interrelations between the obstacles led us to two conclusions. First, it demonstrates the need for a holistic and simultaneous approach to overcome the obstacles. This simultaneous approach should include a variety of solutions to address the identified obstacles. Second, by revealing that the categories of obstacles are not just obstacles themselves but also impact users' attitudes, we also contribute to acceptance and behavioral research (Ajzen & Fishbein, 1980; Davis, 1989; Venkatesh et al., 2003). For example *Data Privacy & Security* are not just obstacles from a technological perspective that must be addressed to fit the strict data regulations but also influence the physicians' attitude as physicians fear potential data misuse due to AI applications' internet access (Buck et al., 2022). By assuming these interrelations, we highlight that the radiologists' attitude is determined by each obstacle category, underlining the central role of the user in the adoption of AI applications.

3.2 Influencing Factors of the Adoption of Health Information Technologies from Individual User Perspectives

3.2.1 Artificial Intelligence in Radiology: A Qualitative Study on Imaging Specialists' Perspectives (Buck, Hennrich, and Kauffmann, 2021)

This research article delved into the perspectives of imaging specialists on AI applications in radiology, a field particularly well-suited for AI applications due to its reliance on data-intensive processes (Hosny et al., 2018). AI applications hold the potential to improve patient care, aiding in critical tasks such as the detection of skin cancer (Esteva et al., 2017) and breast cancer (Rodriguez-Ruiz et al., 2019) or evaluating the effectiveness of radiotherapy for individual patients (Cui et al., 2018). However, a notable gap persists between the expectations on AI applications' capabilities and their actual integration in clinical settings, often due to challenges in real-world integration and technology acceptance (He et al., 2019; Lell & Kachelrieß, 2020). Medical imaging specialists are pivotal as they are often the first to introduce new technologies into clinical practice (Tang et al., 2018; Thrall et al., 2018). Yet, an investigation of imaging specialists' perspectives on AI applications is critical to understand the decision and usage environment. Understanding the perspectives of these key stakeholders will provide valuable insights into what needs to be done to promote the adoption of AI applications in clinical practice.

We chose a qualitative research approach without predetermined theories or hypotheses to gain in-depth insides into medical imaging specialists' perspectives on AI applications. We followed the GTM approach for a detailed description of the phenomenon rather than abstracting relationships between categories (Wiesche et al., 2017). In addition to model development or theory generation, a comprehensive description of a phenomenon is a key outcome of a GTM study (Wiesche et al., 2017). For data collection, we conducted interviews and followed the methodological guidelines of Corbin and Strauss (2008). Before conducting the interviews, we informed ourselves about the context without studying existing theories to gain new insights. This intermediate approach, which is also recommended by Mey and Mruck (2010), allows for meaningful communication with the interviewees while avoiding biased data analysis. For data collection, we conducted semi-structured expert interviews, which are frequently used in GTM studies (Corbin & Strauss, 2008; Saldaña, 2009). This method is particularly suitable for gaining an in-depth understanding of a phenomenon of interest and capturing the opinions and experiences of respondents, which is especially important in social, health, and information systems research (Myers & Newman, 2007; Ryan et al., 2009). We conducted interviews with 15 medical imaging specialists, including radiologists, medical physicists, and a radiotherapist. We carried out the data collection and analysis iteratively (Corbin & Strauss, 2008), i.e., we began analyzing the interview transcripts parallel to conducting further interviews. We followed a flexible approach in which open and axial coding was not strictly separated but combined, as recommended by Corbin and Strauss (2008). We were able to categorize the medical imaging specialists' perspectives on AI applications into two main areas and nine sub-areas: (1) Opportunities (*diagnostic accuracy, process acceleration, objective decision support,* and *workload reduction)* and (2) Concerns *(loss of control, additional effort, job loss, loss of autonomy,* and *unclear responsibilities)* (Table 4).

Table 4 Overview of medical imaging specialists' opportunities and concerns on AI applications (Buck et al. 2021)

Categories	**Subcategories**
Opportunities	Diagnostic accuracy Process acceleration Objective decision support Workload reduction
Concerns	Loss of control Additional effort Job loss Loss of autonomy Unclear responsibilities

Our study makes an important contribution to the academic discussion on the adoption of AI applications in radiology. The results indicate that opportunities and concerns regarding AI applications are the main factors influencing specialists' perspectives. The four main opportunities are consistent with those already discussed in technical research publications (e.g., Burns et al., 2017; McKinney et al., 2020). Considering the identified concerns, the fear of losing control and overlooking errors in AI applications is highlighted by other empirical research (e.g., Chilamkurthy et al., 2018; Jussupow et al., 2021). Thus, medical imaging specialists should be made aware of the weaknesses and limitations of AI applications (Rubin, 2019). Further, the specialists fear that AI applications could cause additional financial expenditure, while research assumes the opposite in the long term (e.g., Hofmann et al., 2019; Laï et al., 2020). Thus, we believe a differentiated evaluation is necessary to determine whether the AI application purchase is sensible. Concerns about medical imaging specialists being replaceable by AI applications are expressed but not prevalent as the specialists perceive AI applications as assistive tools. However, a major concern is the potential loss of decision-making autonomy of physicians to machines, underlying factors such as control and possibly pride, as emphasized in the interviews. There is also concern that the responsibility for decisions made by AI applications is not yet clearly defined. An interesting ethical consideration is the possible discrepancy between perceived and legal responsibility. Overall, respondents have a positive attitude towards AI applications and see themselves as more technologically savvy than other medical specialties. They are interested in using and implementing AI applications in radiology and want to pave the way for it, as they have done in the past with many other technologies in the medical field. We recommend clarifying ethical and regulatory issues with key stakeholders and educating medical imaging specialists about the functionality and limitations of AI applications to avoid blind dependency and increase understanding and acceptance. We further emphasize to educate physicians, as we assume that the medical imaging specialists' understanding of AI is relevant to impact their expectations and thus their perspectives on AI applications.

3.2.2 General Practitioners' Attitudes Toward Artificial Intelligence-Enabled Systems: Interview Study (Buck, Doctor, Hennrich, Jöhnk, and Eymann, 2022)

This article investigated GPs' attitudes towards AI applications in medical diagnosis. GPs are the first point of contact in the healthcare system and often have to make diagnoses under time pressure and uncertainty. They are responsible for the initial diagnosis, which is crucial in determining whether a patient receives the right treatment. Incorrect diagnoses can have serious consequences such as injury, preventable illness, hospitalization, and, in some cases, death (Singh et al., 2013; van Such et al., 2017). Besides harm to the patients, misdiagnosis can also increase healthcare costs (Lambe et al., 2016). Innovative, reliable, and fast decision-making processes are needed to minimize these risks (Police et al., 2010). AI applications can relieve physicians and give them more time for more complex tasks (Aronson & Rehm, 2015). Although AI applications are becoming increasingly practical and useful for diagnosis in primary care, their widespread adoption remains slow (Bryan & Boren, 2008; Davenport & Kalakota, 2019). Besides others, the slow adoption rate can be attributed to a lack of trust and acceptance by physicians (Asan et al., 2020; Bhattacherjee & Hikmet, 2007; Dellermann et al., 2019; Khairat et al., 2018). Understanding GPs' attitudes towards AI applications is crucial to developing user-centered AI applications that support adopting AI applications in primary care.

In-depth insights are needed to capture the attitudes of GPs towards AI applications in diagnosis. Therefore, we used qualitative methods to capture the technological understanding in the medical context (Walsham, 1993) without limiting to specific variables (Kaplan & Maxwell, 2005). Data was collected iteratively by selecting participants, creating and improving the interview guidelines, conducting the interviews, transcribing, and coding. We adapted this process continuously to develop a comprehensive understanding of respondents' attitudes (Polkinghorne, 2005; Schultze & Avital, 2011). In total, we interviewed 18 GPs from Germany. Using GTM technologies, we analyzed the interview data in three coding steps: open coding, axial coding, and selective coding (Corbin & Strauss, 2008). The analysis began with the first data set, with findings from the first interviews influencing the subsequent interviews. The interview data was divided into relevant sections through open coding, resulting in 307 open codes. These codes were further examined, summarized, and categorized. We derived 21 concepts and five categories from the interview data: *concerns, expectations, environmental influences, individual characteristics,* and *minimum requirements of AI applications* (Table 5).

Table 5 Overview of the categories and concepts (Buck et al. 2022)

Determinants of attitudes towards AI applications	**Concepts**	**Open codes**	∑
Concerns	Existential anxiety	12	57
	Change of the doctor-patient relationship	7	
	Misuse of data	14	
	Diagnostic bias	24	
Expectations	Diagnostic quality	35	112
	Diagnostic efficiency	19	
	Legal liability	4	
	Lack of human competences	43	
	Time expenditure	11	
Environmental influences	Changing working conditions	8	37
	Stakeholder influences	13	
	Media	12	
	IT infrastructure	4	
Individual characteristics	Age	11	17
	Affinity with technology	6	
Minimum requirements of AI applications	Time efficiency	40	84
	Diagnostic quality	15	
	Data security	10	
	Economic viability	12	
	Transparency	3	
	Autonomy	4	

In addition to the identified factors, the interviews revealed that physicians' AI literacy influences their perceptions and discussions about AI applications, regardless of whether they are based on sound knowledge or not. We also hypothesized possible interrelationships between the identified categories. The interviews indicated that GPs' concerns and expectations shape the minimum requirements for AI applications. Our main finding is that diagnostic quality and time efficiency are crucial for GPs to consider AI applications. Our results also show that consideration of the affective attitude is important in the medical context, although it is often neglected in well-known acceptance and behavior theories (Davis et al., 1992; Kulviwat et al., 2007; Venkatesh et al., 2003). In particular, GPs' concerns about data privacy and patient safety are crucial and highlight the role of emotional factors in attitudes towards AI applications. Addressing these concerns at an early stage can positively influence GPs' attitudes and promote acceptance of AI applications. By understanding GPs' attitudes based on qualitative interviews, we answer the call of Blease et al. (2019), who recognized the topic's relevance and quantitatively investigated GPs' opinions on the potential impact of AI applications. To improve GPs' knowledge about AI applications and address concerns about changes in the doctor-patient relationship, we suggest intensifying discussions about AI applications in political and health-related institutions. In addition, disseminating evidence-based information through GP-specific journals and the involvement of advocacy groups is important, as GPs value these sources highly. Further, AI applications must be user-friendly, reliable, error-free, and data protection-compliant, and financial subsidies from politicians and health insurance companies promote acceptance and commitment. Finally, transparency and accountability in AI-assisted diagnoses are critical, as is the focus of AI applications on diagnosing rare cases to complement GPs' expertise and free up their time to improve patient relationships. However, integrating AI applications does not solve every challenge. Instead, a critical assessment is needed to decide when AI applications make sense and improve decision-making. Especially in terms of human skills and interpersonal relationships, GPs do not see AI applications to replace them.

3.2.3 Overcoming a Knowledge Gap of Healthcare Professionals: The Influence of Previous Experience on the (Non-)Adoption of VR in Medical Rehabilitation (Schreiter, Hennrich, Wolf, and Eymann, Working Paper)

This study examined how previous experiences with VR technologies influence healthcare professionals' decisions to accept or reject VR technologies in medical rehabilitation. VR technologies in healthcare, particularly in medical rehabilitation, have demonstrated their effectiveness by enabling patient remobilization in virtual environments (Wolf et al., 2022), providing real-time feedback on performance (Butz et al., 2022), improving physical function and quality of life (Pazzaglia et al., 2020; Winter et al., 2021), and allowing patients to exercise independently (Errante et al., 2022). Despite the known and researched potential of VR technologies in medical rehabilitation, their clinical adoption remains limited (Glegg & Levac, 2018; Halbig et al., 2022). To understand the reasons for the limited integration of these technologies, the perspectives of (potential) users need to be considered (Halbig et al., 2022; Kijsanayotin et al., 2009). While, many existing studies are based on hypothetical scenarios, as most participants have not yet used VR technologies in professional context (Bhattacherjee & Hikmet, 2007), we explore healthcare professionals’ perspectives with and without previous experience.

As a theoretical framework, we use Rogers' DOI theory (Rogers, 2003) as it has proven useful in explaining technology adoption in healthcare (Greenhalgh et al., 2004; Iqbal & Zahidie, 2022). DOI theory considers the individual perspective on the adoption of the innovation and the diffusion of the innovation in a social system. Therefore, the adoption decision is seen as a micro view, while diffusion is a macro perspective describing how innovations spread throughout a population (Rogers, 2003). We first focus on the micro level to understand how healthcare professionals perceive VR technologies in medical rehabilitation. We examine prior conditions, knowledge, and the persuasion phase of the adoption decision process. To understand the macro perspective, it is important to look at diffusion within a social system that includes different adopter groups. Rogers distinguishes between innovators, early adopters, the early majority, the late majority, and laggards. Innovators are willing to try out new ideas and have extensive technical knowledge, while early adopters are more constrained by social conditions and act as role models. The early majority collaborates effectively with others, though they do not take on the pioneering leadership roles typical of early adopters. Meanwhile, the late majority delays embracing new innovations until after the majority of their peers have done so, while late adopters have a traditional view and are more skeptical of innovation (Rogers, 2003).

We conducted 23 semi-structured interviews with medical rehabilitation experts in Germany and divided them according to their innovativeness into VR-experienced “innovators” and inexperienced “laggards”. When analyzing the interview transcripts, we followed Mayring's recommendations for combining inductive and deductive category formation using qualitative content analysis (Mayring, 2000). The transcripts were analyzed, and 56 preliminary categories were created, with relevant information recorded in memos. After analyzing 38 % of the material, as recommended by Mayring (2000), the memos and categories were discussed, analogous categories were merged, and contradictory categories were resolved. This allowed connections to be made to the DOI theory adoption process and DOI-based categories to be used for deductive coding. Finally, the preliminary categories were summarized into 26 factors and four main categories, identifying differences between the two user groups, as presented in Figure 3.

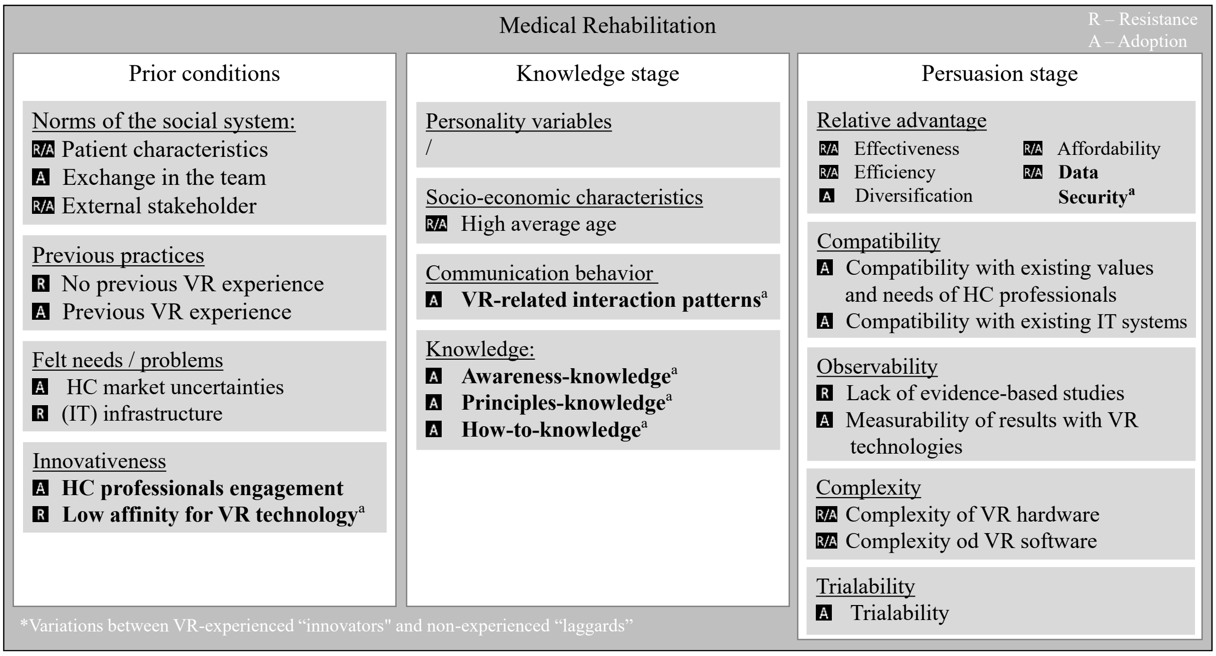

Figure 3 Contributing factors to resistance and adoption of VR technologies in medical rehabilitation (Schreiter et. al., Working Paper)

This article makes theoretical and practical contributions. First, we extend the DOI literature by identifying 26 context-specific factors that influence the adoption or rejection of VR technologies in medical rehabilitation. Second, by categorizing the interviewees into groups with and without prior VR experience, we highlight differences and illustrate that actual usage experience improves the validity of results. People without VR experience consider the costs and training effort high and see them as obstacles. In contrast, people with VR experience consider these costs and the effort involved manageable. As VR technology has matured, acquisition costs have decreased, suggesting that healthcare professionals without experience may rely on outdated knowledge and overestimate the effort involved, discouraging them from adopting new technologies. In addition, non-VR users express concerns about being replaced by VR technologies, that the doctor-patient relationship could be negatively affected, or that data security is not guaranteed. People with VR experience do not share these concerns. Thus, the lack of knowledge about VR technologies reinforces concerns. Both innovators and laggards emphasize the need for evidence-based studies to reduce uncertainties regarding the efficacy and safety of VR technologies. Overall, group-specific and balanced dissemination of information about VR technologies is needed to promote their appropriate use in healthcare and to address potential concerns. Our findings also demonstrate that healthcare professionals require improved education across multiple channels, including executive education, medical education and training, events, and social media. Focusing more on VR technologies in policy, health insurance, and healthcare organizations can help close knowledge gaps and reduce concerns. It is important to disseminate evidence-based information through rehabilitation-specific journals and therapeutic professional organizations. In addition, clear information and guidelines on data safety need to be provided to address concerns and promote acceptance of VR technologies.

3.2.4 Antecedents of Workarounds Related to Information Systems in Hospitals: Interview Study (Doctor, Hennrich, Eymann, and Buck, Working Paper)

This study examined the antecedents shaping nurses' and physicians' workaround behavior in the context of HIS. HIS are intended to support healthcare professionals in their daily work by collecting, processing, and disseminating medical and administrative data (Georgantzas & Katsamakas, 2008). However, HIS are often perceived as a hindrance, for example, due to a non-intuitive user interface and a slow IT infrastructure (Beglaryan et al., 2017). Nurses and physicians often create workarounds, if HIS are poorly integrated into the workflow (Eason & Waterson, 2014). From the perspective of behavioral science, workarounds are reactions to perceived or actual problems that a person wants to solve or avoid (Soffer et al., 2023). In hospitals, this include bypassing documentation requirements, transferring data outside of HIS, and unauthorized use of personal devices (Niazkhani et al., 2011). Such workarounds can jeopardize patient safety (Boonstra et al., 2021). Therefore, this article identifies the causes of workarounds as basis to develop effective strategies to prevent them, ensuring safe and efficient healthcare.

To better understand the emergence of workarounds, several studies have used theoretical approaches to analyze workarounds (Ajzen, 1991; Baker & Nelson, 2005; Dacin et al., 2002; Eisenhardt, 1989; Engeström et al., 1999; Orlikowski & Gash, 1994). We used the theory of planned behavior (TPB), one of the most well-known theories to explain behavior (Ajzen, 1991), which also forms the basis for Alter's theory of workarounds (Alter, 2014). In addition, we integrated Soffer et al.'s (2023) concept that a workaround is performed with the intention of benefiting someone (Figure 4). In line with their call for contextual adjustments, we define the "intention to benefit" in the inpatient medical setting as beneficial either for the persons performing the workaround, for the patients, for the local unit (ward) or for the organization. By including the intention to benefit, we broaden the understanding of the underlying motivations for workaround behavior in the context of HIS in the inpatient setting.

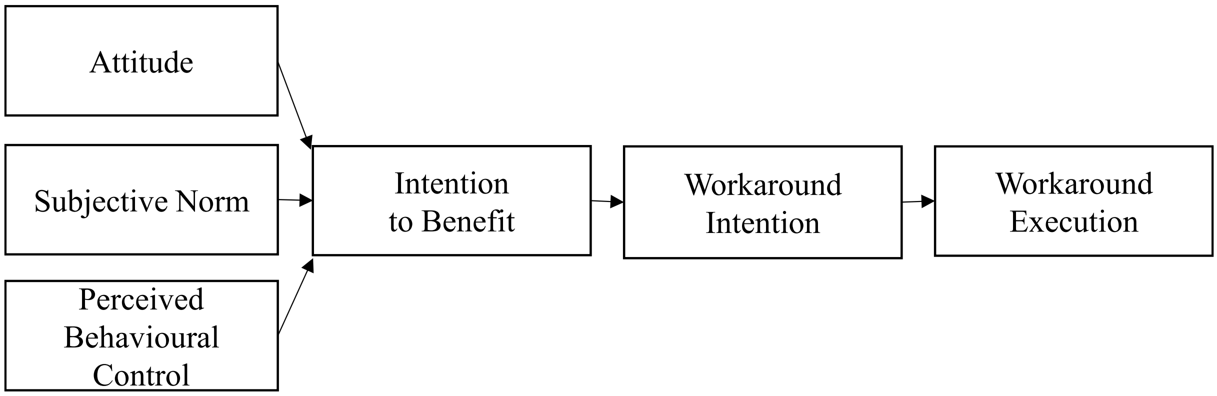

Figure 4 Theory of planned behavior combining Ajzen (1991) and Soffer et al. (2023)

We conducted 26 semi-structured interviews with healthcare professionals working in hospitals in the USA and Germany to obtain in-depth, real-world information from frontline HIS users (Myers & Newman, 2007; Schultze & Avital, 2011). The data analysis was conducted using GTM analysis techniques, which allows researchers to manage unstructured qualitative data sets effectively, identify relevant categories and relationships within the data, and provide meaningful context and interpretation (Corbin & Strauss, 2008). The findings from the first interview influence the researcher and thus shape the approach in the subsequent interview sessions. We followed the three-stage approach, which conducted open, axial, and selective coding to identify antecedents of workarounds. After an initial read-through of the transcripts, we marked relevant phrases, resulting in 506 open codes. We further examined the codes, grouped common themes into concepts, and finally into categories and identified relationships (axial coding). In doing so, we distinguished the core category of antecedents of HIS-related workarounds from other categories (selective coding) (Corbin & Strauss, 2008). We identified 18 antecedents of HIS-related workarounds presented in Figure 5.

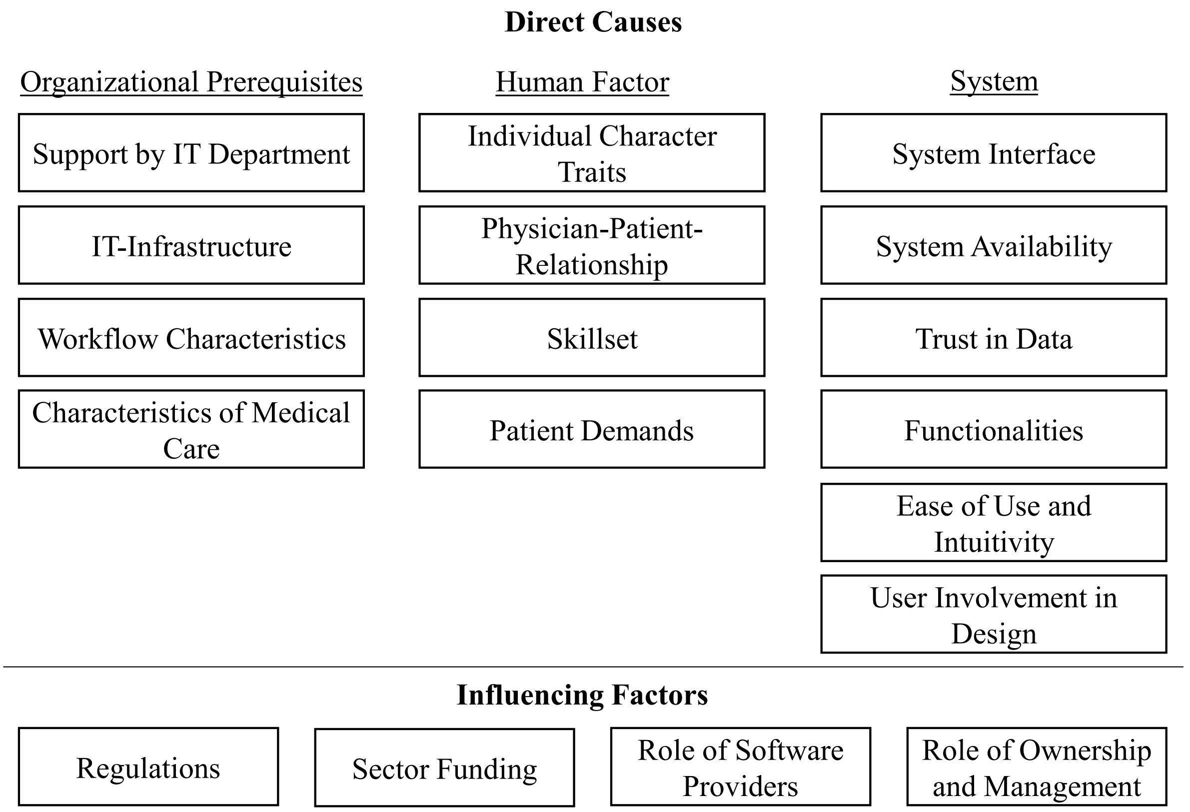

Figure 5 Direct causes and influencing factors (Doctor et al., Working Paper)

In addition to confirming existing research and identifying new antecedents from a static perspective, we have also identified relationships between these antecedents when analyzing them concerning the TPB by Ajzen (1991) and Soffer et al. (2023) (Figure 6).

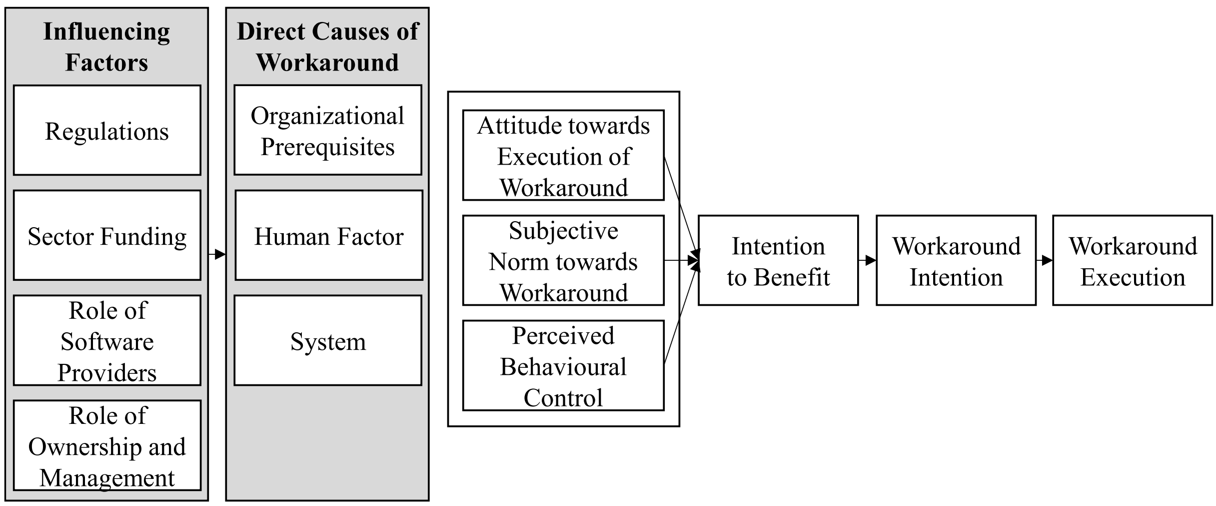

Figure 6 Model of antecedents of workarounds related to HIS (Doctor et al, Working Paper)

Our research makes a valuable theoretical contribution by applying the TPB to workarounds related to HIS, enabling a sequential and detailed understanding. By identifying both direct causes and influencing factors that affect the key determinants of TPB (attitudes toward workarounds, subjective norms, and perceived behavioral control), we have strengthened the explanatory power of TPB. We contextualize not just by adding new factors but also by confirming existing ones. For example, concerning the concept of skillset (human factors), we agree with Flanagan et al. (2013), who found that users' knowledge of how to use HIS influences the frequency of workarounds. Furthermore, we support the extension of the TPB by Soffer et al. (2023) to include the “Intention to Benefit” to explain behavior in the context of patient care. In patient care, workarounds are performed to promote the well-being of patients, as opposed to other contexts where they may be performed for personal gain. Therefore, it is crucial to consider the intention to benefit as an essential factor when evaluating behaviors in patient care (Soffer et al., 2023). Deepening the understanding on antecedents of HIS-related also informs the development of interventions and strategies to prevent workarounds, ultimately improving patient safety and quality of healthcare. Healthcare organizations should invest in better IT infrastructure and equipment to reduce workarounds. This includes stable internet connections and sufficient workstations. In addition, training programs should be developed to improve the skills of medical staff in using HIS. The study provides tips for software developers to improve HIS, such as integrating missing interfaces and functions and increasing user-friendliness. Involving the end users in the development process will support reaching user-friendliness.

3.3 Measures Promoting the Adoption of Artificial Intelligence Applications

3.3.1 Enabling Physicians to Make an Informed Adoption Decision on Artificial Intelligence Applications in Medical Imaging Diagnosis: A Qualitative Approach (Hennrich, Doctor, Körner, Ledermann, and Eymann, Working Paper)

This study aimed to promote the adoption of AI applications in medical imaging diagnosis by enabling physicians to make an informed adoption decision. Among the various disciplines in healthcare, radiology is the most promising in the adoption of AI applications (Hosny et al., 2018). Contrary to expectations, however, the widespread adoption of AI applications is slower than expected (Allen et al., 2021; Becker et al., 2022). Factors influencing the physicians’ perspectives include knowledge gaps, fear of job loss, loss of autonomy, concerns regarding additional effort, and diagnostic bias (Buck et al., 2022; Buck et al., 2021; Jussupow et al., 2021; Roppelt et al., 2024). To exploit the full potential of AI applications in medical diagnosis, a holistic approach is needed (Hennrich et al., 2024). This article identifies specific measures to address these obstacles. However, as technology should not be used for its own sake, the measures are directed at enabling physicians to make an informed adoption decision.

This article used a two-stage qualitative research method to derive specific measures. First, according to Webster and Watson (2002), a structured literature review was conducted to derive measures from the literature. For the literature review, we selected PubMed and Science Direct. The search initially yielded 1019 results. After filtering books, duplicates, and irrelevant abstracts and applying forward and backward searches, 19 final papers remained. We used an inductive approach to analyze the 19 final articles (Bandara et al., 2015). After carefully reading the full texts, we extracted 117 relevant paragraphs with references to enabling measures. These measures varied in specificity. Some were detailed and actionable, others more general. General measures were first evaluated in interviews and then concretized and refined through targeted questions. Interviews were conducted with 14 experts from Europe and Australia, including radiologists who are potential users of AI applications in imaging diagnosis and AI experts who have experience working with physicians. Eleven measures were identified based on the literature and complemented by expert interviews. Nine of these measures can be summarized as *Enabling Adoption Decision Measures* and two as *Supporting Adoption Measures* (Table 6).

Table 6 Enabling adoption measures (Article 6)

Category	**Measures**
Enabling Adoption Decision Measures	Educate Physicians
	Prepare Future Physicians
	Practical Train Physicians
	Integrate Physicians in Technology Development
	Provide Transparency
	Show Medical Value
	Show Business Value
	Establish Central Expert Panels
	Establish Cross-disciplinary Teams
Supporting Adoption Measures	Provide Marketplace for AI Applications
	Provide Implementation Guidelines

Our findings provide detailed guidance for stakeholders such as practitioners and policy makers on how to effectively promote the adoption of AI applications among physicians by enabling them to make informed adoption decisions. This practical approach bridges the gap between theoretical understanding and practical application and aims to support and exploit the promising benefits of AI applications in medical image diagnosis. We identified building knowledge about and gaining prior experiences with the specific AI application as crucial measures for overcoming many obstacles such as existential anxiety or control loss. Another important aspect is demonstrating the added value of AI applications, such as improved diagnostic quality, time savings, and increased revenue. We assume that if physicians recognize the added value of AI applications, they are more willing to adopt them. Concerns, for example, coming from the lack of transparency of some AI algorithms might even be less important to the physicians if the added value of the regarded AI application is great enough. The study also emphasizes the need for a long-term perspective on measures to ensure the continuous use of AI applications in practice. For example, this includes integrating AI content into medical studies and the continuous training of physicians. By identifying measures focusing on sustainable use, we emphasize the importance of including the perspective of continuous use when researching technology adoption, which is mainly neglected in HIT adoption research (Abouzahra et al., 2024).

3.3.2 Capturing Artificial Intelligence Applications' Value Proposition in Healthcare – A Qualitative Research Study (Hennrich, Ritz, Hofmann, and Urbach, 2024b)

This article investigated the mechanisms of value creation and value extraction of AI applications in the specific healthcare context. There are various use cases of AI applications in different areas of healthcare, such as diagnosis (e.g., Hosny et al., 2018), biomedical research (e.g., Kadurin et al., 2017), clinical administration (e.g., Rezazade Mehrizi et al., 2020), therapy (e.g., Dankwa-Mullan et al., 2019), and intelligent robotics (e.g., Bohr & Memarzadeh, 2020). AI applications not only have the potential to improve medical care for the patient but also to create business value (Gilvary et al., 2019). To exploit the value of AI applications, healthcare organizations should understand how to translate the capabilities of AI applications into business value to ensure effective investments. Therefore, our study aims to explore the mechanisms of value creation and value extraction of AI applications in the specific healthcare context.

We employed a qualitative inductive research design consisting of a systematic literature review and semi-structured expert interviews to explore the value creation mechanism. Following the guidelines of Webster and Watson (2002) and incorporating recommendations from Wolfswinkel et al. (2013), we collected data on successful AI use cases across five healthcare application areas: disease diagnostics, biomedical research, clinical administration, therapy, and intelligent robotics. An initial literature screening identified these domains, focusing on AI applications for patients and healthcare providers. We aimed to collect a diverse set of 21 AI use cases, ensuring variability in data, innovation types, and implementation stages. Using PubMed, we selected relevant papers for each use case, leading to 88 papers after applying inclusion criteria and conducting a forward and backward search. We engaged in open, axial, and selective coding of the AI use cases, following GTM techniques (Corbin & Strauss, 2008). This process involved extracting business objectives and value propositions from the literature. To evaluate and refine our findings from the literature review, we conducted 11 semi-structured expert interviews (Schultze & Avital, 2011). Based on the two-step approach, we derived 15 business objectives which translate into the following six value propositions*: risk-reduced patient care, advanced patient care, self-management, process acceleration, resource optimization,* and *knowledge discovery* (Figure 7). This is followed by Table 7, which summarizes the contributions of the AI use cases to the derived value proposition.

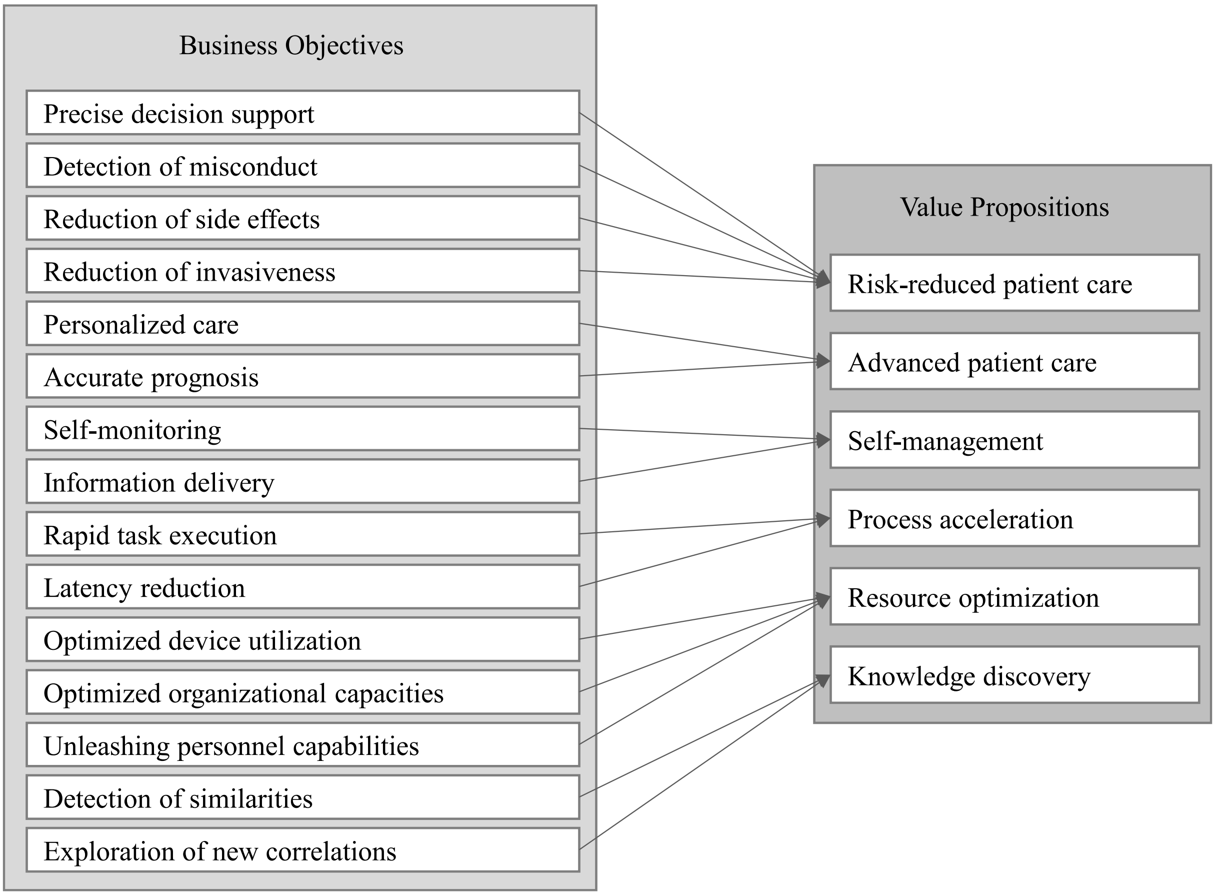

Figure 7 Business objectives and value propositions (Hennrich et al. 2024b)

Table 7 Value propositions of AI use cases (Hennrich et al. 2024b)

AI use cases	**Value proposition**					
	Risk-reduced patient care	**Advanced patient care**	**Self-management**	**Process acceleration**	**Resource optimization**	**Knowledge discovery**
DD1: Automated image recognition	x			x	x	
DD2: Staging of cancer	x	x				
DD3: Objective assessment in image interpretation	x			x		
DD4: Genomic cancer therapy		x				
DD5: Voice analysis for Parkinson's disease	x	x	x			
DD6: Electroencephalography analysis to detect seizures	x	x			x	
DD7: Facial analysis for detection of rare disease		x		x		x
BR1: De novo drug design	x			x		x
BR2: Predictive biomarkers in aging for drug development	x	x				x
BR3: De-identification of private health information				x	x	
BR4: Genomic splicing in research		x		x		x
CA1: Emergency triage	x			x	x	
CA2: Predictions of mortality in the intensive care unit	x	x		x		
CA3: Operating room scheduling					x	
CA4: Automated text summarization				x	x	
T1: Prediction of the required insulin	x	x	x			
T2: Prediction of vasopressor medication dosage	x	x				
T3: Chatbots for patients		x	x		x	
IR1: Intelligent prosthesis		x	x			
IR2: AI-based surgery robots	x	x		x		
IR3: Workflow detection for human-robot surgery	x			x		

By revealing 15 business objectives translating into six value propositions, our research adds to the academic discourse on how AI applications create value within the healthcare sector. Our research emphasizes its relevance not only to the research on value creation but also to understanding how to foster the adoption of AI applications in healthcare. By outlining the value propositions AI applications come along, we provide a strategic basis for accelerating the integration of AI applications into healthcare and may contribute to mitigating existing obstacles to the adoption of AI applications. Besides, our study makes practical contributions by providing insights into how healthcare organizations can derive business value from AI applications.

4 Discussion

The discussion of this thesis is divided into two sections. First, a summary of the results of the individual article contributions is presented which highlights how they each contribute to addressing the three RGs. The second section presents a detailed discussion that connects the results of the seven articles of the thesis with an overarching view. Table 8 presents which study is referenced by which article number.

Table 8 References of the seven research articles

Research Goal	Chapter	Article	Title	Authors
Identifying obstacles hindering the adoption of AI applications in medical diagnosis	Chapter 3.1	Article 1	Accelerating the Adoption of Artificial Intelligence Technologies in Radiology: A Comprehensive Overview on Current Obstacles	Hennrich, J., Fuhrmann, H., Eymann, T. (2024a)
Deepening the understanding of the factors influencing the adoption of HIT from an individual user perspective	Chapter 3.2	Article 2	Artificial Intelligence in Radiology: A Qualitative Study on Imaging Specialists' Perspectives	Buck, C., Hennrich, J., Kauffmann, A.L., (2021)
		Article 3	General Practitioners' Attitudes toward Artificial Intelligence-Enabled Systems: Interview Study	Buck, C., Doctor, E., Hennrich, J., Jöhnk, J., Eymann, T. (2022)
		Article 4	Overcoming a Knowledge Gap of Healthcare Professionals: The Influence of Previous Experience on the (Non-)Adoption of VR in Medical Rehabilitation	Schreiter, M., Hennrich, J., Wolf, A.L., Eymann, T – Working Paper

		Article 5	Antecedents of Workarounds related to Information Systems in Hospitals: Interview Study	Doctor, E., Hennrich, J., Eymann, T., Buck, C. – Working Paper
Providing measures to enable physicians to make an informed decision about the adoption of AI applications in medical diagnosis	Chapter 3.3	Article 6	Enabling Physicians to Make an Informed Adoption Decision on Artificial Intelligence Applications in Medical Imaging Diagnosis: A Qualitative Approach	Hennrich, J., Doctor, E., Körner, M.F., Eymann, T., Ledermann, R. – Working Paper
		Article 7	Capturing Artificial Intelligence Applications' Value Proposition in Healthcare – A Qualitative Research Study	Hennrich, J., Ritz, E., Hofmann, P., Urbach, N. (2024b)

4.1 Summary of Individual Article Results

The overarching goal of this thesis is to *enhance the understanding of obstacles in the adoption of AI applications in medical diagnosis with a special focus on the factors influencing the adoption of HIT from an individual user perspective and on measures to promote the adoption of AI applications in medical diagnosis.* By answering this overarching goal, this thesis contributes to the technology adoption research stream in the healthcare context with a specific focus on AI applications in medical diagnosis.

The RG 1 – *Identifying obstacles hindering the adoption of AI applications in medical diagnosis* is addressed in Article 1, which identified 17 obstacles to the widespread adoption of AI applications in medical imaging diagnosis, clustered into six categories: *Data, Software, Market, Clinical Application, Regulations,* and *User Attitude*. In addition to identifying the various obstacles, Article 1 assumes interrelations between them, and highlights the user's attitude is determined by all obstacle categories, underlining the central role of the user in the adoption of AI applications in healthcare. This provides the bridge to RG 2 – *Deepening the understanding of the factors influencing the adoption of HIT from an individual user perspective.* Article 2 revealed four opportunities and five concerns shaping radiologists' perspectives with AI applications. Article 3 has a similar aim but focuses on a discipline less accustomed to using technology in diagnosis. It uncovers the attitudes of GPs towards AI applications which is shaped by four concerns and five expectations. Furthermore, this article revealed six minimum requirements that must be met by the AI application in the opinion of the physicians. Both articles interviewed physicians without prior experience with AI applications in daily practice. Articles 4 and 5, in contrast, identified factors influencing the continuous usage of a technology by interviewing healthcare professionals who have already had experience with the HIT in question. Article 4 derived 26 factors influencing medical rehabilitation experts to adopt or continuously use VR technologies. The article demonstrates that healthcare professionals with experience with VR technology in medical rehabilitation have fewer concerns than those without experience. Article 5 identified factors hindering the continuous usage of HIS by conducting interviews with healthcare professionals with prior experience and revealed 18 antecedents of workarounds. The antecedents can be divided into three categories of direct causes and four influencing factors. The influencing factors represent overarching influences that do not directly affect the behavior of healthcare professionals and rather represent the conditions that lead to the direct causes of workarounds.

Given the negative example of Article 5 and the physicians' concerns regarding AI applications identified in Articles 2 and 3, measures are needed to address these obstacles to promote the successful adoption of AI applications in medical diagnosis. This relates to RG 3 – *Providing measures to enable physicians to make an informed decision about the adoption of AI applications in medical diagnosis* – and is addressed by Article 6. The article identified eleven measures to enable physicians to make an informed adoption decision on AI applications, classified into nine *Enabling Adoption Decision Measures* and two *Supporting Adoption Measures*. As demonstrated by Article 6, presenting the added value of AI applications is highly relevant to addressing physicians' concerns and promoting adoption. Thus, Article 7 provides specific insights into how AI applications can capture value in healthcare by identifying 15 business objectives grouped into six value propositions.

4.2 Overarching Discussion of the Results

The four most important areas of discussion from an overarching perspective on all seven research articles are outlined in the following.

4.2.1 Comparative Analysis of Influencing Factors among General Practitioners and Radiologists

One interesting point of discussion emerges by comparing the results of Articles 2 and 3. Physicians from different specialties – GPs, who use the technology sparingly (Article 3), and radiologists, who use it regularly (Article 2) – have similar perspectives on AI applications in medical diagnosis. Both groups express expectations and concerns regarding AI applications in medical diagnosis. They expect AI applications to improve the quality and efficiency of diagnosis, resulting in reduced workload and better quality of care. Differences can be seen regarding some of the concerns they expressed. GPs have concern that using AI applications might change the relationship between the physician and patient. They emphasize that AI applications have no human capabilities such as empathy, intuition, gestures, and clinical judgment, which they rate particularly relevant in GP care for collecting all relevant information needed for diagnosis. Contrary to physicians' expectations that AI applications lack empathy, a recent study by Ayers et al. (2023) revealed that patients preferred the answers of AI-based chatbots to those provided by physicians, as these were rated significantly better in terms of empathy and quality. GPs also expressed that using AI applications lead to misuse of patient data. The radiologists do not share these specific concerns, likely due to their minimal direct interaction with patients.

The comparison of those two disciplines leads to the assumption that the intensity of patient contact in a medical discipline influences physicians' concerns and, thus, affects the adoption of AI applications. Articles 2 and 3 therefore not only provide valuable insights for contextualizing technology adoption research but indicate that contextualization might even be necessary at the level of the medical discipline. It can be assumed that in medical disciplines without much patient contact, patient influence can be neglected when explaining the adoption of AI applications. However, the extent to which contextualization at this level is useful must be critically questioned. Excessive contextualization can cause research theories and models to lose their simplicity and become unnecessarily complicated, which counteracts their purpose of simplifying explanations and reduces their transferability and usefulness in other domains.

Furthermore, the comparison of Articles 2 and 3 indicates that although radiologists are generally more accustomed to technology while GPs are not, the general openness to adopt AI applications was not associated with the medical discipline, but rather with the physicians’ age.

4.2.2 Contextualizing Technology Adoption Research

When embedding the factors identified in Articles 2 and 3 into the technology adoption research stream, similarities to the four main factors of UTAUT, as introduced by Venkatesh et al. (2003), can be found. *Time Expenditure* (Article 2) and *Additional Effort* (Article 3) can contextualize the factor *Effort Expectancy* used in UTAUT. Physicians’ expectations of *Diagnostic Accuracy, Process Acceleration, Objective Decision Support*, and *Workload Reduction* (Article 2), along with *Diagnostic Quality* and *Diagnostic Efficiency* (Article 3), can contextualize the factor *Performance Expectancy* of UTAUT. The constructs *Stakeholder Influence, Change of*

Doctor-Patient Relationship, and *Lack of Human Competencies* (Article 3) can be used to contextualize the UTAUT factor *Social Influence,* with a little variation for different disciplines, as explained in 4.2.1. Lastly, the construct *IT Infrastructure* (Article 3) can contextualize the *Facilitating Conditions* of UTAUT. Besides contextualizing well-known influencing factors on technology adoption, Articles 2 and 3 provide indications for further relevant context-specific factors such as *Loss of Control, Existential Anxiety, Data Misuse, Technology Affinity,* and *Unclear Responsibility,* which are relevant to explain physicians' adoption of AI applications in medical diagnosis. Uncovering physicians' concerns emphasizes the importance of emotional aspects in explaining the adoption of AI applications in the medical context, despite being often neglected in known theories of acceptance research (Bagozzi, 2007).

4.2.3 The Importance of Knowledge and Prior Experience

Physicians' concerns regarding AI applications, such as *Existential Anxiety* (Articles 2 and 3) or *Data Misuse* (Article 3) can also be attributed to the lack of the interviewees' prior experience with AI applications in clinical practice. Article 3 assumes that physicians' concerns are primarily based on their knowledge about AI, regardless of whether this is right or wrong. A recent literature review of factors influencing physicians' adoption of AI applications in medical diagnosis further distinguishes between AI literacy - the general knowledge of AI, and system understanding - the specific knowledge about a particular AI application (Hua et al., 2024). Article 4 outlines how healthcare professionals' concerns are influenced by prior experience and a lack of specific knowledge. Comparing healthcare professionals' perspectives on VR technologies with and without prior experience reveals that healthcare professionals with experience have fewer concerns than healthcare professionals without experience (Article 4). Thus, in Article 4, the healthcare professionals who had positive prior experience with the regarded technology had reduced concerns (e.g., the fear of being replaceable only existed among healthcare professionals without prior experience). However, as outlined in Article 5, prior experience can also be negative which reinforces healthcare professionals' concerns regarding the specific technology (e.g., the healthcare professionals perceived using the HIS as requiring more time and effort). Article 5 further highlights that a lack of knowledge among healthcare professionals about how to use the technology is related to its poor usage. As knowledge of the specific technology and prior experience with it are important determinants of healthcare professionals' concerns, measures aimed at building knowledge and enabling experience are crucial to increase confidence and thus to promote the adoption of AI applications in medical diagnosis (Article 6). According to Connolly et al. (2020), a higher frequency of use increases comfort when dealing with the technology and positively affects usage decisions. In this context, physicians must gain familiarity with the AI application tailored to their specific use case. This experience enables them to assess its utility, understand its limitations and possibilities, and decide if adopting AI applications in their specific use case is sensible (Article 6). Exemplary measures to increase knowledge and prior experiences are personalized hands-on training programs and workshops with experts (Article 6). Moreover, as described in Article 6, education should be ongoing and focussed on technological developments. Medical education should also be designed that future physicians gain knowledge and experience in AI topics. These measures are aimed at the continuous use of AI applications and prevention of workarounds, as occurred in Article 5. Only if the technology is continuously used, can the full potential be exploited (Abouzahra et al., 2024).

4.2.4 Added Value: A Core Aspect of Technology Adoption in Healthcare

When analyzing the factors that influence healthcare professionals' adoption of technologies in the healthcare sector, it emerges that healthcare professionals see the added value of technology as a decisive factor in their decision to adopt or continuously use the already implemented technology (Articles 2-5). In Articles 2 and 3, physicians emphasize that they would adopt AI applications if the added value is substantial. Article 4 indicates that if the added value is clear, other adoption obstacles are less important. If the technology is already implemented but not perceived to bring added value, the technology is more likely to not be used (Article 5).

As discussed in Article 6, the value of the new technology must be demonstrated in improved quality of care, time savings, or increased revenue. AI applications can achieve improved quality by providing precise decision support and accurate prognoses, as outlined in Article 7. Time savings can be achieved through faster task execution and reduced latency when using AI applications (Article 7). Study reports on the specific AI application must outline how accurate and time efficient the AI application will be. Improved quality and time savings can also contribute to higher revenue by increasing patient throughput and reducing costs. When demonstrating the value, it must be shown when the technology is integrated into actual workflows and not just in laboratory settings (Article 6). Article 6 further assumes that the added value of AI applications is more important than solving its transparency problem. Physicians often adopt their colleagues' recommendations based on trust in their experience and expertise, often without understanding the underlying assumptions that guided their conclusions. A similar level of trust could be transferred to AI applications. If an AI application is of high-quality and increases efficiency in clinical practice, physicians may place less importance on the complete transparency of AI applications' decisions (Article 6). Consequently, physicians' concerns regarding AI applications might be less important if the added value is evident.

4.3 Theoretical Contribution

Each of the seven research articles makes a unique theoretical contribution, which is discussed in more detail in the respective articles. The following section discusses the overarching theoretical contributions of this thesis by adopting a holistic perspective on all articles.

First, this thesis contributes to the technology adoption research stream by revealing various factors influencing physicians' adoption of AI applications in medical diagnosis. By comparing the identified factors of Articles 2 and 3 with the factors of the well-known acceptance theory UTAUT, but also by revealing additional influencing factors, this thesis responds to the call for contextualizing technology adoption research (Benbasat & Barki, 2007; Holden & Karsh, 2010; Venkatesh et al., 2011). Through contextualization, a more effective understanding and prediction of physicians' adoption of AI applications in medical diagnosis can be reached (Blut et al., 2022). In this regard, this thesis also raises the question of which level of detail (e.g., specific medical discipline) contextualization is sensible. Furthermore, the thesis emphasizes the importance of emotional components in explaining technology adoption in the healthcare context, which is often neglected in well-known technology adoption theories (Bagozzi, 2007).

A second contribution to the adoption research stream is provided by supporting the claim of Abouzahra et al. (2024) that the research of technology adoption should pay more attention to investigating the continuous usage of the regarded technology. While adoption research in healthcare focuses predominantly on the initial acceptance of the technology, just a few emphasize continuous usage (e.g.,Venkatesh et al., 2011). However, successful use of the technology does not end with the implementation of the technology, as it only brings value when used sustainably (Bhattacherjee, 2001). Considering the adoption of AI applications in medical diagnosis, it is therefore important that physicians' concerns are addressed in a way that not only promotes initial adoption of the specific application but ensures its continuous usage.

Third, in addition to contextualizing the adoption research, this thesis also underlines the importance of physicians' prior experience with and knowledge of the respective technology in explaining technology adoption. While positive experiences with the technology can mitigate concerns (Article 4), negative experiences can reinforce concerns (Article 5). Consequently, this thesis further contributes to the field of adoption research by demonstrating that in studies where users are asked about a hypothetical usage scenario, as in Articles 2 and 3, their lack of prior experience and the corresponding level of knowledge - regardless of whether it is correct - shape physicians' perspectives, which need to be kept in mind when interpreting the results.

4.4 Practical Implications

This thesis also provides implications for various stakeholders, such as healthcare organizations, policymakers, and software providers. By providing insights into physicians' concerns, expectations, prior experiences, and knowledge of technology, this thesis highlights areas where measures are necessary to promote the adoption of AI applications.

To mitigate concerns and enable physicians to make an informed decision about the adoption of AI applications, AI knowledge-building measures, such as trainings and workshops, are needed. Medical associations are particularly important, as physicians are often more likely to listen to their colleagues than individuals from other professions. Furthermore, physicians must be fully aware of AI applications' benefits and limitations. This balanced understanding promotes critical judgment and helps to avoid over-reliance on the AI application. Since the use of AI applications is not appropriate in every case, trainings should aim to provide physicians with information about the specific AI applications that are potentially interesting for their clinical scenarios, thus enabling them to make an informed adoption decision. Furthermore to achieve continuous usage, computer science, informatics, and statistics should be included in the curriculum to equip students with the technical skills required to use AI applications competently.

Besides building knowledge and gathering experience, it is crucial to demonstrate the concrete added value of AI applications to promote adoption. Software developers must provide evidence-based information for each AI application, such as concrete details on time saved and improved accuracy, published in comprehensive study reports. Besides providing insights into promising medical value, the question of financing should also be clarified. This challenge is aimed at health insurance companies and other healthcare system financiers. Viable reimbursement models must be developed to ensure the sustainable financing of AI applications and provide clear incentives for their use. For effective implementation, these models should cover both the initial implementation costs and the ongoing operating costs of AI applications.

Finally, software developers should involve physicians in the AI development process to ensure the practical relevance and a better customization to the specific needs of physicians. Involving physicians early ensures that the technology meets their requirements and promotes a sense of ownership and acceptance (Huo et al., 2023), which is crucial for long-term, sustainable use.

4.5 Limitations and Future Research

Below, we discuss the overarching limitations of this thesis and present suggestions for further research, highlighting areas where additional investigation could advance the research field.

The major limitation of this work results from the exclusively qualitative research methods used. Five articles are based on qualitative interviews, one article was based on a structured literature review, and one used a structured literature review only. Both data collection methods have limitations that can have affected the articles' results. Starting with the interview participants, it is likely that only those interview participants who had a general interest in the topic agreed to participate. For the interview-based articles dealing with AI applications it is likely that only those physicians who are predominantly positive about the new technology and have at least an initial interest in the AI topic responded to the interview request positively. However, the physicians expressed expectations but also various concerns. When analyzing the data, the subjective opinions of the authors present further limitations. The subjectivity of the authors influences the identification of concepts in the interview transcripts and the selection of relevant articles when conducting the structured literature search. However, this subjectivity was mitigated by multiple authors reading and analyzing the interview transcripts and articles of the literature review. Furthermore, the qualitative approach excludes a generalization of the findings, so that the statements made in the thesis regarding the impact of the identified enabling measures, the influencing factors, and their interrelations are assumptions that have been supported by existing research but have not been quantitatively verified. Instead, the qualitative approach allows a deeper understanding of the healthcare professionals' perspectives and more profound reflections, which are called for by recent research that challenges traditional technology adoption models in the context of AI (Schuetz & Venkatesh, 2020).

Nevertheless, a quantitative study to validate the identified factors influencing the use of AI applications in medical diagnosis and the effectiveness of the identified enabling measures is needed to verify the context-specific results of this thesis. In this regard, the question should also be answered as to what degree of contextualization, as outlined in the limitations, makes sense. Furthermore, additional research should investigate whether the enabling measures identified in the context of imaging diagnosis are transferrable and helpful to other medical disciplines. There is also a need for further research on developing a step-by-step guide outlining how adoption theories can be contextualized, thereby providing more structure to the contextualization approach. More structure will improve the comparability of the studies which focus on contextualizing and improves the possibility of developing general approaches that are applicable in other contexts aside from healthcare. Additionally, while this thesis focuses solely on the user perspective, further research is needed to identify measures to address the macroeconomic, organizational, and technological obstacles. Moreover, as obstacles in all four areas impact the user, this thesis suggests a holistic and simultaneous solution approach to enable the successful adoption and continuous usage of AI applications in medical diagnosis.

5 Conclusion

AI applications hold significant potential to improve healthcare, particularly in the area of medical diagnosis, where they can achieve greater accuracy and faster processing speed, effectively addressing the growing challenges in healthcare. With the promising advantages of AI applications in medical diagnosis and the rapid technological development in mind, this thesis focuses on the task of deepening the understanding of the adoption of AI applications in medical diagnosis from the individual user's perspective, thereby contributing to the promotion of adoption.

Based on seven research articles, five of which deal specifically with the adoption of AI applications, four of which outline the factors influencing the adoption of HIT from the individual user's perspective, and a total of 107 qualitative interviews, this thesis delivers four key findings. First, this thesis contributes to contextualizing research on technology adoption by identifying factors that influence the adoption of AI applications in medical diagnosis. Second, it highlights the importance of physicians' prior experience and knowledge of the specific technology when examining technology adoption. Third, this thesis argues that research on technology adoption should go beyond initial acceptance and should investigate the continuous usage of technology. Fourth, this thesis offers practical implications in the form of specific measures addressing the identified factors hindering the adoption of AI applications, focusing on enabling physicians to make an informed adoption decision, whereby demonstrating the added value of the technology in clinical use appears highly relevant.

Overall, this thesis contributes to promoting the adoption of AI applications within the field of medical diagnosis, while at the same time emphasizing that AI applications should not be adopted for their own sake. Rather, the adoption of AI applications must aim on increasing efficiency and improving the quality of patient care.

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7 Appendix

7.1 Further Research Projects

#	Authors	Title	Publication Outlet
1	Doctor, E., Hennrich, J., Schwabe, S., Röwer, H., Eymann, T., Buck, C.	Reconsidering the Promise of Digital Transformation - Navigating Maturity in Heterogeneous End-Of-Life Care Networks	Proceedings of the 32nd European Conference on Information Systems (ECIS 2024)
2	Etterer, G., Hennrich, J., König, S., Buck, C.	Wie sich Bauunternehmen auf die Integrierte Projektabwicklung vorbereiten müssen	Der Bauingenieur 10/2023. – S. 320-326
3	Kourani, H., Berti, A. Hennrich, J., Kratsch, W., Weidlich, R., Li, C.-Y., Arslan, A., Schuster, D.	Leveraging Large Language Models for Enhanced Process Model Comprehension	Working Paper. Submitted to Decision Support Systems Journal
4	Hennrich, J., Schick, D., Eymann, T., Buck, C.	Digital Technologies' Characteristics combating Loneliness in the Elderly	Working Paper.
5	Kauffmann, A.L., Hennrich, J., Buck, C.	Künstliche Intelligenz Technologie in der Radiologie: Eine systematische Überprüfung von KI-Anwendungsfällen	Pfannstiel, Mario A. (Hrsg.): Technologien und Technologiemanagement im Gesundheitswesen. – Wiesbaden: Springer Gabler, 2024. – S. 661 - 676
6	Hennrich, J., Kauffmann, A.L., Buck, C., Eymann, T.	Künstliche Intelligenz in der hausärztlichen Versorgung	Pfannstiel, Mario A. (Hrsg.): Künstliche Intelligenz im Gesundheitswesen: Entwicklungen, Beispiele und Perspektiven. - Wiesbaden: Springer Gabler, 2022. – S. 413-430
7	Kauffmann, A.L., Hennrich, J., Buck, C., Eymann, T.	Künstliche Intelligenz in der Radiologie und Strahlentherapie aus der Perspektive von Ärzten und Medizinphysikexperten: Eine Interviewstudie	Pfannstiel, Mario A. (Hrsg.): Künstliche Intelligenz im Gesundheitswesen: Entwicklungen, Beispiele und Perspektiven. - Wiesbaden: Springer Gabler, 2022. – S. 413-430
8	Gimpel, H., Heger, S., Hennrich, J., Schröder, J., Kriner, H.	Krankenhauslogistik: Zusammenfassung und Ausblick	Gimpel, Henner; Schröder, Jürgen (Hrsg.): Hospital 4.0: Schlanke, digital-unterstützte Logistikprozesse in Krankenhäusern. - Wiesbaden: Springer Gabler, 2021. – S. 215-230
9	Baier, M.-S., Hennrich, J., Huff, K., Hufnagl, C., Jung, C., Metz, F., Kriner, H.	Referenzmodell schlanke, digital-unterstützte Bettenlogistik in Krankenhäusern	Gimpel, Henner ; Schröder, Jürgen (Hrsg.): Hospital 4.0: Schlanke, digital-unterstützte Logistikprozesse in Krankenhäusern. - Wiesbaden : Springer Gabler, 2021 . - S. 215-230

7.2 Research Articles and Individual Contribution

Research Paper #1: Accelerating the Adoption of Artificial Intelligence Technologies in Radiology: A Comprehensive Overview on Current Obstacles

Authors:

Hennrich, Jasmin – Chair for Information Systems & Digital Society, University of Bayreuth
Fuhrmann, Hannah – FIM Research Center for Information Management
Eymann, Torsten – Chair for Information Systems & Digital Society, University of Bayreuth

Citation:
Hennrich Jasmin, Fuhrmann Hannah, and Eymann Torsten 2024. „Accelerating the Adoption of Artificial Intelligence Technologies in Radiology: A Comprehensive Overview on Current Obstacles," *Proceedings of the Hawaii International Conference on System Sciences.* Honolulu, Hawaii.

Available at: https://www.fim-rc.de/Paperbibliothek/Veroeffentlicht/1542/wi-1542.pdf

VHB Publication Media Rating 2024 – Information Systems: B

Extended abstract: Chapter 3.1, p. 12-15

Individual Contribution by Jasmin Hennrich:

As Co-Author, I contributed to the research paper through several key activities. These included co-formulating the research question, assisting in the development of the paper structure, and participating in the methodological design. I was also involved in data analysis, ensuring accuracy and relevance of the findings. My role extended to writing parts of the manuscript, including drafting and revising content to meet publication standards. I presented the paper at the 57th Hawaii International Conference on System Sciences.

Research Paper #2: Artificial Intelligence in Radiology: A Qualitative Study on Imaging Specialists' Perspectives

Authors:

Buck, Christoph – Technical University of Applied Sciences Augsburg
Hennrich, Jasmin – Chair for Information Systems & Digital Society, University of Bayreuth
Kauffmann, Anna Lina – Chair for Information Systems & Digital Society, University of Bayreuth

Citation:
Buck, Christoph, Hennrich, Jasmin, and Kauffmann, Anna Lina 2021. "Artificial Intelligence in Radiology: A Qualitative Study on Imaging Specialists' Perspectives," *Proceedings of the International Conference on Information Systems*. Austin, Texas.

Available at: https://aisel.aisnet.org/icis2021/is_health/is_health/20/

VHB Publication Media Rating 2024 – Information Systems: A

Extended abstract: Chapter 3.2, p. 15-1715

Individual Contribution by Jasmin Hennrich:

As a Co-Author, my authorship is reflected throughout the research project. I contributed by analyzing the interview transcript together with my co-authors. In all chapters, I wrote significant parts of the paper. I also engaged in the conceptual and textual elaboration during the review process of the paper. I lead the discussion at the *42nd International Conference on Information Systems* after Anna Lina Kauffmann presented the paper.

Research Paper #3: General Practitioners' Attitudes Toward Artificial Intelligence-Enabled Systems: Interview Study

Authors:

Buck, Christoph – Technical University of Applied Sciences Augsburg

Doctor, Eileen – Chair for Information Systems and Digital Society, University of Bayreuth

Hennrich, Jasmin – Chair for Information Systems & Digital Society, University of Bayreuth

Jöhnk, Jan – FIM Research Center for Information Management

Eymann, Torsten – Chair for Information Systems & Digital Society, University of Bayreuth

Citation:

Buck, Christoph, Doctor, Eileen, Hennrich, Jasmin, Jöhnk, Jan, and Eymann, Torsten 2022. "General Practitioners' Attitudes Toward Artificial Intelligence–Enabled Systems: Interview Study," *Journal of Medical Internet Research* 24(1):e28916.

Available at: https://www.jmir.org/2022/1/e28916

VHB Publication Media Rating 2024 – Information Systems: B

Extended abstract: Chapter 3.2, p. 17-20

Individual Contribution by Jasmin Hennrich:

As a Co-Author, my authorship is reflected throughout the research project. I contributed by developing the research question, the interview guideline, and by conducting all interviews. Moreover, I chose the theoretical framework which we used to analyze the interview data. In all chapters, I wrote significant parts of the paper and managed the review process till the final accept in the journal.

Research Paper #4: Overcoming a Knowledge Gap of Healthcare Professionals: The Influence of Previous Experience on the (Non-)Adoption of VR in Medical Rehabilitation

Authors:

Schreiter, Melina – Chair for Information Systems & Digital Society, University of Bayreuth

Hennrich, Jasmin – Chair for Information Systems & Digital Society, University of Bayreuth

Wolf, Anna Lina – Chair for Information Systems & Digital Society, University of Bayreuth

Eymann, Torsten – Chair for Information Systems & Digital Society, University of Bayreuth

Citation:
Schreiter, Melina, Hennrich, Jasmin, Wolf, Anna, and Eymann, Torsten 2024. "Overcoming a Knowledge Gap of Healthcare Professionals: The Influence of Previous Experience on the (Non-)Adoption of VR in Medical Rehabilitation," *Working Paper*.

Submitted to: Journal of Medical Internet Research (VHB-Ranking 2024: B)

Extended abstract: Chapter 3.2, p. 20-23

Individual Contribution by Jasmin Hennrich:

As Co-Author, my authorship is reflected throughout the research project. As part of the project, my role centered on revising certain sections, particularly those describing our analysis process and findings, ensuring that they were presented accurately and aligned with our research objectives. In addition, I critically evaluated how our results intersect with existing literature and contribute to the field. I also engaged in the conceptual and textual elaboration during the review process of the paper.

Research Paper #5: Antecedents of Workarounds Related to Information Systems in Hospitals: Interview Study

Authors:

Doctor, Eileen – Chair for Information Systems and Digital Society, University of Bayreuth

Hennrich, Jasmin – Chair for Information Systems & Digital Society, University of Bayreuth

Eymann, Torsten – Chair for Information Systems & Digital Society, University of Bayreuth

Buck, Christoph – Technical University of Applied Sciences Augsburg

Citation:

Doctor, Eileen, Hennrich, Jasmin, Eymann, Torsten, and Buck Christoph 2024. “Antecedents of Workarounds Related to Information Systems in Hospitals: Interview Study,” *Working Paper*.

In Revision: Journal of Medical Internet Research (VHB-Ranking 2024: B)

Extended abstract: Chapter 3.2, p. 23-26

Individual Contribution by Jasmin Hennrich:

As Co-Author, my authorship is reflected throughout the research project. I was actively involved in writing the method and findings and in refining all chapters of the paper. In addition, I played a key role in the discussion around our research question and the theory we used. Throughout the review process of the paper, I was involved in both conceptual and substantive revision to ensure the coherence and integrity of the manuscript (ongoing).

Research Paper #6: Enabling Physicians to Make an Informed Adoption Decision on Artificial Intelligence Applications in Medical Imaging Diagnosis: A Qualitative Approach

Authors:

Hennrich, Jasmin – Chair for Information Systems & Digital Society, University of Bayreuth

Doctor, Eileen – Chair for Information Systems & Digital Society, University of Bayreuth

Körner, Marc-Fabian – Chair of Information Systems & Digital Energy Management, University of Bayreuth

Lederman, Reeva – School of Computing and Information Systems, University of Melbourne

Eymann, Torsten – Chair for Information Systems & Digital Society, University of Bayreuth

Citation:

Hennrich, Jasmin, Doctor, Eileen, Körner, Marc-Fabian, Lederman, Reeva, and Eymann, Torsten 2024. "Enabling Physicians to Make an Informed Adoption Decision on Artificial Intelligence Applications in Medical Imaging Diagnosis: A Qualitative Approach," *Working Paper*.

Submitted to: Journal of Medical Internet Research (VHB-Ranking 2024: B)

Extended abstract: Chapter 3.3, p. 26-28

Individual Contribution by Jasmin Hennrich:

As Lead Author, I contributed by initiating and developing the entire research project, including the research question, the research model, and the methodological approach. I conducted the structured literature review, developed the interview guideline, and I conducted the interviews. In all chapters, I wrote significant parts of the paper and lead the research team in the submission process (ongoing).

Research Paper #7: Capturing Artificial Intelligence Applications' Value Proposition in Healthcare – A Qualitative Research Study

Authors:

Hennrich, Jasmin – Chair for Information Systems & Digital Society, University of Bayreuth

Ritz, Eva – University St. Gallen

Hofmann, Peter – appliedAI Initiative GmbH

Urbach, Nils - Faculty Business and Law, Frankfurt University of Applied Sciences

Citation:

Hennrich, Jasmin, Ritz, Eva, Hofmann, Peter, and Urbach, Nils 2024b. "Capturing artificial intelligence applications' value proposition in healthcare – a qualitative research study," *BMC Health Service Research* 24(1), 420.

Available at: https://rdcu.be/dNb32

VHB Publication Media Rating 2024 – Business Administration: C

Extended abstract: Chapter 3.3, p. 28-31

Individual Contribution by Jasmin Hennrich:

As Co-Author, my authorship is reflected throughout the research project. I contributed by initially composing the introduction of the research project, including the research question. Moreover, I wrote the background and results sections. I was in the lead during the review process up to the final approval of the paper.