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*THE VALUE OF DATA AND ANALYTICS
FOR HEALTH CARE PROVIDERS*

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Preface

This dissertation and related publications would not have been possible without the dedicated support of several individuals and institutions. Hence, I would like to take the opportunity to thank everyone who supported my dissertation project conceptually, provided crucial data needed for analysis, or covered my back in private life.

Firstly, I would like to sincerely thank my first advisor Christian Hagist for his consistent and universal support during my dissertation project. In essence, he combined an ideal degree of scientific freedom with availability of discussion and conceptualization time even at a minute's notice. This combination provided essential prerequisites for a highly enjoyable and avid doctoral journey. I would also like to thank my second advisor Stefan Spinler for always making time available for discussions especially of methodological nature. Besides these sparring partners from WHU, I would like to thank all radiologists who took time to discuss the opportunities and challenges of Artificial Intelligence in radiology and, hence, helped to build the foundations for the Discrete Choice Experiment of this dissertation.

Secondly, this dissertation heavily relied on data provided by several individuals and institutions. I would like to thank the more than 100 radiologists who showed the endurance to complete the Discrete Choice Experiment. Furthermore, the third contribution of this work would not have been possible without the comprehensive datasets related to hospital digitization of the Hochschule Osnabrück, hospital quality of the Wissenschaftliches Institut der AOK (WIdO) and hospital patient satisfaction of Weisse Liste. I would also like to thank the Department of Healthcare Management of TU Berlin for facilitating the access to the mentioned datasets. Universal data availability and cooperation can be considered the essence of a well-functioning research community.

Thirdly, and most importantly I would like to wholeheartedly thank my family for continuously encouraging and supporting me to live out my dreams. Ulla, Hasso and Marie are, by far, the best sparring partners and strongest anchors in my life. Thank you for everything.

Lastly, the key goal of this dissertation project has always been to provide practically relevant insights for health care providers and policymakers. I sincerely hope that the results can provide some guidance for providers considering investments in data and analytics or even policymakers working towards meaningful adoption thereof. In the end, all stakeholders of our health care systems benefit from a better understanding of how data and analytics can improve the quality, efficiency and patient experience of care.

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List of abbreviations

2D/3D	-	Two/three-dimensional
AA	-	Advanced Analytics
AI	-	Artificial Intelligence
AICc	-	Corrected Akaike Information Criterion
AOK	-	Allgemeine Ortskrankenkasse
BA	-	Business Analytics
BI-RADS	-	Breast Imaging Reporting and Data System
BIC	-	Bayesian Information Criterion
CBA	-	Cost-benefit Analysis
CBC	-	Complete Blood Count
CCDS	-	Computerized Clinical Decision Support
CI	-	Confidence Interval
CNN	-	Convolutional Neural Network
CPOE	-	Computerized Physician Order Entry
CT	-	Computed Tomography
DCE	-	Discrete Choice Experiment
DL	-	Deep Learning
DRG	-	Diagnosis Related Group
EHR	-	Electronic Health Record
EMRAM	-	Electronic Medical Record Adoption Model
EU	-	European Union
HIMSS	-	Healthcare Information and Management System Society
HIT	-	Health Information Technology
HITECH	-	Health Information Technology for Economic and Clinical Health
ICU	-	Intensive Care Unit
IT	-	Information Technology
KKH	-	Kaufmännische Krankenkasse
ln	-	Natural Logarithm
ML	-	Machine Learning

MRI	-	Magnetic Resonance Imaging
MWTP	-	Marginal Willingness to Pay
O/E	-	Observed over Expected
OECD	-	Organisation of Economic Co-operation and Development
OLS	-	Ordinary Least Squares
PACS	-	Picture Archiving and Communication System
PEQ	-	Patient Experience Questionnaire
QSR	-	Qualitätssicherung mit Routinedaten
RIS	-	Radiology Information System
SD	-	Standard Deviation
SE	-	Standard Error
US	-	United States
VIF	-	Variance Inflation Factor
WIdO	-	Wissenschaftliches Institut der AOK
WL	-	Weisse Liste
WTP	-	Willingness to Pay

Introduction

1 General introduction

“The digital world has been in a separate orbit from our medical cocoon, and it's time the boundaries be taken down.” – Eric Topol in 2013 (Winslow, 2013)

Data and analytics are inseparably connected with almost all facets of our lives today. Digital technologies disrupted the way we communicate, travel, consume, conduct research, and more. Entire industries lived and still live through a process of digital transformation that promises and predominantly delivers benefits to all stakeholders. Unsurprisingly, this development did not spare one of the most intimate and sensitive subjects: our health (Blumenthal & Glaser, 2007). Revisiting the above-noted quote by Eric Topol, a lot seems to have happened since 2013. In 2022, the term “digital health” appears to be omnipresent, with corporations and investment funds investing billions of euros in data and analytics technologies in health care (Sharma et al., 2018). In many areas, the digital transformation is already very much visible. Some pharmaceutical and medical technology companies, for example, rely on Artificial Intelligence (AI) for drug discovery, equipment development, or market access (Hird et al., 2016). Patients are increasingly engaging with smartphone applications and smart devices like the Apple Watch blurring the line between health care and wellness (Sharma et al., 2018). Health insurance companies also participate in this digital race by proactively investing in and offering these applications and other patient-centric technologies with preventive benefits in mind (Raber et al., 2019). The COVID-19 pandemic even pushed notoriously rigid governmental health agencies to adopt data and analytics tools tracking relevant metrics and, hence, facilitating policy decisions (Budd et al., 2020). It seems like the boundaries have been taken down between the digital world and the medical cocoon.

However, one stakeholder group at the heart of our health care systems appears to embrace digital tools in a more limited way. Health care providers, namely hospitals, clinics, or practices, adopt data and analytics technologies at a comparably slower pace, if at all (Hübner et al., 2020; Stephani et al., 2019). In theory, several Health Information Technologies (HIT) are available and promise benefits for aspects of care quality and efficiency. Electronic Health Records (EHR), arguably representing the most thoroughly researched HIT, for example, can reduce medication errors and adverse drug effects and avoid duplicate imaging or laboratory testing (Campanella et al., 2016; Chaudhry et al., 2006). Computerized Clinical Decision Support (CCDS) assisting physicians and nurses in diagnosis and treatment decisions can improve guidelines adherence (Bright et al., 2012). Recent advances in computational power and the continuous compilation of standardized datasets ultimately resulted in powerful AI-based tools relying on Machine Learning (ML) or Deep Learning (DL) techniques. These technologies have the potential to revolutionize the delivery of care fundamentally. For example, ML and DL tools can identify irregular patterns in chest radiographs, scan electrocardiograms for myocardial infarction or detect fractures and breast cancer from imaging on par with or even better than radiologists (Gale et al., 2017; McKinney et al., 2020; Tang et al., 2020; Yang et al., 2018). Furthermore, AI can predict the onset of diseases like diabetes or cancer and provide forecasts of in-hospital mortality, readmissions, length of stay, or infection risks (Desautels et al., 2016; Miotto et al., 2016; Oh et al., 2018; Rajkomar et al., 2018).

In theory, these promising examples should encourage health care providers to adopt data and analytics swiftly. Yet, in 2017, 38.3% to 47.4% of German or 27.8% to 46.4% of Austrian hospitals did not have an EHR system installed and, hence, relied on paper-based documentation (Hübner et al., 2020; Stephani et al., 2019). A recent report of the Healthcare Information and Management System Society (HIMSS) still categorizes the majority of hospitals worldwide on stage zero of five in their Electronic Medical Record Adoption Model (EMRAM) (DigitalRadar, 2022). The adoption of CCDS or even technologies based on AI is still low today (Jiang et al., 2017; Sun & Medaglia, 2019; Sutton et al., 2020). Significant adoption of single technologies, if present, is primarily attributable to comprehensive HIT adoption programs initiated by policymakers. The high adoption rate of EHRs in the United States (US), for example, is strongly driven by the 2008 Health Information Technology for Economic and Clinical Health Act (HITECH) that provided more than US \$28 billion to health care providers adopting EHR systems (Blumenthal, 2010). Hence, when focusing on health care providers, the medical cocoon appears to be slightly more isolated to the digital world compared to other stakeholders.

The reasons for this phenomenon are manifold. Research repeatedly identifies social, ethical, legal, or technological barriers that slow down the digitization of providers (Sun & Medaglia, 2019). Additionally, the economic feasibility of investments in data and analytics is continuously quoted as one of the most critical barriers (Kruse et al., 2016; Sun & Medaglia, 2019). In the end, providers need to perceive value delivered by data and analytics tools to consider adopting them.

Value represents a somewhat generic term and can be defined in various ways. In health care, however, interventions are regularly assessed concerning the following three interlinked value drivers: Economics of care, quality of care, and patient experience (Enthoven & Tollen, 2005; Kumar et al., 2011; Luxford et al., 2011; Luxford & Sutton, 2014). These three value drivers are also at the heart of health care providers' treatment and investment decisions. Firstly, providers need to ensure an economically feasible operation. This at least applies to those parts of the world, where hospitals, clinics, and practices participate in comparably free markets like the US and most countries of the European Union (EU). Accordingly, investment decisions, including the ones on data and analytics, are assessed for their economic feasibility. When evidence on the economic benefits of data and analytics tools either via increases in revenue or decreases in costs is limited or ambiguous, providers are less likely to adopt these technologies. Secondly, it must be assumed that providers strive for improvements in care quality, i.e., continuously improving the care for their patients. In theory, digital technologies which assist providers in this undertaking should be adopted. Accordingly, AI-based tools assisting physicians and nurses by reliably predicting sepsis or other incidents, for example, should be omnipresent. However, as previously explained, this does not appear to be the case. This example shows that it is important to consider existing or missing interlinkages between the three value drivers and specifically between quality and economics of care. In most health care systems, providers are still not significantly financially rewarded for delivering high-quality care (Henkel, 2015; Porter & Guth, 2012). Hence, even though specific digital tools might positively impact care quality and should therefore be adopted from a macro perspective, the investment costs might not be sufficiently compensated for on the micro-level of single

providers. Thirdly, patient satisfaction represents another critical value driver. The most effective and efficient care delivery is worthless if not embraced by patients due to bad experiences. Providers are, hence, incentivized to deliver a sufficient experience. Besides the need for data and analytics to address some or all the three value drivers, however, the digital tools also simply need to be designed in a way that is preferred by providers. Ultimately, even the most advanced data and analytics solution is not adopted if it does not address a problem perceived relevant by providers or does so in a user-unfriendly way.

As previously described, health care providers are constantly confronted with weighing the costs against the benefits, or value, of investments in data and analytics. Even though the three identified value drivers are interlinked, some linkages are stronger than others. On a system level, policymakers have the means to strike a careful balance between them. For example, they can initiate nationwide HIT adoption programs incentivizing investments in technologies perceived value-adding by policymakers. One example is the previously described HITECH Act of 2008 that incentivized and drove the adoption EHRs among US hospitals (Blumenthal, 2010). Another example is the German 2020 Hospital Future Act (Krankenhauszukunftsgesetz) which initiated an up to €4.3 billion fund funding investments in digital infrastructures and emergency capacities among German hospitals (BMFG, 2020). The Hospital Future Act even includes financial penalties for hospitals that do not adopt certain technologies until 2025. These programs significantly lower the bar for hospitals' investments in data and analytics tools covered by the funding requirements. Besides these policy interventions aiming at the costs of data and analytics for providers, policymakers can also adjust reimbursement mechanisms. On the one hand, every single data and analytics tool utilization could be additionally reimbursed. In Germany, for example, this is already the case for specific applications in radiology. On the other hand, policymakers could commit themselves to a comprehensive reform of the underlying reimbursement system towards value-based health care that financially rewards outcome improvements (Henkel, 2015). If data and analytics can improve care outcomes, hospitals will profit from additional reimbursement when investing in promising technologies.

These considerations show that comprehensive information on the value of data and analytics for health care providers is of high interest for several stakeholders. Providers themselves need clarity on how overall digitization and single digital tools affect the efficiency, quality, and experience of care. This enables them to define evidence-based digitization strategies and take informed investment decisions. On the other hand, policymakers rely on this information when designing nationwide HIT adoption programs or reimbursement mechanisms. Ultimately, however, data and analytics adopted by health care providers can impact every single actual and potential patient worldwide. Hence, all stakeholders of our health care systems should be incentivized to work towards mechanisms that reward the adoption of value-adding data and analytics technologies.

2 Research questions

This dissertation examines the relationship between data and analytics and the quality, economics, and patient experience of health care providers. A key goal is to provide practically relevant insights for providers on how overall digitization or single technologies impact value

drivers, if at all. As previously described, policymakers and even patients can also benefit from this information for their decision-making. Figure 1 provides a framework for the thematic scope of this work. Here, health care providers, corresponding data and analytics categories, and their impact on the economics, quality, and patient experience of care are clearly identified as the key subjects under study.

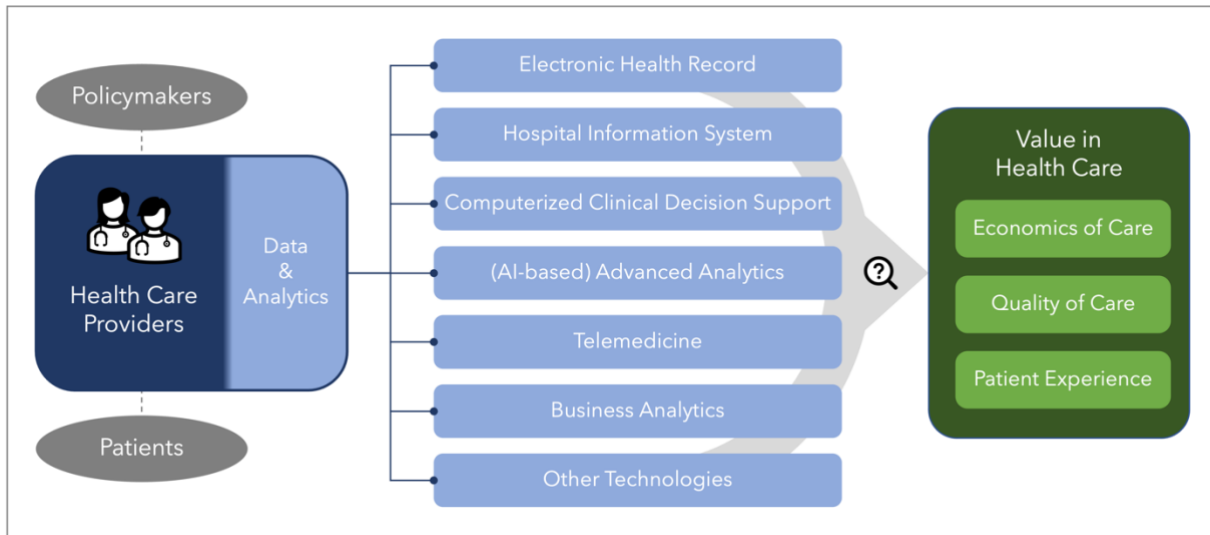


Figure 1: Thematic scope of this work

This work examines the following overarching research questions:

- > What is the relationship between data and analytics and the economics/profitability of health care providers?
- > What is the relationship between data and analytics and the quality and patient experience of health care providers?
- > Which attributes of data and analytics tools influence the adoption decisions of health care providers?
- > What can policymakers derive from answers to the first three research questions to fuel the adoption of value-adding data and analytics among health care providers?

These research questions are examined in the three contributions of this work that cover different aspects of the overall scope illustrated in Figure 1. The following brief overview of the background, aim and results of each contribution concludes the introduction of this dissertation.

3 Contribution 1: Economic Value of Data and Analytics for Health Care Providers

The economic feasibility of health care providers' investments in data and analytics represents one of the most critical barriers for adoption. The first contribution exclusively examines the economic value of HIT for providers by assessing the direct and indirect effects of technologies on profitability. The goal is to capture the impact of a variety of HIT categories and provide providers practically relevant insights for investment decisions. For policymakers,

these insights can point towards potential mismatches related to quality-enhancing, yet economically unfeasible technologies.

A hermeneutic systematic literature review was conducted to generate a comprehensive overview of the scientific evidence available. Two online databases were screened for matching studies. After cleaning of initial results, the identified studies were then categorized into five overarching technologies. For each of these technological categories, the extent and direction of economic impact was determined. It was differentiated between direct impact on either costs or revenue and indirect impact on productivity and efficiency.

The review identified 5 key technology categories: EHRs (n=30 studies), computerized clinical decision support (n=8), advanced analytics (n=5), business analytics (n=5), and telemedicine (n=2). 62% (31/50) of all reviewed studies indicated a positive economic impact for providers either via direct cost or revenue effects or via indirect efficiency or productivity improvements. When looking at differences between the categories, however, an ambiguous picture emerged for EHRs, whereas analytics technologies like computerized clinical decision support and advanced analytics predominantly indicated economic benefits. Hence, the research question of whether data and analytics create economic benefits for health care providers could not be answered uniformly. It could be argued that the mixed results regarding EHRs can create an economic barrier for adoption by providers which can translate into a bottleneck to positive economic effects of analytics technologies relying on EHR data.

4 Contribution 2: Physicians' Preferences and Willingness to Pay for Artificial Intelligence-based Assistance Tools

Research on the value of advanced analytics relying on AI for health care providers is very limited to date. Results of the first contribution of this dissertation also confirmed this general observation. Most current research still focuses on proving the sensitivity or specificity of AI-based applications which can be considered a logical first step. Ultimately, however, the design of these tools needs to meet the preferences of physicians. Moreover, they need to be priced in line with average willingness to pay (WTP). Accordingly, the goal of this contribution is to show physicians' preferences and WTP for AI-based assistance tools. Since the manifestation of AI-based tools strongly varies across use cases and medical specialties, the study focused on a profession currently strongly impacted by emerging technologies, namely radiologists.

This contribution assessed German radiologists' preferences and WTP for AI-based assistance tools by conducting a Discrete Choice Experiment (DCE). Respondents from the two major German professional radiology associations chose between hypothetical tools composed of five attributes and a no-choice option. The attributes included: provider, application, quality impact, time savings and price. A conditional logit model was estimated identifying preferences for attribute levels, the no-choice option, and significant subject-related interaction effects.

114 radiologists were included for statistical analysis. 46% of them were already using an AI-based assistance tool. Average adoption probability for the AI-based tools displayed in the DCE was 81%. Radiologists preferred a tool that assists in routine diagnostics performing at above-radiologist-level quality and saves 50% in diagnostics time at a price-point of €3 per study. The provider type, e.g., startup vs. industry player, was not a significant factor in decision

making. Somewhat surprisingly, time savings were considered more important than quality improvements (i.e., detecting more anomalies). It was concluded that radiologists are overall willing to invest in AI-based assistance tools. Development, funding, and research regarding these tools should, however, consider providers' preferences for features of everyday and economic relevance like time savings. Only by considering these results can adoption of these promising tools by providers be optimized.

5 Contribution 3: Effects of Hospital Digitization on Clinical Outcomes and Patient Satisfaction

The third contribution of this work assesses the impact of health care provider digitization on care quality and patient satisfaction. Specifically, it examines the relationship between digitization on actual clinical outcomes and patient experience among German hospitals. Additionally, it goes beyond assessing the effects of mere HIT adoption and considers user-perceived HIT value, as well. Hence, it aims at differentiating between quantity and quality of installed HIT. Additionally, the impact of various technologies beyond the commonly studied EHR is examined.

Multiple linear regression models were estimated including emergency care outcomes, elective care outcomes, and patient satisfaction as dependent variables. HIT adoption and user-perceived value thereof, as well as controls for case volumes, hospital size, ownership status, and teaching status were included as independent variables. Care outcomes were captured via risk-adjusted observed/expected outcome ratios for stroke, heart attack, and hip replacement patients. The Patient Experience Questionnaire provided information on patient satisfaction. Information on the adoption and user-perceived value of 10 sub-domains of HIT and EHRs was derived from the German 2020 Health Care IT Report.

Statistical analysis was based on an overall sample of 383 German hospitals. HIT or EHR adoption did not have a significant effect on either clinical outcomes or patient satisfaction. However, a higher user-perceived value of installed technologies did significantly improve outcomes and satisfaction. Emergency care outcomes especially benefitted from user-friendly admission-HIT. On the other hand, elective care outcomes benefitted from user-friendly EHR installations. It could ultimately be concluded that hospital digitization is not an end in itself. Hence, both policymakers and hospitals are well-advised to not only focus on the mere adoption of digital technologies but to continuously work towards digitization that is perceived valuable by physicians and nurses.

Economic Value of Data and Analytics for Health Care Providers: Hermeneutic Systematic Literature Review¹

1 Introduction

Data and analytics applications increasingly find their way into our health care systems. Some manifestations of data, like the Electronic Health Record (EHR), have already been more established in many member countries of the Organisation of Economic Co-operation and Development (OECD). Analytics technologies such as Computerized Clinical Decision Support (CCDS) or Advanced Analytics based on Big Data and Artificial Intelligence (AI) seem to be still newcomers in this field. Hopes are high that data and analytics significantly improve quality, efficiency, and patient experience of health care delivery (Blumenthal & Glaser, 2007). Taking the perspective of health care systems, latest research, indeed, shows that adoption of EHRs leads to fewer medication errors, less adverse drug effects and higher guideline adherence (Campanella et al., 2016; Chaudhry et al., 2006). The use of Clinical Decision Support tools is associated with lower morbidity, potentially improving mortality (Bright et al., 2012; Moja et al., 2014). Based on EHR data, Advanced Analytics is already able to predict the onset of several diseases like diabetes, schizophrenia, or cancer, as well as, provide care-related forecasts of in-hospital mortality, unplanned readmissions, length of stay, or infection risks (Desautels et al., 2016; Miotto et al., 2016; Oh et al., 2018; Rajkomar et al., 2018). One of the more recent topics is the possibility to diagnose the novel coronavirus disease (COVID-19) by applying AI to chest computed tomography (CT) scans (Li et al., 2020; McCall, 2020). It becomes clear how the introduction of these technologies can clearly create positive spill-over effects for the entire health care system.

When taking the microperspective of single providers, however, current adoption of data and analytics seems to paint a different picture in many countries. In the United States (US) or Denmark, almost all hospitals work with a sophisticated EHR, while many European countries show much lower adoption rates. For example, reports indicate that 38.3% to 47.4% of German or 27.8% to 46.4% of Austrian hospitals lacked a system entirely in 2017 (Hübner et al., 2020; Stephani et al., 2019). Even though analytics applications relying on AI or Big Data show strong potential, adoption in everyday provider operations is still comparatively low (Jiang et al., 2017). The reasons for this are manifold and include social, ethical, legal, or technological barriers (Sun & Medaglia, 2019). The most powerful barrier, however, is still of an economic nature. Health care providers see the initial and ongoing maintenance costs as key barriers for adoption and oftentimes question overall cost-effectiveness of these solutions (Jamoom et al., 2014; Kruse et al., 2016; Sun & Medaglia, 2019). In a world that has not yet significantly pivoted towards quality-based reimbursement, quality improvements via data and analytics are, ironically, not necessarily directly linked to economic benefits for single health care providers. The much higher adoption of EHRs in the US can, to a large part, be explained by strong financial subsidies by policymakers (Adler-Milstein et al., 2013; Blumenthal, 2010).

¹ von Wedel, P., & Hagist, C. (2020). Economic Value of Data and Analytics for Health Care Providers: Hermeneutic Systematic Literature Review. *Journal of Medical Internet Research*, 22(11), e23315.

Taking the single provider's perspective, the question pertains whether hospitals, clinics and practices can gain economic benefits from the usage of data and analytics. Most existing reviews in this field heavily focus on EHRs, but do not take into consideration other analytics tools (Highfill, 2019; Rahmawati, 2019; Reis et al., 2017; Uslu & Stausberg, 2011). Other more recent reviews focus on the economic impact of single areas of data and analytics like AI, but not specifically on providers (Wolff et al., 2020). Our work attempts to fill this gap by providing a comprehensive review of the literature covering the economic impact of several applications of data and analytics exclusively on providers. In the end, the promising potential of a number of established and rapidly evolving technologies to improve quality of care in our health care systems can only be optimally leveraged via widespread adoption by single providers.

2 Methods

2.1 Hermeneutic Systematic Review

The common systematic review ideally represents a highly structured approach for searching, screening, including and summarizing studies to answer a rather narrowly defined question (Higgins & Green, 2008; Morton et al., 2011). It might not, however, show perfect fit with all research questions. As Greenhalgh et al. (2018) summarized, it often “can be viewed as a set of methodologies characterized by tight focus, exhaustive search, high rejection-to-inclusion ratio and an emphasis on technical rather than interpretive synthesis methods.” The hermeneutic review methodology introduced by Boell and Cecez-Kecmanovic (2014) showed a particularly good fit with the broader nature of this study's research question. This process of a literature review follows two interlinked cycles: (1) search and acquisition and (2) analysis and interpretation (see Appendix 1). The hermeneutic process allows and encourages a (1) constant process of refining and extending the search realm of cycle by (2) deeply engaging with the content of the identified literature via cycle. This enables the researcher to leverage “the importance of reading and dialogical interaction between the literature and the researcher; [...] seeking originality rather than replicability” (Boell & Cecez-Kecmanovic, 2014, p. 258). Nevertheless, to assure the systematic execution of this review, guidelines for scoping studies including a 6-step process by Arksey and O'Malley (2005) were followed. The hermeneutic approach was hereby complemented by the established tools for study identification and charting, assuring a systematic execution of the review. These tools resulted in a clear, reproducible, and structured overview of how studies were identified and for which reasons studies were excluded. In the end, by combining the traits of systematic and hermeneutic reviews, this study attempted to generate a structured, reproducible, comprehensive, and content-focused review of the literature.

2.2 Search Strategy

Literature included in this review was identified via iterative structured keyword searches in the online databases PubMed and Google Scholar, as well as a complementary backward and manual search. The following keyword search on article titles was applied to both databases:

(*x*) AND (cost(s) OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) AND (hospital(s) OR practice(s) OR provider(s)), where *x* represents a placeholder for terms that were iteratively added following the hermeneutic approach and the following segments assured inclusion of studies only covering economic effects for only health

care providers and which remained unchanged for all searches. In an initial search, x was comprised of “Electronic Health Record,” “Electronic Medical Record,” “Electronic Patient Record,” “Analytics,” and “Clinical Decision Support” (including all alternative and plural types of wording and abbreviations). Following the hermeneutic approach both authors independently screened the resulting studies and jointly decided on additional search terms expanding x to also include the terms “Algorithm,” “Artificial Intelligence,” “Big Data,” “Machine Learning,” “Deep Learning,” “Natural Language Processing,” and “Telemedicine.” Interestingly, searches in the field of Mobile Health including health applications did not generate any suitable results. The search was limited to journal articles published in English between January 2009 and December 2019. The exact search queries for both databases can be found in Appendix 2.

3 Results

3.1 Study Selection

The PubMed and Google Scholar searches generated 79 and 165 results, respectively (see Figure 2). Following deduplication, a total number of 165 studies remained for more detailed review. Only published journal articles were considered for the review. Hence, the deduplicated search results were again cleaned, resulting in 113 articles. Titles, abstracts and, if needed, content of these articles were analyzed by both authors independently in order to determine fit to the research question, narrowing results down to 43 results. Frequent reasons for exclusion were articles dealing with effects of data and analytics on stakeholders other than providers or on overarching national health care spending. Other examples were articles covering analogue tools and processes like paper-based decision support or diagnostic testing decision algorithms. An overview of all 113 screened studies and respective reasons for exclusion can be found in Appendix 3. A complementary backward and manual search by both authors independently resulted in an additional 7 articles for inclusion. The final 50 articles were thoroughly reviewed, and key properties were summarized by the first author in a structured manner to facilitate pattern identification and final synthesis generation (see Appendix 4).

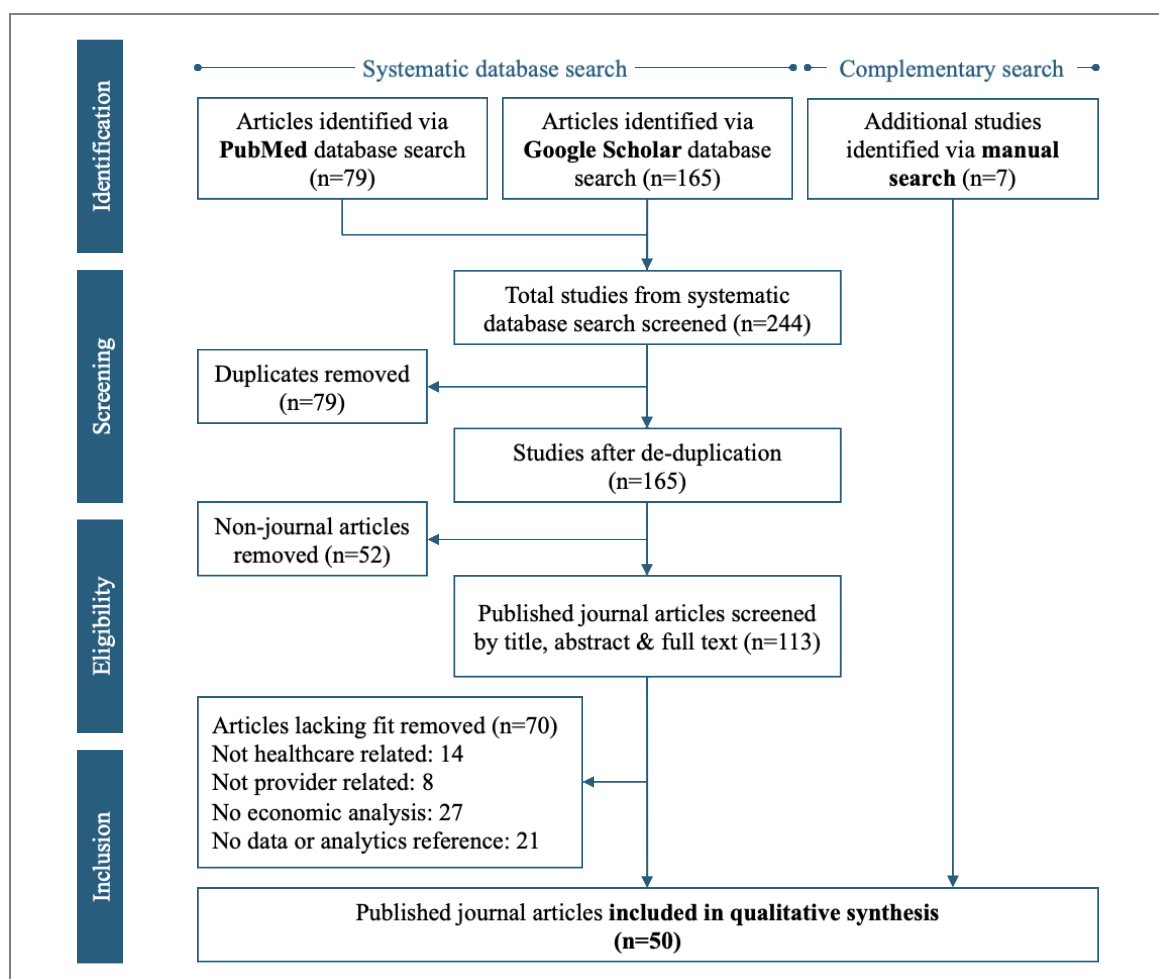


Figure 2: Literature search and study selection process

3.2 Study Categorization

Following in-depth review of the 50 final studies, 2 angles for categorization emerged. Firstly, the studies were sorted according to the technology under research, resulting in 5 key categories, namely Electronic Health Records, Computerized Clinical Decision Support, Advanced Analytics (AA), Business Analytics (BA), and Telemedicine. Secondly, studies were categorized based on the type of identified economic impact. This impact categorization consists of 2 combined components, namely mode (direct vs. indirect) and direction (positive vs. negative vs. neutral vs. mixed). Considering the impact mode, studies were categorized to have an *indirect* impact when no *direct* impact on costs or revenue, but rather on efficiency or productivity was shown (see Figure 3 for a summary and details).

3.3 Electronic Health Records


























AT 60% (30/50) of identified articles, EHRs represented the most comprehensive body of literature by far. In terms of economic impact, overall a rather ambiguous pattern could be observed with 12 studies revealing a positive, 8 studies a negative, 4 studies a neutral and 6 studies a mixed economic effect on providers. The majority of studies was US-based (20/50, 40%) with Asia (3/50, 6%), the rest of the world (2/50, 4%) and Europe (0) showing less research activity. The remaining 5 articles represented international literature reviews.

The 5 literature reviews included in the sample predominantly indicated mixed economic impacts of EHRs. All reviews included studies proving positive effects mostly via increased efficiency; however, for almost every review, another identified article indicated the opposite (Rahmawati, 2019; Reis et al., 2017; Thompson et al., 2015; Uslu & Stausberg, 2011). Only Highfill (2019) revealed overall positive economic effects, determining a 1.1%-13.8% cost decrease (95% CI) after EHR introduction in their meta-analysis.

Cost-benefit analyses (CBA) were presented in 5 articles and also painted a slightly ambiguous picture, with significantly varying timelines for EHR installations to break even. The majority of studies indicated an average break-even timeline between 3 and 8 years for EHR implementations in hospitals (Choi et al., 2013; Li et al., 2012; Zimlichman et al., 2013). Jang et al. (2014) indicated a much shorter 6.2-17.4-month (95% CI) break-even timeframe for primary care clinics. Only 1 study revealed a clear negative impact, showing a negative 5-years return on investment (Adler-Milstein et al., 2013). In general, the CBAs provided some interesting practice-oriented insights for EHR implementations. Results from Choi et al. (2013) and Adler-Milstein et al. (2013) both emphasized the importance of fully eliminating legacy costs like paper-based records and related dictation services. Parallel digital and analog structures resulted in fewer efficiency gains and, hence, longer break-even timelines. Besides decreasing costs, a successful EHR introduction also focused on additional revenue generation via improved charge capture and reduction of billing errors (Adler-Milstein et al., 2013; Choi et al., 2013; Li et al., 2012). Lastly, Jang et al. (2014) showed that more recent EHR systems and those using flow diagrams also came with shorter break-even timelines, implying potential important technological advances by vendors over the years.

Besides the full CBAs, 6 studies examined the effects of EHR introductions on a variety of single cost or revenue items. Encinosa and Bae (2013) showed how introduction of advanced EHRs reduced adverse drug effects from 3.6% to 1.4% of all cases, saving an average of US \$4790 per avoided case. Joseph (2010) revealed how personnel formerly needed for paper-based record keeping could be reduced, thereby saving more than US \$6 million over 5 years. Zlabek et al. (2011) showed how transcription costs were significantly reduced, resulting in US \$667,896 in costs saved 1 year after EHR introduction. A different source of cost savings was the avoidance of redundant laboratory tests and imaging exams. A Computerized Physician Order Entry (CPOE) system within an EHR resulted in an 18% decrease in laboratory test orders, as well as 6.3% fewer radiology exams (Silow-Carroll et al., 2012; Zlabek et al., 2011). However, Schnaus et al. (2017) revealed the importance of an appropriate execution of a CPOE implementation. The authors examined a temporary change regarding the pre-selected laboratory test type when physicians searched for a Complete Blood Count (CBC) within the CPOE tool. For 23 days, the system pre-selected a slightly more costly version of a CBC. Presumably due to time constraints, a number of physicians did not double-check on this pre-selected test type which resulted in an average daily cost increase for CBC testing of US \$293.10. Besides the direct economic impact via costs, some studies demonstrated positive effects via revenue. Terry (2014) highlighted the potential from value-based reimbursement based on EHR data. The author saw the lack of an EHR system as “an ‘opportunity cost’ that can be quantified and weighed against the cost of installing a system” (Terry, 2014, p. 145).

Finally, a significant share of papers (14/30) examined indirect economic impacts of EHRs via changes in efficiency or productivity. Here, a rather negative image emerged, with only 4 studies revealing positive effects, and the remaining showing either negative (6/30) or neutral (4/30) effects. Due to significant heterogeneity, it was difficult to draw generalizable insights from this sample of literature. As a takeaway, the identified systematic reviews also revealed that 5 studies examined productivity changes after EHR introduction, where productivity was mostly defined as average patient volumes. Of these studies, 3 revealed no statistically significant changes, hence neutral economic impacts (Dandu et al., 2019; Redd et al., 2014; Voleti et al., 2011). Kaneko et al. (2018) showed a negative impact on multi-factor productivity following EHR introduction in Japanese municipal hospitals. Only 1 study revealed positive long-term effects on productivity (De Leon et al., 2010). In 9 studies, efficiency implications were examined, where efficiency was defined rather heterogeneously as treatment times, waiting times, length of stay, or personnel volumes. While 1 study showed no effects (Kadish et al., 2018), 5 studies revealed a negative economic impact (Chuang et al., 2019; Furukawa et al., 2010; Hollenbeck et al., 2017; Huerta et al., 2013; McDowell et al., 2017). Especially the implementation of a fully-fledged EHR in a relatively short period of time, a so-called “big bang” introduction, seemed to be detrimental to hospital efficiency (Huerta et al., 2013). Only 3 studies showed somewhat limited positive effects on provider efficiency following EHR implementation (Furukawa, 2011; Kazley & Ozcan, 2009; Pyron & Carter-Templeton, 2019).

Technology categorization	Description	Economic impact categorization (# studies)				
 Electronic Health Records (EHR)	Studies examine the economic impact of Electronic Health Records in general without necessarily differentiating between single components (e.g. Computerized Physician Order Entry, Clinical Decision Support, etc.)	Total: 30				
		Direct	8	2	-	6
		Indirect	4	6	4	-
 Computerized Clinical Decision Support (CCDS)	Studies examine the economic impact of a Computerized Clinical Decision Support tool such as laboratory order alerts that do not rely on Advanced Analytics	Total: 8				
		Direct	7	-	-	-
		Indirect	1	-	-	-
 Advanced Analytics (AA)	Studies examine the economic impact of Advanced Analytics applications (e.g. Artificial Intelligence, Machine Learning, Deep Learning, etc.) utilizing mainly health data from EHRs to support diagnosis, decision-making or workflows	Total: 5				
		Direct	-	-	-	-
		Indirect	5	-	-	-
 Business Analytics (BA)	Studies examine the economic impact of Business Analytics tools mainly analyzing operational, workflow or billing/claims data	Total: 5				
		Direct	5	-	-	-
		Indirect	-	-	-	-
 Telemedicine	Studies examine the economic impact of Telemedicine applications like remote monitoring	Total: 2				
		Direct	-	-	1	-
		Indirect	1	-	-	-





Economic impact:  Positive  Negative  Neutral  Mixed Direct: Cost and/or revenue impact; Indirect: Productivity and/or efficiency impact

Figure 3: Overview of reviewed studies categorized by technology and economic impact

3.4 Computerized Clinical Decision Support

Studies examining the economic impact of CCDS on providers represented the second-largest share of identified articles, at 16% (8/50). A strong picture regarding the impact emerged, with all 8 studies revealing a positive economic impact on providers, predominantly of a direct

nature. Again, the majority of articles was US-based (5/8, 63%), and others were located in the rest of the world (2/8, 30%). The remaining article represented an international literature review.

Bright et al. (2012) presented the only included systematic review of CDS tools also assessing their impact on costs. Of a total 148 identified papers, 22 studies analyzed costs, of which 13 implied cost reductions. The authors saw this as “modest evidence from academic and community inpatient and ambulatory settings” (Bright et al., 2012, p. 16). Not all included studies, however, examined fully computerized CDS tools.

In 3 articles, it was shown how CCDS systems could reduce the number of imaging studies, laboratory tests, or the amount of medicine utilized. Fleddermann et al. (2018) assessed the introduction of an automated alert to avoid unnecessary ordering of echocardiography studies. Over the study period, 20% of the respective studies were cancelled, thereby saving the associated costs. Okumura et al. (2016) examined the cost savings associated with implementing a tool to optimize antibiotics use in surgical prophylaxis. By reminding physicians of common standards of care, the system decreased the usage significantly by 1.26 defined daily doses per 100 bed days to -0.2 defined daily doses per 100 bed days (95% CI), thereby saving an estimated US \$50,000 per 100 bed days. Lastly, Levick et al. (2013) assessed an alert for B-type natriuretic peptide testing. Again, the alert resulted in a test reduction of 21% saving an estimated US \$92,000 per year.

Besides effects via reduced volumes in tests or studies, 3 other articles revealed cost savings via supporting decisions regarding care processes and workflows. Quadros et al. (2019) examined CDS that supported fast tracking the discharge of certain patients after brain tumor surgery. The tool resulted in a significant length of stay reduction of 2 days on average, saving US \$630 per hospitalization. Collins et al. (2019) showed how decisions on the timing of nasal feeding tube insertions for post-stroke patients with dysphagia supported by CDS reduced the number of nasal tube replacements and repeat x-rays and the associated costs. It is important to mention here, however, that these 2 papers did not reveal whether the CDS tools were fully computerized or not. Lastly, Waghlikar et al. (2015) presented the impact of a CCDS tool in an outpatient setting. Here, the tool supported physicians with chart review via a computerized checklist to decide on preventive services and management of chronic diseases. The tool showed an indirect positive economic impact by reducing review times by 65% per patient.

The eighth article in the CCDS category by Elkin et al. (2010) is the only one examining direct cost savings based on supporting diagnosis. The authors applied a differential diagnosis support tool to cases in diagnostically challenging Diagnostic Related Groups and found that for these patients the provider costs per case were reduced by 3.7%, to 19.5% (95% CI).

3.5 Advanced Analytics

The recently increasingly prominent field of AA including AI, Machine and Deep Learning represented only 10% of the identified literature (5/50). A very homogenous picture was painted, with all 5 studies indicating indirect positive economic effects on providers; 3 articles were US-based, and others originated from Europe (1/5) and Asia (1/5).

The identified articles showed two main use cases of AA. Firstly, 2 articles showed how AA could support decision making in the field of imaging. Lee (2018) applied a Convolutional Neural Network (CNN) to determine musculoskeletal magnetic resonance imaging (MRI) scanning protocols. The authors hypothesized that this assistance in protocol generation could potentially save personnel time and hence improve provider efficiency. The second article presented the deployment of the IBM Watson natural language processing model to automatically decide on the usage of intravenous contrast for MRI protocols (Trivedi et al., 2018). Again, the authors hypothesized that this support in decision-making has the potential to drive provider efficiency.

The second use case represented the prediction of patients' disease progression and the associated care processes. Wang et al. (2018) showed how a CNN-based tool using hospital EHR data could predict readmissions. Readmission predictions can be valuable information since a majority of readmissions is associated with penalties for providers. Nevertheless, the authors only hypothesized this potential benefit. Almeida (2016) presented a case study of a hospital center in Portugal that applied a Big Data analytics platform. Based on EHR and vital sign data, the system was able to correctly predict 30% of intensive care unit (ICU) admissions and 50% of non-ICU inpatient deaths. Again, the author hypothesized potential efficiency improvements. Lastly, Peck et al. (2014) represented the only article in the AA category, which proved actual efficiency improvements instead of only hypothesizing them. The authors presented the impact of a tool predicting the patient flow from the emergency department to the inpatient units via discrete event simulation. By sharing this information on crowding levels and total expected beds needed with physicians and nurses, the boarding time from the emergency department to inpatient units was reduced by 11.69% to 18.38% depending on hospital type.

3.6 Business Analytics

Studies examining the economic impact of BA on providers represented 10% of identified articles (5/50). All 5 studies revealed a positive economic effect on providers, mostly of a direct nature. The majority of articles represented US-based (4/5) or Europe-based (1/5) case studies.

BA tools analyzing equipment utilization were examined in 2 articles. Stekel et al. (2019) examined the example of an ultrasound practice that used probe utilization data to support purchasing decisions. The analysis of procedure data resulted in the decision to not replace a broken probe, thereby saving US \$10,000. Swedberg (2013) showed how attaching radio-frequency identification tags to all equipment in a 1,100-bed hospital increased equipment utilization rates from 5% to 40%. The system was able to reduce the need to rent or purchase additional equipment, saving an estimated US \$200,000 per year.

Examples of how BA applications improved billing by reducing revenue leakage or avoiding penalties were presented in 3 articles (Dulac et al., 2017; Rivera & Delaney, 2015; Schouten, 2013). For example, Dulac et al. (2017) showed in a case study how a US-based hospital used data analytics to uncover root causes for an increase in preventable complications and readmission rates that implied payment reductions totaling 3.5% of total revenue. The tool helped the hospital to ultimately reduce penalties to 0%.

3.7 Telemedicine

Studies examining the economic impact of Telemedicine on providers represented the smallest share of identified articles (2/50). Both articles originated from Europe, with 1 study revealing an indirect positive effect and 1 a neutral effect.

Stoves et al. (2010) examined the advantages of an electronic medical round connecting general practitioners with nephrologists in the field of chronic kidney care. The program was perceived to improve efficiency for both physicians and nephrologists, as indicated in interviews and questionnaires; however, no quantitative efficiency improvements were reported. Heidbuchel et al. (2015), on the other hand, specifically analyzed differences in costs and financial impact between remote and in-office follow-ups for implantable cardiac defibrillators. On average, the total cost and net financial impact for providers were neutral not showing differences between remote and in-office follow-ups. Importantly, however, regional heterogeneity could be observed where providers in countries with remote follow-up reimbursement in places like Germany showed maintained or improved economics.

4 Discussion

4.1 General discussion

At first indication, the previously presented results appear to generate an overall positive answer to the overarching research question of the impact data and analytics have on health care providers. Of the 50 reviewed articles, 31 indicated a positive impact either via direct cost or revenue effects or via efficiency or productivity improvements. Studies showed how EHRs can, for example, directly save storage and personnel costs associated with paper records or increase physician productivity by making information available right when and where it is needed. Other studies proved that CCDS can save material and labor costs by avoiding redundant laboratory tests and imaging studies. A more nuanced look at the results, however, shows that it is very important to differentiate between the 5 identified technology categories. In line with other literature reviews, a mixed overall picture, at best, was revealed for the economic impact of EHRs, or “data,” on providers. From a provider’s perspective, 12 studies revealing a positive result and 18 revealing either negative, neutral, or mixed results do not necessarily promote a quick decision on EHR investments, at least from an economic point of view. On the other hand, “analytics” applications like CCDS, AA, and BA seem to predominantly generate positive economic effects. Nevertheless, the small number of identified papers covering these technologies, yet again, points at the risk of discouraging rapid adoption by providers from an economic point of view. Ultimately, this review reveals a rather uncomfortable decision-making situation for providers with the economic impact of “data,” represented by EHRs, being exhaustively researched but revealing ambiguous results and “analytics” indicating positive results but being only sparsely investigated.

Considering the positive effects of EHRs on health care outcomes, the identified ambiguous results regarding the economic impact for providers also implies potentially missing out on the associated welfare gains across populations. Some nations’ policymakers already acknowledged this and incentivize EHR adoption. The US Health Information Technology for Economic and Clinical Health Act from 2009 injected several billions of dollars into the system for subsidized EHR installations (Blumenthal & Glaser, 2007). This approach seemed to have

worked as intended by pushing EHR adoption closer to 100% for US hospitals (Adler-Milstein & Jha, 2017). Of course, national health systems strongly vary, but this outcome should at least foster a discussion of whether EHR subsidization might also be a solution in other countries with comparably low current EHR adoption rates. Germany, for example, announced a “hospital future law” (Krankenhauszukunftsgesetz) as part of a COVID-19 stimulus package in 2020, which envisions an up to €4.3 billion fund for investments in digital infrastructures and emergency capacities (BMFG, 2020). Here, it is important to point out the positive spill-over effects of data and analytics for the entire health care system again. Even though this review predominantly takes a microperspective of the single provider, in the end adoption on the micro-level is a key prerequisite for changes or improvements at the system level. Data and analytics might provide proven positive effects on quality of care, but until the world does not significantly pivot towards quality-based care and reimbursement, alternative ways to foster technology adoption should be considered.

Another effect involving EHRs is also important to consider. Several of the included studies showed how EHR installations can act as a door-opener to other technologies that actually seem to predominantly have positive economic effects for the provider. Especially 2 other technology categories identified in this review, namely CCDS and AA, strongly rely on data contained in EHRs. More precisely, 75% (6/8) of the CCDS tools and 60% (3/5) of the AA tools in the identified studies needed some sort of EHR input. Even if somewhat limited in quantity, the current identified research in these 2 fields revealed only positive economic effects for providers. Hence, EHR adoption can become a bottleneck to the positive economic effects of technologies further down the line like CCDS and AA. Following EHR adoption, providers are likely able to derive economic benefits from adjoined technologies identified in this review. More research dedicated to these economic effects of supplementing EHRs with adjoined technologies like CCDS and AA is needed to derive a more targeted evidence base.

Leaving policy implications aside, our work generates insights for providers as well. For providers considering an EHR installation, this review showed important factors for an economically feasible introduction. Eliminating all legacy costs like paper-based records and related dictation services, repurposing paper record space into clinical space, or installing new technology in a stepwise fashion (avoiding a big bang) are all important take-aways from this review. For hospitals or practices already using an EHR, adjacent technologies, like CCDS or AA, can provide economic benefits, potentially even resulting in a shorter break-even time for the EHR installation. Additionally, the emerging opportunities to participate in value-based care plans utilizing EHR data or the utilization of BI should not be fully neglected. Nevertheless, a number of other potential sources of economic value from data seems not to be currently covered by research. For example, no study was identified that covered the potential for direct monetization of anonymized patient data or the ability to drive patient volumes by marketing the application of advanced digital tools.

Ultimately, it is important to note that research on the economic impact of data and analytics on providers remains rather limited in geographies other than the US and in technologies other than the EHR. In general, this review did not identify geography as a predictor for the type of economic impact. However, with almost 65% (32/50) of included articles being US-based, more research in other geographies is needed to draw a definite conclusion whether geographies

and related health care systems are significant drivers. From a technology perspective, the few studies covering technologies other than the EHR revealed proof for economic advantages; however, no comprehensive cost-benefit analyses and few systematic reviews were identified for these technologies. In the field of AA, 80% (4/5) of identified studies only hypothesized economic benefits. In the near future, however, vendors of AA tools need to also provide high-quality proof for the economic advantages of their solutions.

4.2 Limitations

This work is exposed to limitations that are mostly inherent to literature reviews in general. Only PubMed and Google Scholar online databases were searched; hence, relevant research captured exclusively by other databases could have been excluded. The sample of identified articles potentially lacks certain avenues of research not captured by the structured keyword search, thereby missing other technologies. The applied hermeneutic systematic search approach, however, worked against these limitations by explicitly allowing for iterative searches. Additionally, the systematic search was complemented by manual search techniques. On a different note, most identified studies are based in the US; hence, conclusions might not be fully applicable to other geographies. Ultimately, it is important to note that the research subject “data” is almost exclusively represented by studies focusing on EHRs, thereby not touching on other potentially relevant sources and applications of data. Nevertheless, EHRs can be considered as a key data container in the context of health care. The research subject “analytics,” on the other hand, faces a very limited body of evidence, which strongly impacts the generalizability of this study’s findings. More research covering these other technologies is needed to generate a more holistic and reliable evidence base. Lastly, the intended broad spectrum of reviewed studies prevents a clear and uniform definition and quantification of “economic value.” Studies and respective results can, hence, not be compared on the same scale, also since the methodological quality of the original studies was not analyzed.

4.3 Conclusion

This review synthesized literature examining the economic value of data and analytics for health care providers. Five key technologies were identified, namely EHRs, CCDS, AA, BA, and Telemedicine. Overall, 31 of the 50 reviewed articles indicated a positive economic impact, either via direct cost or revenue effects or via efficiency or productivity improvements. A more nuanced view showed that this is especially the case for less studied technologies like CCDS, AA (including AI and Big Data analysis), and BA. For the most extensively studied technology of EHRs, a more ambiguous view with varying economic impacts emerged. Since technologies like CCDS and AA strongly rely on EHR data, these ambiguous research findings have the potential to turn EHR adoption into a bottleneck for the adjoined technologies with mostly positive economic effects. This review also encourages discussions around how subsidization of EHRs, like that implemented in the US and planned for Germany, could potentially unlock the proven economic potential of second-order adjoined technologies. It can be concluded that more research covering the economic effects of technologies other than EHRs would significantly improve the current evidence base and potentially drive adoption by health care providers.

Physicians' Preferences and Willingness to Pay for Artificial Intelligence-based Assistance Tools: A Discrete Choice Experiment Among German Radiologists²

1 Introduction

1.1 Artificial Intelligence and doctors with patterns

After the general foundations of AI research were defined in the early 1960s, studies on intelligent computer systems supporting physicians in treatment decisions already followed in the early seventies (Minsky, 1961; Shortliffe et al., 1973). Recent advances in computing power resulted in a revival of AI being more capable than ever thanks to techniques like Machine Learning (ML) or Deep Learning (DL). Today, ML and DL tools identify abnormalities in chest radiographs, scan electrocardiograms for myocardial infarction or detect hip fractures and breast cancer from imaging data at or above radiologist-level performance (Gale et al., 2017; McKinney et al., 2020; Tang et al., 2020; Yang et al., 2018). A current example is the application of AI to Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) scans to facilitate diagnosis of COVID-19 (Fang et al., 2020; Li et al., 2020; Mei et al., 2020). Besides these effects related to the quality of care, research also shows positive economic effects of AI in health care via efficiency or productivity improvements (von Wedel & Hagist, 2020). From these examples it becomes apparent, that the so-called doctors with patterns that include radiologists, dermatologists or cardiologists are currently impacted by AI the most (Jha & Topol, 2016; Topol, 2019). These specialties generate rich sets of structured data which are essential to the training and application of AI-based algorithms. Especially radiologists are confronted by media and research with ever-improving algorithms even achieving above-physician performance and, hence, with a supposedly uncertain future (Gale et al., 2017; Jiang et al., 2017; Krittanawong, 2018). Indeed, these specialists seem to think rather conservatively of AI. A survey among European radiologists, for example, revealed that almost 50% expect an increased workload due to the deployment of AI-based tools and 55% claim that patients will not be happy with an AI-based report. However, the same radiologists also seem to accept that a future without AI cannot be expected with 50% planning to use or already using AI (Codari et al., 2019). Pressure also comes from other stakeholders of the health care system. In a recent survey among German patients, 57% supported a mandatory second opinion if the AI-tool was to perform better than the physician (BVDW, 2019). It becomes apparent that many radiologists and other doctors with patterns are already or will soon be confronted with the choice of AI-based assistance tools.

1.2 Understanding preferences & willingness to pay for AI

It appears surprising that research on preferences regarding AI-based tools particularly of doctors with patterns is limited. Additionally, no study in this field has yet analyzed the monetary value physicians attach to these solutions. As already described, AI can positively impact the quality and cost-efficiency of health care. However, for health care systems to realize

² von Wedel, P., & Hagist, C. (2022). Physicians' preferences and willingness to pay for artificial intelligence-based assistance tools: a discrete choice experiment among german radiologists. *BMC Health Serv Res*, 22, 398. Also presented at the 14th conference of the Deutsche Gesellschaft für Gesundheitsökonomie (dggö) 2022 in Hamburg, Germany.

this value, physicians need correctly designed and acceptably priced assistance tool options. This study attempts to fill this research gap by empirically analyzing German radiologists' preferences and willingness to pay (WTP) for assistance tools powered by AI. It thereby answers the research question of whether radiologists are generally willing to invest, and if so, what designs and pricing of these tools is preferred. To achieve this goal, a discrete choice experiment (DCE) was conducted. Whereas the majority of DCE studies in health care involves eliciting preferences from patients, this study takes a twist and highlights providers as the key decision-makers for AI-based investments. It attempts to create transparency on whether radiologists' preferences are in line with industry's current development trajectory. Furthermore, provider preferences can also provide room for thought for policymakers when deciding on potential industry sponsorships or research grants. In the end, the potential positive impact of AI in health care can only be leveraged via sufficient acceptance by the stakeholders relying on it every day.

2 Methods

2.1 The Discrete Choice Experiment and research question fit

The DCE is considered an established tool in health economics research today (de Bekker-Grob et al., 2012; Lancsar & Louviere, 2008; Viney et al., 2002). DCEs represent a stated preference technique where participants face a hypothetical or contingent market scenario (Ryan et al., 2007). More precisely, Mangham et al. (2009, p. 152) describe the DCE as “a quantitative technique for eliciting individual preferences. It allows researchers to uncover how individuals value selected attributes of a program, product or service by asking them to state their choice over different hypothetical alternatives”. A price attribute can be included varying over different price levels to estimate WTP. Participants are then repeatedly asked to choose their preferred, or utility-maximizing, option (McFadden, 1973). These numerous decisions are econometrically analyzed to estimate the contribution of the single attributes to the overall utility. DCEs are regularly applied to examine patient preferences and WTP to derive recommendations on how to optimize care delivery from a patient perspective (Ostermann et al., 2020; Phillips et al., 2021; Sadri et al., 2005). Provider preferences are significantly less studied; however they can also be an important factor in assuring optimal care delivery in specific cases. AI-based assistance tools are a perfect example here since these tools have the potential to positively impact health care, but providers are generally not obliged to adopt them. For several reasons, the DCE is a good methodological fit with the research question. Firstly, the researcher cannot observe an established market revealing preferences and WTP of radiologists due to limited information on the rather new market segment. The DCE resolves this situation by creating a choice scenario in a contingent yet realistic market. Secondly, this work does not solely focus on WTP, for which contingent valuation methods could be applied, but attempts to comprehensively analyze radiologists' preferences for different compositions of AI-based assistance tools. DCEs allow for this analysis of multi-attribute goods and services. This study follows a comprehensive 8-step process of conducting a DCE derived from the established literature (see Figure 4) (Bridges et al., 2011; Bryan & Dolan, 2004; Lancsar & Louviere, 2008; Ryan & Farrar, 2000; Ryan et al., 2007; Telsler, 2002; von Wedel et al., 2018). The most pivotal steps of this process are covered in the following sections. All methods were

carried out in accordance with relevant guidelines and regulations and in accordance with the 1964 Helsinki declaration and its later amendments.

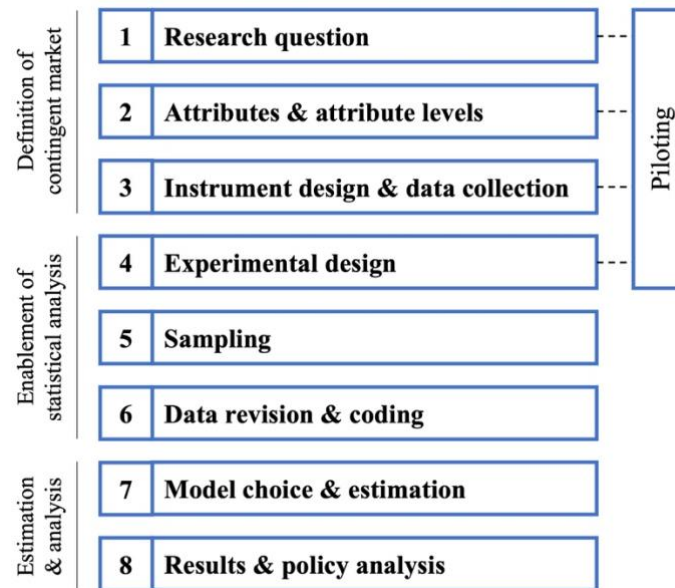


Figure 4: 8-step process of conducting discrete choice experiments derived from literature

2.2 Identification of attributes and attribute levels

The identification of attributes and levels is considered a critical step when conducting a DCE (Coast et al., 2012). The research question of this study requires the creation of a realistic contingent market for AI-based assistance tools for radiologists. To optimally mirror this market, an established four-step process including 1) raw data collection, 2) data reduction, 3) removing inappropriate attributes and 4) final wording was followed (Helter & Boehler, 2016). In the first stage, a long list of attributes and corresponding levels was developed based on online research on AI in radiology, information on commercially available AI-based solutions and recent scientific studies. Additionally, expert interviews with five radiologists from both hospitals (3) and outpatient practices (2) were conducted to complement the initial list resulting in a total of 7 attributes (see Appendix 5). In the second and third stages, the experts were again asked to rank the attributes by perceived importance and perform sanity checks on attribute levels, ultimately defining a final shortlist. Experts clearly found 7 attributes to be too cognitively complex, especially keeping in mind the relatively high complexity of the application attribute. The aim was, hence, to include a maximum of 4 to 5 attributes. This process resulted in the exclusion of two initially developed attributes, namely “Automatic report creation” and “Automatic differential diagnosis proposal”. An automatic proposal of differential diagnosis implies the hypothetical assistance tool to execute the main application but to also simultaneously analyze all areas of the respective scan. Based on an AI-based analysis, the tool would then generate a proposal for differential diagnosis. Initial research, however, clearly showed that this kind of tool has not yet been introduced in practice and will likely need more time for development. Initial tests with the experts showed that tool options including this functionality were chosen less often. Experts indicated they were skeptical about the realizability of this functionality. This skepticism related to one attribute ultimately dominated the remaining attributes and levels. “Automatic report creation” was excluded since

it was ranked less important in comparison with the remaining attributes. Furthermore, these attributes also provided minor policy relevance which is a key aspect to consider when choosing DCE attributes (Viney et al., 2002). After wording was finalized, the final product option was composed of 5 attributes with a maximum of 3 varying levels each (see Table 1). As expected, the application attribute was discussed most in the interviews since it defines a key feature of the composed product. Together with the experts it was concluded that the application levels should ideally represent different archetypes of AI-based support. At the same time levels had to remain non-dominant, i.e., similarly interesting to respondents, thereby avoiding lexicographic behavior (Helter & Boehler, 2016; Ryan et al., 2007). The final levels of the application attribute represent three main categories of AI-based tools: routine diagnostics (level 1), process efficiency (2) and diagnostic screening (3). The option to include an application related to COVID-19 detection was discarded due to insufficient everyday relevance and to avoid time-dependent effects. For the routine diagnostics level, the aim was to choose an application that can be considered routine in the majority of radiology work environments. Hence, initially developed levels concerning brain and prostate scans involving rather delimited analyses were excluded. The application was then complemented by the attributes: provider, quality, and time savings. The experts agreed that impact on quality and time savings of the tools, as well as the trade-off between these were other key factors of interest. Furthermore, these attributes are also highly policy-relevant. Initially, the Quality attribute included the level “worse”. The interviews with experts, however, showed that tool options including this level overpowered all other attributes and options resulting in avoidance. Ultimately, the “worse” level was excluded to avoid dominant choice processes. Price was included as the fifth attribute to allow for WTP estimations. Price levels were chosen to be on a per study basis, compared to one-time investments or yearly payments, to mitigate a possible effect of differing study volumes in respondents' practices or hospitals and to abstract from different economic endowments of the probands such as liquidity or credit constraints. The experts and information on pricing schemes of existing commercial solutions provided input on realistic price levels. As an additional sanity check, the final price levels were compared with the average reimbursement for MRI (€117.14), CT (€65.19), or mammographic screening (€62.07) scans included in the DCE for statutorily insured patients in Germany (KBV, 2021).

Table 1: DCE attributes and attribute levels for AI-based assistance tools in radiology

Attributes		Attribute levels		
		1	2	3
1	Provider	Modality manufacturer	RIS/PACS software provider	AI-software startup
2	Application	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI <i>[Routine diagnostics]</i>	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation <i>[Process efficiency]</i>	Presorting of mammographic screening reports into “100% normal” (BI-RADS 1&2) and “suspicious” incl. automatic lesion marking <i>[Screening]</i>
3	Quality	Same: Detects anomalies you would detect, too	Better: Detects anomalies you would not detect even with long inspection	
	Displayed only for “Application” level 2:	Same: Same image quality	Better: Higher image quality	
4	Time savings	Low: Diagnostics process 10% faster	Medium: Diagnostics process 30% faster	High: Diagnostics process 50% faster
	Displayed only for “Application” level 2:	Low: MRI scan process 10% faster	Medium: MRI scan process 30% faster	High: MRI scan process 50% faster
5	Price	3€ per study	6€ per study	9€ per study

Note: Italic text in *[brackets]* indicates application archetype here but was not shown to respondents

2.3 Creation of realistic and efficient instrument and experimental designs

In this study, radiologists were confronted with a situation in which they were asked to choose between offers for AI-based assistance tools from different providers. As proposed by literature, respondents were also able to select a “no-choice” option to mirror a realistic decision process (Haaijer et al., 2001). Respondents were asked to complete 10 choice sets consisting of 2 product variants each and the “no-choice” option (example in Figure 5). As suggested by the literature, we added a detailed written-out explanation of the alternatives below each choice set to minimize choice inconsistencies (Miguel et al., 2005). The goal was to create a comprehensive yet simple instrument keeping scarce time of radiologists in mind. To achieve this, the instrument was piloted by the same experts the interviews were conducted with. Preceding the DCE, the first part of the instrument collected additional information keeping later statistical analysis of interaction effects in mind (see Appendices 11 and 12 for the

complete instrument). Defining an efficient experimental design represents another key step in the setup of a DCE. A perfectly efficient design would consist of all possible combinations which is often not feasible. An established approach in design theory to circumvent this issue is the creation of fractional factorial designs that draw samples from all possible combinations (Ryan et al., 2007). To assure a statistically efficient way, researchers predominantly rely on the established measure of D-efficiency (Kessels et al., 2011; Lancsar & Louviere, 2008). For this study, a D-efficient design was generated utilizing the JMP 15 software by SAS. The resulting design with 92.35% D-efficiency is presented in Appendix 6.

	Offer 1	Offer 2
Provider:	RIS/PACS software provider	AI software startup
Application:	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI
Quality:	Same: Same image quality	Better: Detects anomalies you would not detect even with long inspection
Time savings:	Medium: MRI scan process 30% faster	High: Diagnostics process 50% faster
Price:	6 € per study	3 € per study

Which offer do you choose? Offer 1 Offer 2 None of these

Figure 5: Example of choice set with two alternative offers and no-choice option

2.4 Sampling approach

A sampling approach involves the definition of a sample frame, the setup of a sampling strategy and the determination of a minimum sample size via power analysis (Ben-Akiva & Boccara, 1995; Louviere et al., 2000; Orme, 1998). The sample frame was defined as fully trained radiologists and resident radiologists actively practicing radiology in Germany, hence excluding retired specialists. This results in a sample frame of 9,313 fully trained German radiologists in December 2020 (Bundesärztekammer, 2020). Unfortunately, there is no reliable public information on the number of resident radiologists. Germany represents a robust study region since it can be considered as one of the largest uniform health care markets worldwide with very similar (statutory) reimbursement and treatment patterns applying to all providers and patients (Busse et al., 2017). In terms of sampling strategy, the authors initiated a partnership with the two major professional associations of German radiologists. An online link to the

survey including the DCE was circulated via established mailing lists to members of the “Berufsverband der Deutschen Radiologen e.V.” (BDR) and the “Deutsche Röntgengesellschaft” (DRG). To assess statistical power, the common rule of thumb by Orme (1998) is applied resulting in a minimum sample size of $n > \frac{500*3}{10*2} = 75$ to allow for the estimation of a reliable model.

2.5 Model specification and analysis

A DCE attempts to mirror the process of utility maximization of the respondents. Following established literature, this utility (U) is composed of an observable part (V) and an unexplainable (random) component (ε) representing unmeasured preference variation (McFadden, 1973; Ryan et al., 2007):

$$U = V + \varepsilon \quad (\text{Equation 1})$$

The observable part is regularly described as an estimated linear-in-parameters function where the β s represent part-worth utilities or preference weights of the attribute levels x :

$$V = \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k \quad (\text{Equation 2})$$

The conditional logit model introduced by McFadden (1973) has established itself as the workhorse for statistical estimation of the preference weights in choice experiments. We estimated fixed effects conditional logit models via the JMP 15 software. The software applies effects coding which can be detected when taking a closer look at the resulting parameter estimates. The no-choice option is represented as an additional dummy variable by JMP. Marginal Willingness to Pay (MWTP) for the single levels was calculated by dividing the estimated beta of the attribute level by the negative of the estimated price beta (Marti, 2012). Relative attribute importance was calculated by dividing the range of marginal utilities of the respective attribute by the sum of all attributes' ranges (Hauser & Toubia, 2005). General choice or investment probability was calculated as

$$P(1) = \frac{1}{1 + \exp(\beta_0)} \quad (\text{Equation 3}),$$

where β_0 represents the estimate of the no-choice dummy variable (Dong et al., 2016; Ryan et al., 2007). To determine model fit, -2LogLikelihood , the corrected Akaike Information Criterion (AICc) and Bayesian Information Criterion (BIC) were determined. A total of four MNL models were estimated incorporating several subject-related interactions. These were considered only when being statistically significant at 5% indicated by the p-value. The first MNL model, or simple model, represents main effects only without interactions. For this model, comprehensive utility metrics, MWTP and relative importance weights were additionally prepared.

3 Results

3.1 Sample size and characteristics

A total of 119 radiologists completed the survey between September 2020 and March 2021. Of those, four retired respondents and one respondent with a different department were excluded resulting in a final sample size of 114. For quality control, a minimum required time for the

choice set completion of 15 seconds for the first and 5 seconds for the following choices was defined. All 114 respondents passed this test. Taking power analysis into account, our final sample size exceeded the calculated minimum required size of 75. Respondents were mostly male (78%), on average 51 years old (SD: 9.63) and predominantly working in an outpatient setting (74%) with mostly more than 13 years of fully trained years of work experience (68%) (see Table 2). The study sample shares several similarities with the underlying sample frame as presented in Appendix 7 except for the practice-hospital split. Almost half of the respondents (46%) reported to use AI-based applications already today, which is in line with previous research (Codari et al., 2019). The most utilized ones were applications that support or speed up the diagnostic process (42%). Only 35% indicated they were planning to invest in AI in the future with 46% being unsure about future investments (see Table 3). Interestingly, today's users are more likely to also invest in further AI in the future. Non-users appear to be much more skeptical with the majority having no plans or being unsure (see Appendix 8). Besides this finding, users and non-users do not significantly differ in terms of other respondent characteristics.

Table 2: Sample characteristics

Sample characteristics		Absolute	% or (SD)
n=114			
Gender	Male	89	78%
	Female	24	21%
	Diverse	1	1%
Age	Mean	51	(9.63)
	Min	27	
	Max	72	
Job position	Total outpatient	84	74%
	Employed in practice	18	16%
	Self-employed in practice	66	58%
	Total inpatient	29	25%
	Head physician in hospital	8	7%
	Consultant physician in hospital	16	14%
	Assistant physician in hospital	5	4%
	Employed in public authority	1	1%
Specialization	No specialization	66	58%
	Interventional radiology	2	2%
	Pediatric radiology	1	1%
	Mamma (breast) diagnostics	14	12%
	Musculoskeletal diagnostics	11	10%
	Neuroradiology	8	7%
	Oncological diagnostics	9	8%
	Other	3	3%

Years of work experience as fully trained radiologist	1-3	4	4%
	4-6	7	6%
	7-9	10	9%
	10-12	10	9%
	13+	78	68%
	Not fully trained	5	4%
Average # of reports created per day	Mean	43	(26.6)
	Min	0	
	Max	200	

Note: Rounded figures

Table 3: Sample exposure to AI

Sample exposure to AI n=114		Absolute	%
AI-based applications used today?	Yes	53	46%
	No	57	50%
	Unsure	4	4%
Type of AI-based applications used today*	Supporting/speeding up diagnosis	45	42%
	Prognosis of course of disease	4	4%
	Creation of reports	23	21%
	Improvements for image quality	16	15%
	Shortening scan processes	8	7%
	Replacing/reducing contrast agent usage	5	5%
	Practice/station management (e.g., claims processing, process optimization)	5	5%
	Other	2	2%
Plans for future investments in AI-based applications?	Yes	40	35%
	No	21	18%
	Unsure	53	46%

*Numbers do not add up to 53 users since respondents could choose multiple options; Note: Rounded figures

3.2 DCE results

The estimation of the simple model yielded significant effects at a 1% significance level for all but the provider attribute. The significant attributes were, hence, relevant for respondents when deciding between the different AI-based assistance tools and can be considered to derive the preferences of the sample. The single utility parameter estimates, MWTP and importance weights are presented in Table 4. A detailed overview of model statistics can be found in Appendix 9. A summary of all parameter estimates and general answer to the research question yields the following: Radiologists prefer an AI-based assistance tool which supports in routine diagnostics with a better-than-radiologist quality and time savings of 50% at a price level of

€3.00. A startup as provider generates the highest utility, however, is not statistically significant. The negative estimate of the no-choice option ($\hat{\beta}$ -1.4499; SE 0.1198) indicates that respondents derived negative utility from not choosing one of the two tools offered. It can, hence, be concluded that radiologists are in general interested in AI-based assistance tools. The price estimate ($\hat{\beta}$ -0.1607; SE 0.1198) indicates typical cost-averse preferences. The provider attribute is not statistically significant (p 0.1404) implying it did not significantly impact the radiologists' choice. The application type, on the other hand, was of significant interest (p <0.0001) with the routine diagnostics option being preferred ($\hat{\beta}$ 0.2984; SE 0.0622) and the scan time reduction tool being the least preferred option ($\hat{\beta}$ -0.3896; SE 0.0579). According to expectations, higher quality tools ($\hat{\beta}$ 0.2421; SE 0.039) and highest time savings ($\hat{\beta}$ 0.3949; SE 0.0587) resulted in higher utility. When applying the conjoint-based approach of calculating relative importance weights, time savings represent the most important attribute (37.98%), followed by the application type (31.52%). Considering these results, radiologists cared more about the time savings than the actual application type itself or its quality impact when choosing between tools. This can also be observed regarding MWTP where time savings of 50% result in €2.46 MWTP and better quality only in €1.51 MWTP.

Table 4: Simple model utility estimates, marginal willingness to pay and relative importance of attribute levels (n=114)

Attribute & attribute levels	p-value	Marginal utility $\hat{\beta}$	Marginal WTP	Relative importance
Provider	0.1404			8.32%
Modality manufacturer		-0.05853	-0.36 €	
RIS/PACS software provider		-0.06151	-0.38 €	
AI-software startup		0.12004	0.75 €	
Application	<0.0001			31.52%
Routine diagnostics		0.29843	1.86 €	
Process efficiency		-0.38958	-2.42 €	
Screening		0.09115	-0.57 €	
Quality	<0.0001			22.18%
Same		-0.24206	-1.51 €	
Better		0.24206	1.51 €	
Time Savings	<0.0001			37.98%
Low		-0.43392	-2.70 €	
Medium		0.03899	0.24 €	
High		0.39493	2.46 €	

3.3 Adoption probability simulation

Applying Equation 3, a general average tool adoption probability of $P(1) = \frac{1}{1 + \exp(-1.4499)} = 80.98\%$ was determined (95% CI 77.1% - 84.4%). To derive the impact on adoption probability of the single attribute levels, the least preferred combination was defined as a base case (B).

The average utility derived from the base case can be calculated as $U_B = -0.061 + (-0.3896) + (-0.2421) + (-0.4339) + (-0.1607 * 9) = -2.5736$. Building on Equation 3 again, the probability of choosing the base case over the no-choice option was $P(B) = \frac{\exp(-2.5736)}{\exp(-2.5736) + \exp(-1.4499)} = 25\%$. To determine the individual impact on adoption probability of the single attribute levels, single levels were altered keeping all others constant. For example, reducing the price of the base case to €3 implies an adoption probability of $\frac{\exp(-1.6093)}{\exp(-1.6093) + \exp(-1.4499)} = 46\%$, hence an increase of 21%. Figure 6 visualizes how these improvements to the most preferred levels impact on adoption probability. The highest impact can be identified for time savings and price here.

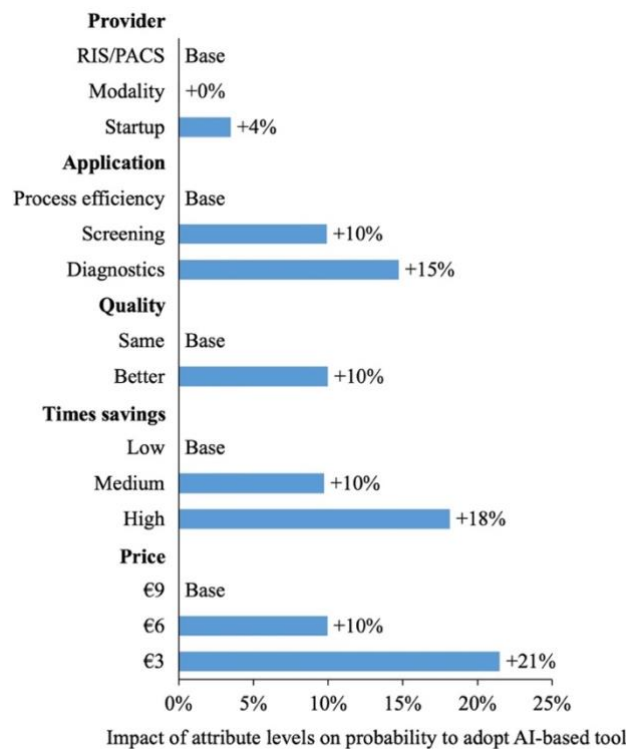


Figure 6: Effects of marginal changes in attribute levels on probability to adopt AI-based assistance tools

3.4 Subject-related interaction effects

Models II to IV of Appendix 9 incrementally add subject-related interaction effects to the simple model. Considering model II, gender shows significant interaction effects with the application and quality attributes. On average, male radiologists prefer the process efficiency application (i.e., scan time reduction) more than women or diverse respondents (p 0.0014; $\hat{\beta}$ 0.3435 SE 0.2523). Women, derive a higher utility from a tool that provides better-than-human quality than men or diverse respondents (p 0.0161; $\hat{\beta}$ 0.1605 SE 0.1663). The estimation of model III introduces the relationship between financial responsibility of respondents and WTP. In this case, chief physicians in hospitals and self-employed practice owners were defined as budget responsible since these individuals are factually also responsible for the financial performance in Germany. Model III implies that respondents with budget responsibility are

more cost-averse deriving an even lower utility from the price estimate ($p < 0.001$; $\hat{\beta} -0.0347$ SE 0.0105). It is, however, important to make the reader aware that factual “budget responsibility” does not necessarily imply “budget awareness” or “financial skills”. Theoretically, some of the respondents defined as responsible for the budget might not have considered economic aspects when completing the experiment, even though these results imply the opposite. Lastly, and somehow intuitively, respondents that were specialized in mammography diagnostics and screening also preferred the screening application ($p < 0.0001$; $\hat{\beta} 0.3873$ SE 0.0932). The model fit consistently improved from model I to IV as indicated by decreasing AICc, BIC and -2LogLikelihood values.

At this point it is also important to mention tested interaction effects that did not generate statistically significant results. These include age, specialization, perceived level of knowledge regarding AI in general and in radiology specifically, trust in AI in radiology, level of technophilia and the opinion on whether AI in radiology can save costs or increase efficiency. Moreover, no statistically significant differences could be observed when differentiating between users and non-users of AI in radiology, as well as, between the inpatient/hospital and outpatient/practice sectors.

4 Discussion

4.1 General discussion

The described results provide concrete answers to the research question of this work. Firstly, radiologists are willing to invest in AI-based assistance tools as presented in the DCE indicated by an average 81% investment probability. Secondly, the most desired design of a tool was also identified. On average, radiologists preferred a tool that assists in routine diagnostics which performs at above-radiologist-level quality and saves 50% in diagnostics time at a price-point of €3 per study. The provider type of the respective tool did not appear to be a relevant factor for investment decisions. This fact can be considered good news for unestablished startup companies competing with the established modality and software players. Keeping an industry perspective, the current predominant development trajectory of diagnostics-related applications seems to meet radiologists' preferences. In terms of pricing, radiologists are in general rather cost-averse with an increase in price from €3 to €9 decreasing the investment probability by 21%. A look at attribute importance generates insights, as well. More than for the application itself or its quality impact, radiologists care for the time it saves them. Considering that the average radiologist in the sample creates 43 reports per day, this appears comprehensible. Similarly, radiology is considered as one of the most capital intense medical specialties with high investments for equipment. Radiologists could therefore strongly consider the economics of their operations. Significant time savings can ultimately lead to an increased patient capacity, equipment utilization and, hence, amortization. An economically thinking profession would ultimately attach the highest importance to an attribute related to efficiency. Interestingly, female radiologists derive a higher utility from an improved quality than their male colleagues. One can only speculate whether this could be related to a more risk-averse mindset among female radiologists. Previous research has shown that female physicians are in general more likely to adhere to clinical evidence-based guidelines (Tsugawa et al., 2017). An assistance tool could simplify and automate this adherence resulting in higher quality care. In contrast to the

expectations of most of the consulted experts, an application that reduces scan times and thereby improves process efficiency was the least preferred application type. In theory, reduced scan times also imply a higher equipment capacity and thereby additional economic benefits. However, the results imply that radiologists are primarily interested in tools that are immediately related to their everyday work, i.e., diagnostics. Scan processes could be mentally further away since they are mostly executed by medical technical assistants.

At this point it is important to also mention tested subject-related interaction effects that turned out not to be statistically significant. For example, preferences were not significantly different when accounting for the age of respondents. In line with existing research, one would assume younger radiologists to be more open to new technologies like AI. A sample bias seems unlikely, since the average age of 51 years in this study is very much in line with the average age of the research population (52,4 years) (Bundesärztekammer, 2020). Nevertheless, a possible goal for future research could be to capture a larger share of younger radiologists still in training. Secondly, the knowledge level regarding AI in radiology and trust in AI in radiology did also not significantly impact preferences. One would assume that radiologists who are more informed about AI or put high trust in AI would be willing to show a higher adoption probability or even a higher WTP. Thirdly and maybe most surprisingly, no significant differences in preferences could be identified between the 46% users and 50% non-users of AI, as well as, between the 25% of inpatient/hospital and 75% outpatient/practice radiologists. Considering AI usage, this could indicate that the hopes and ideas regarding AI of current non-users very much mirror the actual experience of users. For example, non-users did not choose the “no-choice” option significantly more often than users and vice versa. Keeping in mind the relatively high adoption probability of 81%, hopes and ideas and actual experience would then most likely be of positive nature. When looking at differences between the inpatient and outpatient sector, one must consider the significant bias towards outpatient respondents in the study sample. These working environments do differ in practice and reimbursement mechanisms. Directly related to this is also the degree of specialization which tends to be higher in hospitals (Bundesärztekammer, 2020). Future research considering a more balanced study sample could, hence, identify differences.

In the end, the results also provide important information for policymakers attempting to drive future adoption of quality-enhancing AI-based tools in radiology. The past has shown that health care providers are oftentimes not willing to invest in digital solutions. Until 2017, for example, more than half of German hospitals did not have an electronic health record installed and still relied on paper-based documentation (Stephani et al., 2019). The lawmaker ultimately reacted via the 2020 Hospital Future Law which also introduces sanctions for not installing several digital tools starting from 2025 (BMFG, 2020). This study, however, shows that radiologists are likely to voluntarily invest and that this is especially the case for tools promising significant efficiency gains. Policymakers are highly interested in improving quality of care via innovative technology like AI. When setting up governmental funding programs for the development of new technology, however, also properties like efficiency improvements should be considered. This ultimately increases the probability that funded technology is also adopted by providers like radiologists without the need for controversial instruments like sanctions. Similarly, most partly publicly funded research currently still focuses on proving the sensitivity

or specificity of AI-based applications, which is a logical first step. In the future, however, researchers need to broaden the study spectrum to also include efficiency parameters keeping physicians' preferences in mind.

Ultimately, our results also provide insights for policymakers on a systemic level. As previously mentioned, scientific proof for quality-enhancing effects of AI in radiology, but also of digitization in health care overall, exists. Even though one must expect most practitioners to care about quality of care, the same practitioners also need a viable business case when investing in quality-enhancing technology. Hence, there needs to be a financial incentive either in the form of cutting costs, increasing productivity or additional revenue via higher reimbursement. It can be argued that additional revenue represents the most immediate and impactful incentive among these options. Productivity improvements, for example, are very much dependent on the specific circumstances in practices and hospitals. So far, the German health care system has not significantly pivoted towards value-based reimbursement that rewards improvements in care quality (Porter & Guth, 2012). In the outpatient sector, reimbursement is strictly provided by volume. In the hospital sector, the introduction of Diagnosis Related Groups (DRGs) in 2003 represented a limited move towards considering outcomes in reimbursement schemes, e.g., via financial penalties for early readmissions (Beivers & Emde, 2020). In summary, the financial rewards, in terms of reimbursement for increasing care quality are very limited. It can be assumed that the results of this work might be impacted by this underlying reimbursement system. In terms of pricing, radiologists were comparatively cost-averse with an increase in price reducing the adoption probability more than any other attribute level change. Additionally, time savings were considered more important than an increase in quality. Finally, one could hypothesize that a significant shift towards value-based health care systems and, hence, quality-based reimbursement also increases the relative perceived importance of quality or even the adoption of quality-enhancing technology in health care.

4.2 Limitations

The previously discussed results also face potential limitations. First and foremost, the creation of a contingent market including the choice of attributes and attribute levels always implies simplification. Attributes not included in the DCE could have been of interest to radiologists. This especially applies to the application attribute considering the variety of AI-based solution currently under development. The authors, however, tried to address this limitation by defining three options that represent three archetypes of tools (routine diagnostics, process efficiency & screening). Moreover, the expert interviews helped to correctly frame the application levels and to assure a similar attractiveness avoiding level dominance. On a similar note, differently phrased levels for the quality attribute were used depending on the application displayed. An improvement in image quality might not have the same perceived quality impact as an improvement in diagnostics quality for some respondents. One last potential limitation related to the contingent market is the choice of price levels. Radiologists are currently rarely confronted with fees on a per-study basis since equipment and software providers usually negotiate long-term service contracts. Hence, respondents likely did not have other prices for comparison in mind. This could have resulted in an anchor effect related to the chosen price

points distorting actual WTP. Nevertheless, the authors tried to minimize this limitation via expert interviews and by linking the prices to reimbursement.

Besides limitations related to the contingent market, the sample should be considered. Firstly, only the preferences of German radiologists are mirrored here. Despite partnerships with the major professional associations of German radiologists, only 119 radiologists completed the DCE. This clearly has a potential for bias in our results. Nevertheless, for several reasons this bias can be considered limited. Firstly, the study sample shares several similarities with the underlying sample frame as presented in Appendix 7 except for the practice-hospital split. Specifically, our sample represents a similar average age, gender split and specialization structure when compared with publicly available statistics on all German radiologists. Secondly, the final sample exceeds the identified minimum required sample size of 75 enabling the estimation of a statistically reliable model. Thirdly, in terms of sample size, this study is in line with a large share of other DCEs in health care. For example, de Bekker-Grob et al. (2015) show that reviewed DCE-based studies in health care rely on a sample size of less than 300 respondents in 50% and less than 100 in 25% of the cases. At the same time, it is important to consider that most of these studies are patient-focused with underlying sample frames of several million individuals. This study was confronted with a comparably small sample frame of 9,313 fully trained radiologists in Germany. More importantly to the generalizability of results, the sample was skewed towards respondents working in the outpatient sector (74%) potentially limiting validity of results for the hospital sector. As mentioned in the Discussion, work environments and reimbursement do significantly differ between these sectors. We did not identify statistically significant differences between them, which could have been the case with a more balanced sample. Since hospitals also have a higher degree of specialized radiologists, the same holds for differences between specialized and non-specialized respondents which were not detected in this study. Finally, the sampling strategy of collecting responses via mailing lists can result in a biased final sample that is more open for the topic than the average German radiologist.

4.3 Conclusion

This study suggests that physicians, here exemplified by German radiologists, are overall willing to invest in AI-based assistance tools. This applies to both current users and non-users of AI-based tools with no significant difference. They prefer applications that immediately support everyday tasks like routine diagnostics or diagnostic screening over applications that are focused on process efficiency via scan time reductions. The provider type of the tool is of no significant interest in the choice process, hence leveling the playing field between established equipment or software providers and uprising startups. The most important feature when choosing a tool appears to be its potential to save time. This feature is even considered more important than quality improvements (e.g., detecting anomalies at above-human-level performance). AI-based assistance tools do have the potential to improve the quality of our health care. This work shows, however, that tool development and funding should always consider the features of immediate everyday and economic relevance for the physicians like time savings.

Effects of Hospital Digitization on Clinical Outcomes and Patient Satisfaction: Nationwide Multiple Regression Analysis Across German Hospitals³

1 Introduction

1.1 The promises and policy-based promotion of digital health

For decades, digitization has been discussed as a promising answer to the various issues health care systems face today. A significant share of scientific research has identified digitization benefits related to quality, efficiency, and patient experience of care (Blumenthal & Glaser, 2007). In line with this development, a growing stream of research has revealed positive effects of Health Information Technology (HIT) on the quality of health care providers, specifically (Buntin et al., 2011; Chaudhry et al., 2006; Kruse & Beane, 2018; McCullough et al., 2010). At the same time, however, the adoption of promising technologies such as Electronic Health Records (EHR) or Computerized Clinical Decision Support (CCDS) continues to lag expectations, particularly in Western Europe. In 2017, for example, 38.3% to 47.4% of German or 27.8% to 46.4% of Austrian hospitals lacked an EHR system entirely and relied on paper-based documentation (Hübner et al., 2020; Stephani et al., 2019). The adoption of CCDS and more advanced technologies based on Artificial Intelligence (AI) is still comparatively low today (Jiang et al., 2017; Sun & Medaglia, 2019; Sutton et al., 2020). Seeing the promised benefits, policymakers reacted and introduced comprehensive financial incentives for HIT adoption. In the United States (US), the 2008 Health Information Technology for Economic and Clinical Health Act (HITECH) provided more than US \$28 billion to health care providers adopting EHR systems (Blumenthal, 2010). The success of this program, at least in terms of adoption rates, speaks for itself, with more than 80% of hospitals having EHR systems installed since 2015 (Adler-Milstein & Jha, 2017). Unsurprisingly, the HITECH act can be considered an important reference point for similar policy measures in other countries. In 2020, for example, German policymakers announced the establishment of a so-called Hospital Future Fund (Krankenhauszukunftsfonds) that will provide up to €4.3 billion to hospitals for investments in digital infrastructures and emergency capacities (BMFG, 2020). Hence, going significantly beyond mere EHR installations. Policymakers clearly state expected clinical outcome improvements due to higher degrees of hospital digitization as a fundamental goal of these policy measures. Hospital decision-makers share the same hopes and see better clinical outcomes as the most important reason to apply for funds (kma, 2021). However, what appears to be a thoroughly studied and intuitive relationship on the surface, reveals significant uncertainties when inspected on a more detailed level.

1.2 A closer look at the relationship between hospital digitization and quality

Existing research covering the relationship between provider digitization and quality can be split into two overarching categories. The first category consists of single-center studies and reviews assessing the impact of single technologies, like an EHR installation, on quality

³ von Wedel, P., Hagist, C., Liebe, J.-D., Esdar, M., Hübner, U., Pross, C. (2022). Effects of Hospital Digitization on Clinical Outcomes and Patient Satisfaction: Nationwide Multiple Regression Analysis Across German Hospitals. *Journal of Medical Internet Research*, 24(11), e40124.

measures of a single institution (Ali et al., 2016; Atasoy et al., 2019; Bennett & Hardiker, 2017; Blum et al., 2015; Bright et al., 2012; Buntin et al., 2011; Campanella et al., 2016; Chaudhry et al., 2006; Jaspers et al., 2011; Jones et al., 2014). Most of these studies did indeed identify positive effects on care quality. For example, HIT deployment supported timely pneumococcal vaccinations, improved guideline adherence related to antibiotic prescription, or drove medication adherence among diabetes patients (Ali et al., 2016; Dexter et al., 2004; Evans et al., 1999). The most comprehensive reviews covering single-center HIT effects summarize benefits as “increased adherence to guideline-based care, enhanced surveillance and monitoring, and decreased medication errors” (Chaudhry et al., 2006, p. 1). It becomes apparent that these positive effects predominantly relate to process quality in contrast to ultimate clinical outcomes. Studies that assessed both sub-types of quality frequently reported no or only a weak relationship between providers’ digitization degree and clinical outcomes (Ali et al., 2016; Bright et al., 2012; Campanella et al., 2016; Jaspers et al., 2011). Only in emergency care, digitization indeed appeared to reduce mortality (Bennett & Hardiker, 2017). This brief overview of the first research category provides limited evidence for policymakers and hospitals attempting to improve clinical outcomes via digitization. Furthermore, most research covers the application of customized user-developed solutions in single organizations, and the potential existence of publication bias is frequently stated (Buntin et al., 2011; Jones et al., 2014). It can, hence, be considered difficult for policymakers to derive insights related to the effects on actual clinical outcomes of nationwide HIT adoption programs.

The second research category represents studies that analyze nationwide data on HIT adoption and quality (Appari et al., 2013; Jones et al., 2010; Linder et al., 2007; McCullough et al., 2010; McCullough et al., 2016; Romano & Stafford, 2011; Zhou et al., 2009). Again, most studies focused on the relationship between hospital digitization and process quality measures. For example, Jones et al. (2010) analyzed data of 2021 US hospitals and identified process quality improvements for heart failure patients following the installation of basic EHRs. Here, process quality was represented by metrics like the provision of smoking cessation advice or discharge instructions. When considering clinical outcomes such as mortality, several studies showed no, limited or mixed effects (Linder et al., 2007; McCullough et al., 2016; Restuccia et al., 2012; Romano & Stafford, 2011; Zhou et al., 2009). For example, McCullough et al. (2016) only showed a positive impact of hospital digitization on the mortality of exceptionally high-risk patients. For policymakers, this second category of research appears to represent a better fitting source of information when deciding on nationwide HIT adoption programs. A relatively small stream of literature even delivered some evidence that hospital digitization could positively impact actual clinical outcomes like mortality. Unfortunately, studies to date almost exclusively covered the US, which could result from data availability related to the comparably early introduction of the 2008 HITECH act. Policymakers in other geographies like Europe can have reason to doubt the applicability of results to their respective health care system.

1.3 Study goals: Differentiating between availability and user-perceived value of HIT

As previously described, evidence for quality improvements in terms of clinical outcomes resulting from higher hospital digitization remains scarce and ambiguous. Yet, the hypothesis that technology can assist physicians and nurses in providing better care appears to follow common sense and is underpinned by multi-billion-euro investments in digital care projects

worldwide. A possible explanation for this mismatch could be that an important aspect is largely ignored in health economics research to date. Across industries, experts agree that digitization is not an end in itself. Especially in health care, research identified human, or soft, factors as the most significant barriers to adoption and proper utilization of HIT (Buntin et al., 2011; Kruse et al., 2016; Sun & Medaglia, 2019). Hence, it seems reasonable to also consider the value of hospital digitization as perceived by everyday users in the analysis. Furthermore, research covering nationwide HIT implementation regularly focused on a limited scope of digital tools such as EHRs or CCDS. Today, several technologies assist physicians and nurses from admission to discharge. Lastly, only one US-based study could be identified that considered patient satisfaction as an additional measure for perceived quality (Restuccia et al., 2012). This work attempts to address this research gap comprehensively. It assesses the effect of availability and user-perceived value of multiple digital HIT tools on clinical outcomes and patient satisfaction in German hospitals representing the most extensive uniform health care system in Europe. On the one hand, it aims to provide policy-relevant insights for the meaningful design of nationwide HIT incentivization programs. Additionally, it can also generate insights for hospitals chasing the promise of clinical outcome improvements via digitization. Ultimately, however, understanding how hospital digitization, perceived and actual care quality are related is of interest to all stakeholders of health care systems.

2 Methods

2.1 Measures for hospital digitization

Digitization degrees of hospitals are captured by a variety of maturity models, often with a strong geographic focus. Most of these models rely on surveys periodically sent to hospitals and answered by Information Technology (IT) employees or physicians and nurses. The Electronic Medical Record Adoption Model (EMRAM) by the Healthcare Information and Management System Society (HIMSS) represents arguably the most internationally established model with participating hospitals from the US, Europe, and Asia (Mangiapane & Bender, 2020). Many of the previously described US-based nationwide studies utilized EMRAM data (Jarvis et al., 2013; Jones et al., 2010; McCullough et al., 2010; McCullough et al., 2016). However, in the context of this work, relying on EMRAM faces two specific limitations. Firstly, the latest available survey from 2017 only captures less than 170 hospitals in Germany (Stephani et al., 2019). Considering 1,942 German hospitals in 2017, this represents a relatively small share of the study population (DESTATIS, 2017). The second limitation relates to the underlying systematic of EMRAM, which takes the form of a stage-based adoption model. Based on the survey answers, hospitals are allocated to one of seven stages from lowest to highest digitization level. This allocation, however, is predominantly based on the mere adoption of specific technologies, mainly ignoring the fact that adoption alone does not necessarily imply utilization or even user-friendly implementation (Liebe et al., 2020). Since the perceived value of hospital digitalization is an essential measure of this work, a more fitting maturity model was sought. The Health Care IT Report (IT Report Gesundheitswesen) represents a comprehensive survey of German, Swiss and Austrian hospitals first executed in 2002 and continued with varying core themes until today. Due to changing core themes and target respondents throughout the years, however, the report does not allow for robust longitudinal analysis. The 2020 version of the report that in 2017 surveyed 492 German

physicians and nurses goes far beyond mere adoption of technologies (Hübner et al., 2020). The report structures hospital digitization around the workflow from admission to discharge and captures comprehensive information on adoption, utilization, and user satisfaction related to more than 50 sub-technologies. Furthermore, the survey methodology is constantly scientifically validated in- and externally (Liebe & Hübner, 2013; Liebe et al., 2020). Due to its comprehensive nature beyond mere adoption and the comparably high number of respondents, this work relied on the 2020 Health Care IT Report data.

Table 5: Overview of sub-domains of hospitals' digital maturity captured by the 2020 Health Care IT Report (incl. maximum attainable scores)

HIT domain	Maximum attainable scores	
	<i>Adoption</i> "HIT availability"	<i>User-perceived value</i> "HIT value"
Admission	30	
Surgery preparation	30	
Discharge	35	
Clinical documentation	77	
Order entry and reporting	42	10
Decision support	42	
Patient safety	49	
Supply functions	40	
Interface functions	50	
Telemedicine & -monitoring	20	
Total digital maturity	415	10

The 2020 report captures hospitals' digital maturity across ten domains composed of several technologies. A sub-score was determined for both adoption and user-perceived value of the underlying technologies for each domain. See Table 5 for an overview of all domains and maximum attainable sub-scores. The domain admission, for example, is composed of three underlying technologies, namely occupancy control, support of anamnesis and patient information, and steering of emergency patients (triage). The underlying technologies of the other domains can be found in the report publication (Hübner et al., 2020). Summing the adoption sub-scores of all domains ultimately results in an overall maturity in terms of "HIT availability". Likewise, averaging the user-perceived value across all domains results in an overall maturity in terms of "HIT value". The report also covers EHR installations' availability and user-perceived value in a separate question. Hence, this is not captured in the score illustrated in Table 5. EHR adoption is captured via a simple Yes/No question and user-perceived value of EHRs on a scale from 1 to 10. This comprehensive set of information shows a good fit with the research goal of this work to capture a variety of technologies and to differentiate between the mere availability and value of HIT. Additionally, separate information on EHRs allows for comparing results with the existing stream of research explicitly covering EHR effects on clinical outcomes.

2.2 Measures for clinical outcomes

This work assesses hospital quality in terms of clinical outcomes in contrast to process quality measures at the center of most existing research. The challenge related to clinical outcomes, such as mortality or surgical revisions, is that absolute values are prone to several confounding factors and impede comparability across hospitals. For example, death within 30 days after hip replacement surgery is ideally evaluated differently based on patient characteristics such as age, gender, or co-morbidities. Relative outcome measures involving patient-specific risk-adjustment resolve these issues and can be considered the gold standard in terms of clinical outcome metrics (Iezzoni, 1994; Restuccia et al., 2012). On a hospital level, these measures take the form of observed over expected (O/E) ratios, with the value of expected incidents being risk-adjusted. This implies worse-than-expected performance at values greater than one. In Germany, a reliable source of risk-adjusted, or patient-based, clinical outcomes is the hospital data of Germany's largest statutory sickness fund, the Allgemeine Ortskrankenkasse (AOK). The internal research institute of the AOK, WIdO (Wissenschaftliches Institut der AOK), is responsible for central calculation of risk-adjusted outcome data consolidated in the QSR (Qualitätssicherung mit Routinedaten) database (Günster et al., 2013; WIdO, 2007). This work relied on the comprehensive QSR dataset. Previous research gives reason to assume that the influence of hospital digitization on outcomes potentially differs between unpredictable emergency care and planned elective treatments (Bennett & Hardiker, 2017; Jones et al., 2010; McCullough et al., 2016). Whereas elective care relies on a comprehensive overview of patients' medical history collected over time, emergency care is facilitated by rapid anamnesis and decision-making. Hence, this work differentiated between elective and emergency care clinical outcomes when assessing the effects of digitization thereon. A consolidated O/E-ratio for elective care was determined by averaging four risk-adjusted indicators related to hip replacement surgery due to coxarthrosis. The QSR dataset also includes several other indicators for elective care treatments such as prostatectomy, knee replacement or cholecystectomy. These treatments were not considered in analysis, since, unfortunately, only a limited data overlap between the hospitals captured by the 2020 Health Care IT Report and QSR data was observed. This would ultimately have reduced the sub-sample size even further. The consolidated O/E-ratio for emergency care was determined by averaging 30-day risk-adjusted standardized mortality rates for stroke and myocardial infarction (heart attack) patients representing the most important and representative emergency care cases. An overview of all indicators included in calculating the two final consolidated scores can be found in Appendix 10. Details on patient-based risk adjustments can be found in the indicator handbook for QSR data (WIdO, 2018).

2.3 Measures for patient satisfaction

Patient satisfaction represents this work's third measure of interest. Several studies have assessed the relationship between HIT adoption and patient satisfaction, with some showing benefits and others no relationship (Jarvis et al., 2013; Restuccia et al., 2012). In a review study, Werder (2015) argues that HIT might affect specific facets of the patient experience. For example, EHRs potentially improve the communication between providers and patients. At the same time, however, excessive digitization in areas where patients value interpersonal experiences can also negatively affect satisfaction. Since this work considers HIT adoption and hospital user-perceived value, revisiting the effects on patient satisfaction appears meaningful. Ultimately, one can hypothesize that technology adopted in a way that is deemed supportive by

hospital users also benefits patient-focused processes and hence patient satisfaction. In Germany, Weisse Liste (WL) executes the government mandate for public publication of hospital quality measures. Additionally, WL collects data on patient satisfaction in cooperation with the statutory insurance funds AOK, BARMER, and KKH and is regularly considered best-in-class in this field (Fischer, 2015). WL relies on the Patients' Experience Questionnaire (PEQ), covering 15 questions sent to patients two to four weeks after hospital discharge (Gehrlach et al., 2010). The questions cover various factors from personnel friendliness to admission and discharge process satisfaction. The complete questionnaire is publicly available for review (WeisseListe, 2016). Experience is rated on a 1-6 scale from best to worst. This work relied on PEQ data to assess the relationship between HIT adoption or user-perceived value and patient satisfaction in German hospitals.

2.4 Model development and estimation

A three-equation multiple linear regression model was formulated with emergency care outcomes, elective care outcomes, and patient satisfaction defined as dependent variables:

Emergency care outcomes

$$\begin{aligned} &= \alpha_0 + \alpha_1(HIT_{adoption(t-1)}) + \alpha_2(HIT_{user_value(t-1)}) \\ &+ \alpha_3(\#emergency\ cases) + \alpha_4(\#emergency\ cases)^2 + \alpha_5(\#total\ cases) \\ &+ \alpha_6(Private\ ownership) + \alpha_7(Teaching\ status) + \alpha_8(\#beds) + \varepsilon \end{aligned}$$

(Equation 4)

Elective care outcomes

$$\begin{aligned} &= \alpha_0 + \alpha_1(HIT_{adoption(t-1)}) + \alpha_2(HIT_{user_value(t-1)}) \\ &+ \alpha_3(\#elective\ cases) + \alpha_4(\#total\ cases) + \alpha_5(Private\ ownership) \\ &+ \alpha_6(Teaching\ status) + \alpha_7(\#beds) + \varepsilon \end{aligned}$$

(Equation 5)

Patient satisfaction

$$\begin{aligned} &= \alpha_0 + \alpha_1(HIT_{adoption(t-1)}) + \alpha_2(HIT_{user_value(t-1)}) + \alpha_3(\#total\ cases) \\ &+ \alpha_4(Geography) + \alpha_5(Private\ ownership) + \alpha_6(Teaching\ status) \\ &+ \alpha_7(\#beds) + \varepsilon \end{aligned}$$

(Equation 6)

In Equations 4 and 5, capturing care outcomes, the dependent variables were represented by the consolidated O/E-ratios based on the QSR database for emergency or elective care. Since this work deliberately differentiates between technology adoption and user-perceived value, both measures $HIT_{adoption}$ and HIT_{user_value} were included as independent variables. Here, the total digital maturity scores or the ones of select domains of the Health Care IT Report (see Table 5) were considered. Importantly, a time-lag of one year ($t - 1$) was introduced for both HIT

scores. This incorporates that full technology operability and user education require time after initial installment (Blumenthal & Glaser, 2007; Kruse et al., 2016). Additionally, several other independent variables were included to control for hospital-level effects. Firstly, the underlying number of cases related to clinical outcomes was included to capture potential volume effects directly linked to emergency or elective case volumes. Since several studies identified a positive relationship between case volume and quality, this is a critical confounding factor to control for (Marcin & Romano, 2004; Wright et al., 2017). Secondly, the total number of inpatient cases *#total cases* was included capturing the overall busyness of the respective hospital (Jarvis et al., 2013). The hospital ownership status was considered via the independent dummy variable *Private ownership* controlling for potential organizational effects (Eggleston et al., 2008). Similarly, teaching effects were included by another independent dummy variable *Teaching status* (Ayanian & Weissman, 2002; Eggleston et al., 2008). Lastly, the number of hospital beds *#beds* was considered to capture possible size effects of hospitals (Choi et al., 2017; Menon et al., 2000). Equations 4 and 5 only differ in the inclusion of *(#related cases)²* in Equation 4. Existing research has indicated an inversed U-shaped relationship between case volumes and outcomes for emergency care (Choi et al., 2017). By including both the regular and squared emergency case volumes, this effect could be captured if present in the underlying data.

In Equation 6, the dependent variable *patient satisfaction* was represented by the averaged PEQ score across all questions or for select questions such as admission satisfaction. Independent variables remained mostly the same as in Equation 5, except that potential volume effects were captured by considering only all inpatient cases, *#total cases*, of the hospital. Interestingly, controlling for geographic effects seems important when considering patient satisfaction since research has shown higher average satisfaction in Eastern Germany (Kraska et al., 2017). One can only hypothesize why this is the case. One explanation could be that the average hospital age after German reunification is lower in Eastern Germany which might have subjective effects on patient perceptions of the “look and feel” of hospitals.

The linear-in-parameter models were separately estimated relying on Ordinary Least Squares (OLS) regression analysis. The HIT-related independent variables $HIT_{adoption(t-1)}$ and $HIT_{user_value(t-1)}$ were captured as 2017 values based on the 2020 Health Care IT Report. Considering the previously mentioned assumed one-year lag of full operability and user education, all other variables were based on 2018 values. All dependent variables and all independent variables capturing case volumes were measured in natural logarithms to account for unequal variation and keeping OLS assumptions such as normally distributed residuals in mind.

3 Results

3.1 Overall study sample

The initial 492 responses of the 2020 Health Care IT Report were cleaned for significantly incomplete questionnaires and contradictory answers of two respondents from the same hospital. Secondly, only hospitals were included for which information on either clinical outcomes or patient satisfaction was available. The final overall study sample included a total

of 383 hospitals. Sample characteristics and the sample frame corresponding to all 1,925 German hospitals in 2018 are depicted in Table 6.

Table 6: Sample characteristics

Sample n=383	characteristics			Sample frame ¹
		Absolute	% or (SD)	
Structural				
Ownership	Private	88	23%	37%
	Non-private	295	77%	63%
Teaching status	Teaching	199	52%	51%
	Non-teaching	184	48%	49%
Beds	Mean	319.72	(318.35)	258.8
Total inpatient cases	Mean	12,861.6	(14,194.0)	10,290.2
Geography	Eastern states	72	19%	18%
	Western states	311	81%	82%
Digital maturity				
$HIT_{adoption(2017)}$ (max. 415)	Mean	183.1	(98.4)	
$HIT_{user-value(2017)}$ (max. 10)	Mean	6.3	(1.7)	
EHR adoption (2017)	Yes	126	33%	
	No	118	31%	
	Unsure	6	2%	
	No information	133	35%	
Clinical outcomes				
O/E ratio emergency care ²	Mean	1.07	(0.48)	1.07
O/E ratio elective care ³	Mean	1.05	(1.23)	1.07
Patient satisfaction				
Overall PEQ score ⁴	Mean	1.99	(0.31)	2.02

Note: Rounded figures; ¹Sources: Official 2018 hospital report (DESTATIS, 2018), Nationwide QSR data, Nationwide PEQ data; ²value of 1 indicates as-expected outcome performance (i.e., higher values indicate worse outcomes), n=267; ³value of 1 indicates as-expected outcome performance (i.e., higher values indicate worse outcomes), n=249; ⁴on a 1-6 scale from best to worst (i.e., higher values indicate lower satisfaction), n=354

The overall sample of 383 hospitals represented approximately 20% of the 2018 sample frame (1,925 hospitals) and appeared primarily representative. In line with the sample frame, most sample hospitals were of a non-private kind, followed teaching activities, and were situated in the Western states of Germany. With on average 319.72 beds and 12,861.6 inpatient cases, the sample seemed to capture slightly larger hospitals than the 2018 German average. Clinical outcome and patient satisfaction measures were almost perfectly aligned with the nationwide sample frame values. Interestingly, clinical outcomes indicated a slightly worse-than-expected average performance for both types of care, which significantly varied across hospitals as indicated by the standard deviations. Overall, patients appeared to be relatively satisfied with

an average patient satisfaction score of 1.99 on a scale from 1 to 6 (best to worst). Considering digital maturity, hospitals still failed to adopt several technologies, resulting in a comparably mediocre average score of 183.1 of maximum attainable 415. Lastly, 50% of hospitals that provided information on EHRs indicated adoption, which is largely in line with existing research (Hübner et al., 2020; Stephani et al., 2019). As previously explained, this overall sample represents hospitals captured by the IT Report for which information on either clinical outcomes or patient satisfaction was available. The number of hospitals for which information on all dependent variables was available was comparably low, hence, it was decided to consider sub-samples of this overall sample in the single regression analyses.

3.2 Model estimation results: HIT and EHR effects on clinical outcomes

Several regressions were estimated based on the linear-in-parameters model in Equations 4 and 5. The dependent variables capturing clinical outcomes were represented by the O/E ratios of emergency care and elective care. For both dependent variables separately, the effects of overall HIT adoption and user-perceived value, the adoption of EHRs, and user-perceived EHR value were captured in three separate regressions. Hospitals with less than 5 cases as the basis for the clinical outcomes O/E ratio calculations were excluded due to high outcome variability. Hence, based on the dependent variable of interest, differently sized sub-samples were relied on as indicated in Tables 7 to 9.

HIT and EHR effects on emergency care outcomes

In summary, adoption alone of either HIT or EHRs did not significantly affect emergency care outcomes. However, this picture slightly changed when the user-perceived value of the installed technologies was considered. The users' perceived value of overall HIT did have a significant positive effect on outcomes mirrored by a decrease in the O/E-ratio ($\hat{\beta} -0.032$, SE 0.016). This indicates that the O/E ratio improves by approximately $1 - \exp(-0.032) = 0.0315 \approx 3.15\%$ for every one-point improvement in user-perceived HIT value. On the other hand, EHR adoption or user-perceived value did not influence emergency outcomes. The overall significance of these EHR-related models (II and III) also indicated a low data fit, as shown by F-values. When looking at the control variables, model I indeed revealed an inverted U-shape relationship between emergency case volumes and outcomes. This is represented by a positive influence of regular volumes ($\hat{\beta} -0.559$, SE 0.167) and a negative influence of squared volumes ($\hat{\beta} 0.058$, SE 0.019). Additionally, hospitals with higher overall inpatient case volumes generated worse emergency care outcomes ($\hat{\beta} 0.102$, SE 0.051). Table 7 provides an overview of the three estimated regression models.

Table 7: OLS estimates for linear-in-parameter regressions capturing the impact of HIT and EHR on emergency care clinical outcomes

Dependent variable:	ln(O/E ratio emergency care) ¹					
	I (HIT)		II (EHR adoption)		III (EHR user value)	
Model	$\hat{\beta}$	SE	$\hat{\beta}$	SE	$\hat{\beta}$	SE
Intercept	0.557	0.506	0.479	0.65	-0.563	1.007
$HIT_{adoption}^2$	-0.001	0.001				
$HIT_{user-value}^3$	-0.032**	0.016				
$EHR_{adoption}^4$			0.053	0.034		
$EHR_{user-value}^3$					-0.018	0.022
#beds						
<150	0.037	0.087	-0.082	0.108	-0.087	0.147
150-300	0.027	0.046	-0.002	0.061	0.033	0.077
301-600	-0.035	0.049	-0.002	0.064	0.065	0.082
>600	-0.028	0.086	0.087	0.114	-0.01	0.14
ln(#total cases)	0.102**	0.051	0.026	0.068	0.134	0.086
ln(#emer. cases)	-0.559***	0.167	-0.288	0.214	-0.203	0.286
ln(#emer. cases) ^{^2}	0.058***	0.019	0.027	0.025	0.018	0.033
Teaching[YES]	-0.036	0.032	-0.015	0.214	-0.022	0.054
Private[YES]	0.007	0.037	0.017	0.046	0.059	0.060
Sub-sample size	261		174		82	
R^2	0.098		0.047		0.117	
F-value	2.727***		0.905		1.061	

Note: Rounded figures; ¹O/E ratio implies better performance with lower values; ²on a 0-415 scale from worst to best; ³on a 1-10 scale from worst to best; ⁴implies adoption of EHR; Significance levels: ***1%; **5%; *10%

As described in the methods section of this work, the user-perceived value of overall HIT represents the average of all HIT sub-domain values listed in Table 5. Additional regressions were estimated to better understand whether any sub-domain had a prominent effect on the identified significant relationship on the overall HIT level. All HIT sub-domains were separately regressed against emergency care outcomes following an exploratory approach. The admission sub-domain generated statistically significant results. User-perceived value of admission-HIT had significant effects on emergency care outcomes ($\hat{\beta}$ -0.023, SE 0.013). The inverted U-shape relationship between emergency case volumes and outcomes was also identified in this regression. See Table 8 for details on the regression model.

Table 8: OLS estimates for linear-in-parameter regressions capturing the impact of admission-HIT on emergency care clinical outcomes

Dependent variable:		ln(O/E ratio emergency care)¹	
Model	I (HIT)		
	$\hat{\beta}$	<i>SE</i>	
Intercept	0.887	0.553	
<i>Admission</i> _{adoption} ²	0.001	0.004	
<i>Admission</i> _{user-value} ³	-0.023*	0.013	
#beds			
<150	0.066	0.096	
150-300	0.012	0.047	
301-600	-0.031	0.053	
>600	-0.046	0.091	
ln(#total cases)	0.083	0.174	
ln(#emer. cases)	-0.68***	0.174	
ln(#emer. cases) ²	0.072***	0.02	
Teaching[YES]	-0.02	0.035	
Private[YES]	0.007	0.039	
Sub-sample size	232		
<i>R</i> ²	0.113		
F-value	2.824***		

Note: Rounded figures; ¹O/E ratio implies better performance with lower values; ²on a 0-30 scale from worst to best; ³on a 1-10 scale from worst to best; Significance levels: ***1%; **5%; *10%

HIT and EHR effects on elective care outcomes

The analysis of HIT and EHR effects on elective care outcomes revealed similarities but also differences to emergency care results. In line with emergency care results, adoption alone of either HIT or EHRs did not significantly affect elective care outcomes. Whereas a higher user-perceived value of overall HIT did not affect outcomes either, users' satisfaction with EHRs appeared to have a significant effect, as shown in model III ($\hat{\beta}$ -0.138, SE 0.05). This indicates that the O/E ratio improves by approximately $1 - \exp(-0.138) = 0.1289 \approx 12.9\%$ for every one-point improvement in user-perceived EHR value. Of the control variables included in the regression, the number of elective care cases showed significant effects in models I and III. Hence, indicating a positive relationship between case volume and outcome quality in the elective care field. Interestingly, hospital size was a significant factor, with smaller hospitals performing better than larger ones. Table 9 provides an overview of the three estimated regression models.

Table 9: OLS estimates for linear-in-parameter regressions capturing the impact of HIT and EHR on elective care clinical outcomes

Dependent variable:	ln(O/E ratio elective care) ¹						
	Model	I (HIT)		II (EHR adoption)		III (EHR user value)	
		$\hat{\beta}$	SE	$\hat{\beta}$	SE	$\hat{\beta}$	SE
Intercept		3.005**	1.495	3.4	2.07	2.973	2.741
$HIT_{adoption}^2$		0.001	0.001				
$HIT_{user-value}^3$		0.038	0.034				
$EHR_{adoption}^4$				-0.013	0.063		
$EHR_{user-value}^3$						-0.138***	0.05
#beds							
<150		-0.529***	0.199	-0.716***	0.229	-0.42	0.329
150-300		-0.075	0.099	-0.071	0.125	-0.089	0.189
301-600		0.415***	0.108	0.5***	0.123	0.393***	0.181
>600		0.189	0.191	0.287	0.228	0.116	0.329
ln(#total cases)		-0.239	0.157	-0.266	0.211	-0.132	0.283
ln(#elect. cases)		-0.324***	0.064	-0.269***	0.079	-0.278**	0.115
Teaching[YES]		-0.059	0.065	-0.114	0.078	-0.03	0.12
Private[YES]		-0.054	0.072	-0.062	0.082	-0.173	0.119
Sub-sample size	184			118		59	
R^2		0.237		0.265		0.375	
F-value		5.997***		4.915***		3.753***	

Note: Rounded figures; ¹O/E ratio implies better performance with lower values; ²on a 0-415 scale from worst to best; ³on a 1-10 scale from worst to best; ⁴implies adoption of EHR; Significance levels: ***1%; **5%; *10%

3.3 Model estimation results: HIT and EHR effects on patient satisfaction

Several regressions were estimated based on the linear-in-parameters model in Equation 6, where PEQ scores represented patient satisfaction. To assure representativeness, the estimation excluded patient satisfaction PEQ scores based on less than 20 respondents per hospital. An overview of all estimated models and respective sub-sample sizes are shown in Table 10. In line with the effects on clinical outcomes, mere technology adoption did not significantly affect overall patient satisfaction, i.e., the overall PEQ score. However, the user-perceived value of HIT did significantly affect patient satisfaction ($\hat{\beta}$ -0.009, SE 0.037) as indicated by model I of Table 10. Ultimately, a higher hospital-user satisfaction with HIT translated into higher patient satisfaction. The effect magnitude, however, can be considered limited with a $1 - \exp(-0.009) = 0.0089 \approx 0.9\%$ improvement in PEQ score for every one-point improvement in user-perceived HIT value. Models II and III examining the impact of EHRs did not identify any significant EHR-related effects. Nevertheless, several other control variables revealed interesting insights. Across all models, higher bed numbers negatively impacted satisfaction.

Additionally, and in line with previous research, patients visiting hospitals in Eastern German federal states were on average more satisfied.

Table 10: OLS estimates for linear-in-parameter regressions capturing the impact of HIT and EHR on patient satisfaction

Dependent variable:	ln(Overall PEQ score) ¹						
	Model	I (HIT)		II (EHR adoption)		III (EHR user value)	
		$\hat{\beta}$	SE	$\hat{\beta}$	SE	$\hat{\beta}$	SE
Intercept		0.694***	0.098	0.658***	0.124	0.822***	0.172
$HIT_{adoption}^2$		0.001	0.001				
$HIT_{user-value}^3$		-0.009***	0.004				
$EHR_{adoption}^4$				0.001	0.007		
$EHR_{user-value}^3$						-0.006	0.005
#beds							
<150		-0.097***	0.017	-0.087***	0.02	-0.122***	0.034
150-300		-0.008	0.009	-0.019	0.013	-0.014	0.018
301-600		0.032***	0.011	0.026*	0.014	0.033	0.021
>600		0.072***	0.018	0.08***	0.022	0.104***	0.031
ln(#total cases)		0.002	0.01	0.002	0.013	-0.013	0.019
Geography[East]		-0.031***	0.007	-0.029***	0.01	-0.029*	0.015
Teaching[YES]		0.003	0.008	0.002	0.009	0.001	0.014
Private[YES]		0.003	0.007	-0.001	0.009	-0.016	0.015
Sub-sample size		310		203		93	
R^2		0.322		0.259		0.35	
F-value		15.824***		8.516***		5.669***	

Note: Rounded figures; ¹on a 1-6 scale from best to worst; ²on a 0-415 scale from worst to best; ³on a 1-10 scale from worst to best; ⁴implies adoption of EHR; Significance levels: ***1%; **5%; *10%

Since the Patient Experience Questionnaire also covers a separate question on admission satisfaction, an additional regression explicitly examining the relationship between admission-HIT and admission satisfaction was estimated (see Table 11). Interestingly, the adoption of more technology in the admission as indicated by a higher $Admission_{adoption}$ score implied a decrease in patients' admission satisfaction ($\hat{\beta}$ 0.002, SE 0.001). On the other hand, however, the user-perceived value of admission-HIT and patients' admission satisfaction are positively related ($\hat{\beta}$ -0.009, SE 0.004). Again, a higher hospital-user satisfaction with HIT translated into higher patient satisfaction. Interestingly, patients tend to be less satisfied with the admission process when hospitals have higher overall case volumes ($\hat{\beta}$ 0.061, SE 0.013).

Table 11: OLS estimates for linear-in-parameter regressions capturing the impact of admission-HIT on patient satisfaction with admissions

Dependent variable: ln(Admission PEQ score)¹		
Model	I (Admission-HIT)	
	$\hat{\beta}$	<i>SE</i>
Intercept	0.073	0.121
<i>Admission_{adoption}</i> ²	0.002**	0.001
<i>Admission_{user-value}</i> ³	-0.009**	0.004
#beds		
<150	-0.091***	0.021
150-300	0.008	0.012
301-600	0.022	0.014
>600	0.061***	0.021
ln(#total cases)	0.061***	0.013
Geography[East]	-0.029***	0.009
Teaching[YES]	-0.003	0.009
Private[YES]	0.003	0.009
Sub-sample size	267	
<i>R</i> ²	0.489	
F-value	27.29***	

Note: Rounded figures; ¹on a 1-6 scale from best to worst; ²on a 0-30 scale from worst to best; ³on a 1-10 scale from worst to best; Significance levels: ***1%; **5%; *10%

The robustness of all estimated OLS regressions was tested to assure that coefficients were unbiased and close to the actual population values. Results of the Shapiro-Wilk test suggested that the null hypothesis of normally distributed residuals cannot be rejected. Heteroscedasticity was assessed by applying the White test, which generated negative results. Multicollinearity was tested by determining Variance Inflation Factors (VIF) for all estimated coefficients. Besides the VIFs for (*#emergency cases*) and (*#emergency cases*)², none of these was higher than five and, hence, it can be assumed that the model is not significantly affected by multicollinearity. Additionally, *R*² was determined to capture the proportion of variance for the dependent variables explained by independent variables. F-tests were executed, determining the overall significance of regressions.

4 Discussion

4.1 Principal Results

The previously described results provide concrete answers to the research question of this work. It was shown that the adoption of HIT alone does not have a significant effect on either clinical outcomes or patient satisfaction. This first result appears to align with the previously described stream of literature that assesses digitization effects on both process quality and clinical outcomes with similar results (Ali et al., 2016; Bright et al., 2012; Campanella et al., 2016; Jaspers et al., 2011). However, the degree of user-perceived value of HIT did significantly affect

both measures in several cases. Hence, adding this important information to the analysis reveals new insights. When it comes to hospital digitization, it appears to be about quality instead of mere quantity.

Firstly, the results related to clinical outcomes revealed interesting insights, also due to their differing nature. In the elective care field, higher user-friendliness of EHRs appears to result in better outcomes, whereas digitization in other areas seems not to matter significantly. On the contrary, emergency care outcomes benefit from user-friendly overall digitization. Admission-HIT deemed valuable by physicians and nurses appears to be the strongest driver. Looking at the underlying processes related to these care realms, the identified differences follow logic. In this work represented by hip replacement surgery, elective care relies on the comprehensive compilation of patients' medical history, imaging, and laboratory work. A user-friendly EHR is at the center of this collection and preparation process representing a single source of information for each patient. Additionally, in the non-urgent sector, EHRs simply have the time to develop their potential fully. The results of this work imply that physicians and nurses who can rely on easy-to-access EHRs also generate better elective surgery outcomes. However, EHRs do not appear to be a key factor when looking at emergency care outcomes. Here, the user-perceived value of overall hospital digitization positively affects outcomes. This overall effect is especially driven by user-friendly digital technology supporting the admission process. Again, these results appear reasonable. Firstly, it is likely that even the user-friendliest EHR simply cannot develop its full potential due to the spontaneous nature of heart attack and stroke cases. What most likely determines outcomes, in this work represented by 30-day mortality, is rapid decision-making shortly after the incident. Hence, it appears reasonable that this work identified significant effects on outcomes due to user-friendly admission technologies. These include organizational tools like occupancy control and the triage or steering of emergency patients. Physicians and nurses optimally supported by technology appear to achieve better outcomes in time-crucial emergencies. At this point, a brief look at the control variables of Equations 4 and 5 also reveals interesting insights. Maybe even comforting for German patients, outcome quality does not seem to depend on hospitals' teaching and ownership status. However, clinical outcomes for elective care, hip replacements, in this case, do benefit from higher procedure volumes. This finding is very much in line with existing research (Bozic et al., 2010). The same applies to emergency care outcomes, at least to some extent. Here, an inverted U-shape relationship between case volume and outcomes was identified, implying that emergency departments are simply overburdened at some point.

Secondly, the results related to patient satisfaction should be revisited. Yet again, a similar picture emerges with the mere adoption of overall HIT not having significant effects on patient satisfaction. However, digitization that appears value-adding from a hospital user perspective also positively impacts patients' experiences, even though to a somewhat limited magnitude. Apparently, HIT-related user satisfaction partly channels down to patients. There are several potential reasons why this is the case. Firstly, well-designed digital tools covering admission, clinical documentation, order entry, discharge, or even catering management help physicians and nurses effectively execute care. This could mean shorter waiting times, better informed treating doctors, and smooth patient discharge processes, influencing patient satisfaction. Secondly, however, one can also assume hospital staff being content with their everyday work

environment, which includes HIT, to approach patients in a better, less stressed mood. This can ultimately also influence patient satisfaction via interpersonal mechanisms. A mix of these two reasons most likely explains the results of this work. Nevertheless, the user-perceived value of HIT is only one factor in the equation. Results show that patients are on average less satisfied in hospitals of larger size, as indicated by the number of beds. Here, one can hypothesize that large hospitals also imply a higher degree of anonymity and potentially less personalized care. Like existing research, this work also identifies geographic differences in patient satisfaction with patients in Germany's eastern federal states being on average more satisfied (Kraska et al., 2017). Lastly, an interesting phenomenon related to patients' satisfaction with admission was revealed. Results showed that higher levels of admission digitization, e.g., via tools for patient education and anamnesis, resulted in lower admission satisfaction. The actual reasons behind these results remain uncertain. However, research has repeatedly warned of the undesired effects digitization has on the patient-physician relationship considering the very personal topic of health care (Cresswell & Sheikh, 2013). When process digitization is introduced in impersonal ways, it can damage this very sensitive relationship. Since the admission represents the first contact with the hospital, it can generate an impression that lasts. Fortunately, results also show that a higher degree of hospital user-perceived value of admission digitization can work against this effect and improve patient satisfaction. Hence, in cases like admission, mere digitization can even be detrimental to patient satisfaction if not executed in a user-friendly way.

As intended by this work, the discussed results provide valuable insights for both policymakers and hospitals. As previously described, an important goal for policymakers designing nationwide HIT incentivization programs is the improvement of clinical outcomes via digital technologies. This work indicates that an exclusive focus on driving HIT adoption will likely not be sufficient to achieve this goal. Additional mechanisms need to be in place, assuring that user needs and preferences are considered. Only via a high user-perceived value of installed HIT can clinical outcomes, as well as patient satisfaction, be improved. The 2020 German Hospital Future Act, for example, also covers expenses for training and user education for the funded digital tools. This represents a good first step. However, policymakers could even consider introducing a mandatory minimum share for training of total project budgets. Keeping the focus on Germany, the Hospital Future Act also introduced a mandatory yearly digital maturity survey among all hospitals that applied for funding. Survey results could even be utilized to identify and sanction hospitals that do not have specific technologies installed by 2025. Considering the limited data on hospital maturity in Germany, which also this work relied on, this represents a desirable approach. However, of the 209 final questions included in the questionnaire, only six capture aspects of user satisfaction (Geissler & DigitalRadar Krankenhaus, 2021). The results of this work advise policymakers to focus on the value of digitization as perceived by everyday users instead of incentivizing, capturing, and imposing mere adoption of advanced digital tools. This, at least, applies when aiming at improvements in clinical outcomes and patient satisfaction.

When taking the hospital's perspective, much of the previously discussed applies. Hospitals that aim to improve clinical outcomes or patient satisfaction via digitization can derive several practical insights from this work. Firstly, they are well-advised to consider the views of the

ultimate users in their procurement decisions. Technology that is evaluated as user-friendly even before installation is more likely to generate user-perceived value once in place. Secondly, hospitals should not consider digitization projects completed after mere adoption but emphasize ongoing user training. Thirdly, digitization strategies of health care providers benefit from differentiated approaches based on the respective area of care. This work, for example, implies that elective care outcomes benefit from a user-friendly EHR, whereas value-adding admission technologies can improve emergency care outcomes. Considering patient satisfaction, the simple adoption of admission-HIT can even negatively impact satisfaction if not implemented in a user-friendly way for the hospital staff. In the end, these decisions also have a potential impact on hospital revenue since case volumes are likely driven by patient satisfaction, and clinical outcomes drive average revenue per case via reimbursement penalties. Hospitals are advised not to stop strategic or operational considerations after adopting technologies but to work towards high user-perceived quality of digitization constantly.

However, a simple yet important fact should be realized at the very end. Indeed, this work does not identify effects on clinical outcomes and patient satisfaction via mere adoption of HIT, but only via high user-perceived value of technologies. Nevertheless, without the initial adoption of digital tools in hospitals, there is simply no prerequisite for a user-friendly version of it. Hence, both policymakers and hospitals are strongly advised to work towards the adoption of promising digital technologies, but not stop there.

4.2 Limitations

Results of this work are subject to several potential limitations. Firstly, this work had to rely on a somewhat limited dataset on hospital digitization degrees in Germany. Even though the 2020 Health Care IT Report captured almost 500 initial answers, the exclusion of significantly incomplete questionnaires and contradictory answers of two respondents from the same hospital resulted in a final overall sample of 383 hospitals. Moreover, responses related to adoption and user-perceived value of EHRs were even more limited. This ultimately resulted in very differently sized sub-samples, potentially impairing the comparability of the estimated regressions. However, also keeping the even smaller sample of the internationally renowned HIMSS assessments in mind, this work is based on one of the most comprehensive datasets on German hospital digitization available to date. On a similar note, the unavailability of longitudinal panel data resulted in the static nature of the model applied in this work. It would be interesting to apply a longitudinal model to capture the effects of changes in digitization levels on changes in dependent variables. Lastly, the latest available data capture 2017 digitization levels. Considering the rapid development in HIT also involving advanced Artificial Intelligence-based tools, results might not be fully applicable to the situation today. All three limitations strongly reveal the need for a structured, periodical digital maturity assessment among hospitals. Fortunately, as previously described, the 2020 Hospital Future Act introduces this assessment for Germany. However, the collected data must also be made available to the research community.

Secondly, the work relied on patient satisfaction data from the Patient Experience Questionnaire, which collects answers on a Likert-Type scale. There is some controversy about whether Likert-type responses can be averaged when used in statistical analysis with no

unanimous result. However, since the PEQ data used in this study were normally distributed, we followed the standard approach of utilizing averaged values (Sullivan & Artino Jr, 2013).

Thirdly, clinical outcome data were provided by the QSR database of the statutory insurer AOK. Hence, only clinical outcome data captured for patients insured by AOK was captured. However, since the AOK is the most significant statutory insurer in Germany with approximately 35% market share, the representativeness of the data can be assumed. Moreover, this work deliberately focuses on clinical outcomes exclusively. More precisely, outcomes for two emergency care cases, stroke and myocardial infarction, and one elective care indication, namely hip replacement, are considered. Whereas stroke and heart attack indeed represent the most essential emergency care indications in Germany, the results of this work might not be fully applicable to other areas of elective care. In addition, clinical outcomes represent only one aspect of hospital quality. The impact of digitization on process quality, for example, is not captured.

Besides these critical variables of interest, this work also relied on several control variables when estimating OLS regressions. Looking at the R-squared values of regressions, including care outcomes as the dependent variable, a significant share of variance was seemingly not explained by the included independent variables. Hence, risk-adjusted care outcomes appear to be influenced by a much wider variety of factors not captured by this work. This seems reasonable since care represents a highly personalized process that is also related to activities outside the hospital. Nevertheless, this work included the most prominent control variables used in research when assessing effects on clinical outcomes (Chaudhry et al., 2006; Jarvis et al., 2013; Jaspers et al., 2011; Jones et al., 2014).

4.3 Conclusion

This study examined the effect of digitization on clinical outcomes and patient satisfaction among German hospitals. It was shown that the adoption of HIT alone does not significantly influence either outcomes or patient satisfaction, whereas the value of these technologies as perceived by physicians and nurses does. A short answer to the question proposed in the title of this work is hence: Yes, digitized hospitals treat patients better, but only if digitization is adopted in a value-adding way from the perspective of everyday users. However, results also showed that it is essential to differentiate between indications and HIT sub-types. Whereas emergency care outcomes significantly benefit from user-friendly admission-HIT, elective care outcomes do so via user-friendly EHR installations. These results appear reasonable, keeping the need for rapid decision-making shortly after emergency incidents and for the comprehensive compilation of patients' medical history during elective care in mind. Besides clinical outcomes, the user-perceived value of HIT also influenced patient satisfaction, even though to a limited extent. Hospital staff working with HIT that is value-adding from their perspective appears to contribute to overall patient satisfaction positively. The importance of this relationship is amplified when revisiting the admission process. Results showed that adopting more digital tools during admission resulted in lower patient satisfaction. However, improvements in the user-perceived value of admission-HIT worked against this effect and improved satisfaction. Hence, in cases like admission, mere hospital digitization can even be detrimental to patient satisfaction if not executed in a user-friendly way. Ultimately, the results of this work provide valuable insights for both policymakers and hospitals. Policymakers

attempting to improve care quality via HIT are advised to focus on the value of digitization as perceived by everyday users instead of incentivizing, capturing, or even imposing mere adoption of digital tools. On the other hand, hospitals are well-advised to consider views of the ultimate users in their procurement decisions and invest in continuous training. They should not stop strategic or operational considerations after adopting technologies but constantly work towards high user-perceived quality of digitization. In conclusion, hospital digitization can improve both clinical outcomes and patient satisfaction, but only if deemed value-adding by the physicians and nurses that rely on it every day.

Summary

This dissertation examined the overarching question whether data and analytics influences quality, economics, and patient experience of health care providers. The short answer to this question is: Yes, digitization of providers does influence all three value-drivers in health care. Better yet, for most of the cases and technologies, this relationship is of positive nature. For example, investments in advanced analytics technologies and CCDS can result in economic benefits via direct cost savings or revenue gains and indirect efficiency improvements. Hospital digitization perceived valuable by the users can positively impact actual outcomes like mortality in emergency and elective care, as well as improve patient satisfaction. Ultimately, the DCE of this work also illustrates that physicians are willing to invest in technologies such as AI-based assistance tools if these tools are designed and priced in a way preferred by the users.

At the same time, however, the previously stated results also point at a very important finding. These positive effects on quality, economics and patient experience do not apply for all technologies and are often subject to specific preconditions. As with many things, provider digitization is not an end in itself, but needs to be highly intent on important details thereby being mindful of the complex working environments in health care. A few examples illustrate this statement quite clearly. Whereas adoption of data and analytics tools on an overarching level does improve provider economics, this relationship is more ambiguous for single technologies like the EHR (von Wedel & Hagist, 2020). These mixed results regarding EHRs can create an economic barrier for adoption by providers which can translate into a bottleneck to positive economic effects of analytics technologies relying on EHR data. When looking at effects on quality and patient experience, details matter again. Results of this work show that mere adoption of data and analytics does not have any effect on outcomes or patient satisfaction. In the case of admission technologies, patients are even less satisfied with simply introducing higher digitization levels. What does, however, come with benefits is digitization that is perceived valuable by physicians and nurses being the everyday users of technologies. Hence, providers should not simply focus on adopting technologies, but on continuously ensuring high user-friendliness of these installations. Lastly, the DCE of this work takes the micro perspective of single providers, namely radiologists, and reveals important insights on attributes that matter for data and analytics investment decisions. Radiologists prefer affordable assistance tools that support in everyday tasks such as lesion detection or screening examinations (von Wedel & Hagist, 2022). More than for quality improvements (i.e., detecting more lesions), they care for the time these tools save them per study. All these examples provide evidence that the success of data and analytics installations in terms of care quality, care economics, patient experience and user acceptance is in the details.

Considering these details improves health care providers' chances of successfully adopting data and analytics. However, discussions of all contributions of this dissertation clearly show that policymakers could significantly aid adoption of value-adding technologies. A pivotal element appears to be that the positive effects of certain technologies on care outcomes are not necessarily linked to economic benefits for health care providers. The results of the DCE provide a tangible example of this phenomenon. Radiologists valued assistance tools that saved time and hence improved productivity over tools that improved care quality.

Taking a system perspective, this mismatch in incentives could and should be addressed by targeted measures and reimbursement refinements by policymakers. In the end, also improvements in care quality need to be associated with financial incentives for health care providers. Establishing and strengthening this link has the potential to significantly fuel adoption of valuable data and analytics technologies.

Data and analytics has come a long way since 2013 when Eric Topol considered the digital world to be separated from the medical cocoon (Winslow, 2013). Advanced technologies such as CCDS and AI-based assistance tools open new and seemingly endless possibilities. Now is the time to put value-creating and viable concepts into operation at large scale. Today, it rests with health care providers to embrace the provided evidence on improvements in profitability, quality and patient satisfaction and make courageous investment decisions. Furthermore, policymakers need to rethink and adjust funding and reimbursement structures to the digital age to provide a basis for and incentivize the adoption of value-creating data and analytics by providers. It is about time for all health care providers to fully abandon their medical cocoon, embrace the digital world and take off with the help of data and analytics.

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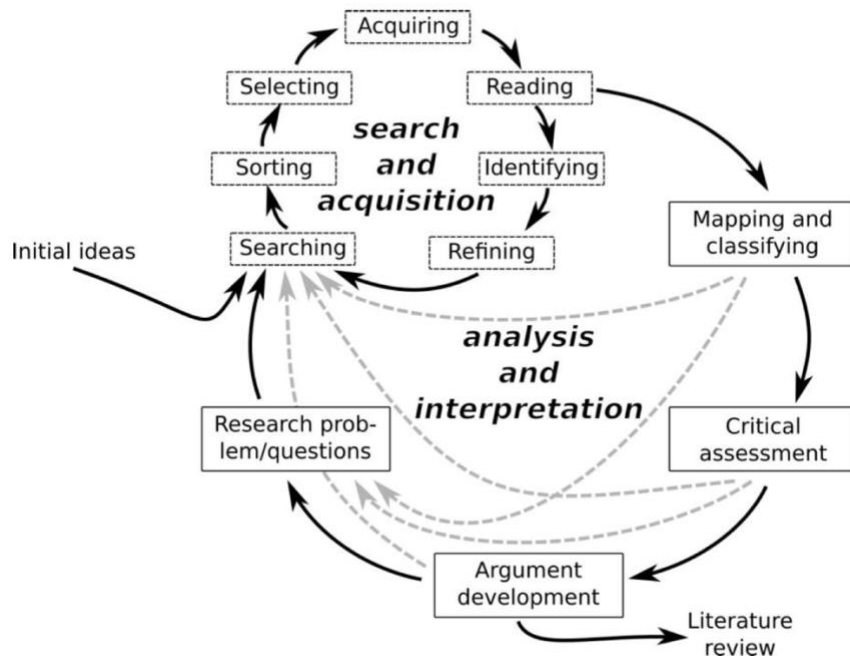
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Appendices

Appendix 1: The interlinked cycles of the hermeneutic process by Boell et al. (2014)



Appendix 2: Detailed search queries used for the PubMed and Google Scholar database searches

Google Scholar (01.01.2009 – 31.12.2019):

EHR (n=39)

allintitle: (EHR OR "electronic health record" OR "electronic health records") (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

EMR (n=35)

allintitle: (EMR OR "electronic medical record" OR "electronic medical records") (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

EPR (n=1)

allintitle: (EPR OR "electronic patient record" OR "electronic patient records") (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

Analytics (n=22)

allintitle: (analytics) (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

AI & Big Data (n=19)

allintitle: (AI OR "artificial intelligence" OR "big data") (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

Algorithms, ML & DL (n=31)

allintitle: (algorithm OR algorithms OR "machine learning" OR "deep learning") (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

Decision Support (n=18)

allintitle: ("decision support") (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

NLP (n=0)

allintitle: ("natural language processing" OR NLP) (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

Telemedicine (n=0)

allintitle: (telemedicine) (cost OR costs OR revenue OR benefit OR return OR ROI OR value OR efficiency OR productivity) (hospitals OR hospital OR practices OR practice OR provider OR providers)

Σ n=165

PubMed (01.01.2009 – 31.12.2019):

EHR (n=28)

((EHR[Title] OR "electronic health record"[Title] OR "electronic health records"[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

EMR (n=16)

((EMR[Title] OR "electronic medical record"[Title] OR "electronic medical records"[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

EPR (n=0)

((EPR[Title] OR "electronic patient record"[Title] OR "electronic patient records"[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

Analytics (n=10)

((analytics[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

AI & Big Data (n=1)

((AI[Title] OR "artificial intelligence"[Title] OR "big data"[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

Algorithms, ML & DL (n=17)

((algorithm[Title] OR algorithms[Title] OR "machine learning"[Title] OR "deep learning"[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

Decision Support (n=7)

(("decision support"[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

NLP (n=0)

(("natural language processing"[Title] OR NLP [Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

Telemedicine (n=0)

((telemedicine[Title])) AND (cost[Title] OR costs[Title] OR revenue[Title] OR benefit[Title] OR return[Title] OR ROI[Title] OR value[Title] OR efficiency[Title] OR productivity[Title]) AND (hospitals[Title] OR hospital[Title] OR practices[Title] OR practice[Title] OR provider[Title] OR providers[Title])

Σ n=79

Σ Σ n=244 (incl. duplicates)

Appendix 3: Overview of all published articles screened by title, abstract, and text (including reasons for exclusion)

Authors & Year	Title	Journal	Included?	Reason for exclusion
Adler-Milstein J, Green CE, Bates DW (2013)	A survey analysis suggests that electronic health records will yield revenue gains for some practices and losses for many	Health Affairs	✓	
Adler-Milstein J, Salzberg C, Franz C, Orav EJ, Newhouse JP, Bates DW (2013)	Effect of electronic health records on health care costs: longitudinal comparative evidence from community practices	Annals of Internal Medicine	✗	Not provider related
Almeida JP (2016)	A disruptive Big data approach to leverage the efficiency in management and clinical decision support in a Hospital	Porto Biomedical Journal	✓	
Andemariam B, Odesina V, Owarish-Gross J, et al. (2014)	A fast-track emergency department acute sickle cell pain management algorithm results in fewer hospital admissions, decreased length of stay and increased hospital revenue	The Journal of Pain	✗	No data or analytics (analogue)
Aponte P, Ballard DJ, Becker E, et al. (2011)	Exploring Financial and Non-Financial Costs and Benefits of Health Information Technology: The Impact of an Ambulatory Electronic Health Record on Financial and Workflow in Primary Care Practices and Costs of Implementation	Grant Final Report	✗	No economic analysis
Arunambika T, Senthilvadivu P (2019)	A survey on cost optimization across cloud storage providers: Offline and Online Algorithms	Journal of Analysis and Computation	✗	Not health care related
Bandera C (2017)	Value-added service providers for mobile education: empirical challenges and analytics	Electronic Commerce Research	✗	Not health care related
Bazzoli F (2016)	Analytics All-Stars: HDM Clinical Visionary Clive Fields, MD, believes data can help providers cope with value-based care	Health Data Management	✗	No economic analysis
Beresniak A, Schmidt A, Proeve J, et al. (2016)	Cost-benefit assessment of using electronic health records data for clinical research versus current practices: Contribution of the Electronic Health	Contemporary Clinical Trials	✗	Not provider related

Authors & Year	Title	Journal	Included?	Reason for exclusion
	Records for Clinical Research (EHR4CR) European Project			
Berger A, Zhao Q, Murphy B, Leeper NJ, Ting W, Berger JS (2018)	Patterns of Utilization and Cost of Health Care Among Patients With Chronic Coronary Artery Disease And/Or Peripheral Arterial Disease in Clinical Practice: Analyses of a Large Us Integrated Claims-EMR Database	Circulation	✗	Not provider related
Beria P, Bertolin A, Grimaldi R (2018)	Integration between Transport Models and Cost-Benefit Analysis to Support Decision-Making Practices: Two Applications in Northern Italy	Advances in Operations Research	✗	Not health care related
Brooks PB, Fulton ME (2019)	Demonstrating advanced practice provider value: Implementing a new advanced practice provider billing algorithm	Journal of the American Association of Nurse Practitioners	✗	No data or analytics (analogue)
Choi J, Lee S, Lee K, Lee J-h (2017)	Development of a Decision Support System for Estimation of Transportation Cost of 3PL Provider	Korean Management Science Review	✗	Not health care related
Choi JS, Lee WB, Rhee P-L (2013)	Cost-benefit analysis of electronic medical record system at a tertiary care hospital	Healthcare Informatics Research	✓	
Chuang T-YA, Yii N, Nyandowe M, Iyer R (2019)	Examine the impact of the implementation of an electronic medical record system on operating theatre efficiency at a teaching hospital in Australia	International Surgery Journal	✓	
Cinaroglu S, Baser O (2017)	Examination of Technical Efficiency of Public Hospital Associations Using Data Envelopment Analysis and Machine Learning Techniques	Ekonomik Yaklasim	✗	No data or analytics (analogue)
Coatney K (2018)	Big Data Analytics Capabilities, The Business Value Of Information Technology, And Healthcare Organizations: The Need For Consensus In Evidence-Based Medical Practices	American Journal of Medical Research	✗	No economic analysis
Collins LB, Ward CW, Boggs B (2019)	Dysphagia Severity and Decision Making Algorithm Impact on Length of Hospital Stay, Restraint Use and Cost in Stroke Patients	Stroke	✓	

Authors & Year	Title	Journal	Included?	Reason for exclusion
Cook J (2016)	Driving hospital efficiency: Data analytics is the key to insightful asset management	Health Management Technology	✗	No economic analysis
Cornide-Reyes H, Noël R, Riquelme F, et al. (2019)	Introducing Low-Cost Sensors into the Classroom Settings: Improving the Assessment in Agile Practices with Multimodal Learning Analytics	Sensors	✗	Not health care related
Cykert S, Lefebvre A (2011)	Regional extension coordinators: use of practice support and electronic health records to improve quality and efficiency	North Carolina Medical Journal	✗	No economic analysis
Dad K, Khan MJ, Jie W, Lee MC (2017)	A low cost genetic algorithm based control scheme for wheelchair control in hospital environment	Journal of Robotics, Networking and Artificial Life	✗	No data or analytics (analogue)
Dandu N, Zmistowski B, Chen AF, Chapman T, Howley M (2019)	How are Electronic Health Records Associated with Provider Productivity and Billing in Orthopaedic Surgery?	Clinical Orthopaedics and Related Research	✓	
De Leon S, Connelly-Flores A, Mostashari F, Shih SC (2010)	The business end of health information technology: Can a fully integrated electronic health record increase provider productivity in a large community practice?	Journal of Medical Practice Management	✓	
Demleitner NV (2015)	How to Change the Philosophy and Practice of Probation and Supervised Release: Data Analytics, Cost Control, Focus on Reentry, and a Clear Mission	Federal Sentencing Reporter	✗	Not health care related
Dias MM, Moreno AS, Maia LSM, et al. (2020)	A cost-effective algorithm for diagnosis of hereditary angioedema with normal C1 inhibitor: Applying molecular approach to clinical practice	Journal of Allergy and Clinical Immunology: In Practice	✗	No data or analytics (analogue)
Doub T (2013)	Your future as a provider: it's all in the data: problem: behavioral health providers lack the analytics capability to extract data's value	Behavioral Healthcare	✗	No economic analysis
Dulac JD, Pryor RW, Morrissey WW (2017)	A data-driven approach to improving clinical care and reducing costs the experiences of an academic health center and a hospital system in applying data	Healthcare Financial Management	✓	

Authors & Year	Title	Journal	Included?	Reason for exclusion
	analytics provide valuable lessons for other organizations that are just beginning such efforts, which are critically important for success under value-based payment			
Elkin PL, Liebow M, Bauer BA, et al. (2010)	The introduction of a diagnostic decision support system (DXplain™) into the workflow of a teaching hospital service can decrease the cost of service for diagnostically challenging Diagnostic Related Groups (DRGs)	International Journal of Medical Informatics	✓	
Encinosa WE, Bae J (2013)	Will meaningful use electronic medical records reduce hospital costs?	The American Journal of Managed Care	✓	
Everett BR, Sitton JT, Wilson M (2017)	Efficacy and cost-benefit analysis of a global environmental cleaning algorithm on hospital-acquired infection rates	Journal of Patient Safety	✗	No data or analytics (analogue)
Fleddermann A, Jones S, James S, Kennedy KF, Main ML, Austin BA (2018)	Implementation of best practice alert in an electronic medical record to limit lower-value inpatient echocardiograms	The American Journal of Cardiology	✓	
Fleming NS, Culler SD, McCorkle R, Becker ER, Ballard DJ (2011)	The financial and nonfinancial costs of implementing electronic health records in primary care practices	Health Affairs	✗	Not provider related
Furukawa MF (2011)	Electronic medical records and the efficiency of hospital emergency departments	Medical Care Research and Review	✓	
Furukawa MF, Raghu T, Shao BB (2010)	Electronic medical records and cost efficiency in hospital medical-surgical units	INQUIRY: The Journal of Health Care Organization, Provision, and Financing	✓	
Gardner E (2009)	Trial runners: A two-physician practice goes on a roll with its EHR, generating extra revenue from clinical trials	Health Data Management	✗	No economic analysis

Authors & Year	Title	Journal	Included?	Reason for exclusion
Gillespie G (2016)	IT solves the payment puzzle: Providers deploy analytics, cost estimators as model changes	Health Data Management	✗	No economic analysis
González-Del Vecchio M, Catalán P, de Egea V, et al. (2015)	An algorithm to diagnose influenza infection: evaluating the clinical importance and impact on hospital costs of screening with rapid antigen detection tests	European Journal of Clinical Microbiology & Infectious Diseases	✗	No data or analytics (analogue)
Haq SM (2009)	Anemia analyzer: algorithm and reflex testing in clinical practice leading to efficiency and cost savings	Studies in Health Technology and Informatics	✗	No data or analytics (analogue)
Hargreaves JS (2010)	Will electronic personal health records benefit providers and patients in rural America?	Telemedicine and e-Health	✗	No economic analysis
Haynes N, Egan D (2017)	Revisiting the relevance of economic theory to hotel revenue management education and practice in the era of Big Data	Research in Hospitality Management	✗	Not health care related
Highfill T (2019)	Do hospitals with electronic health records have lower costs? A systematic review and meta-analysis	International Journal of Healthcare Management	✓	
Hill Jr RG, Sears LM, Melanson SW (2013)	4000 clicks: a productivity analysis of electronic medical records in a community hospital ED	The American Journal of Emergency Medicine	✗	No economic analysis
Hollenbeck SM, Bomar JD, Wenger DR, Yaszay B (2017)	Electronic medical record adoption: the effect on efficiency, completeness, and accuracy in an academic orthopaedic practice	Journal of Pediatric Orthopaedics	✓	
Huang L, Shea AL, Qian H, Masurkar A, Deng H, Liu D (2019)	Patient clustering improves efficiency of federated machine learning to predict mortality and hospital stay time using distributed electronic medical records	Journal of Biomedical Informatics	✗	No economic analysis
Huerta TR, Thompson MA, Ford EW, Ford WF (2013)	Electronic health record implementation and hospitals' total factor productivity	Decision Support Systems	✓	

Authors & Year	Title	Journal	Included?	Reason for exclusion
Hughes CA, Guirguis LM, Wong T, Ng K, Ing L, Fisher K (2011)	Influence of pharmacy practice on community pharmacists' integration of medication and lab value information from electronic health records	Journal of the American Pharmacists Association	✗	No economic analysis
James T, Jones C, Lafrance D, Nix M (2014)	Applying Data Analytics to Value-Based Cancer Care: Effects and Cost of Hospital Reencounters Following Cancer Surgery	Value in Health	✗	Not provider related
Jang Y, Lortie MA, Sanche S (2014)	Return on investment in electronic health records in primary care practices: a mixed-methods study	JMIR Medical Informatics	✓	
Jones KM, Afnan T (2019)	"For the benefit of all students": Student trust in higher education learning analytics practices	Proceedings of the Association for Information Science and Technology	✗	Not health care related
Joseph M (2010)	Meaningful streamlining: Hybrid practice management/EMR system boosts quality, reduces costs	Modern Healthcare	✓	
Kadish SS, Mayer EL, Jackman DM, et al. (2018)	Implementation to Optimization: A Tailored, Data-Driven Approach to Improve Provider Efficiency and Confidence in Use of the Electronic Medical Record	Journal of Oncology Practice	✓	
Kaneko K, Onozuka D, Shibuta H, Hagihara A (2018)	Impact of electronic medical records (EMRs) on hospital productivity in Japan	International Journal of Medical Informatics	✓	
Kazley AS, Ozcan YA (2009)	Electronic medical record use and efficiency: A DEA and windows analysis of hospitals	Socio-Economic Planning Sciences	✓	
Keenan MM, Firchau M, Kimura R, Fogg L, Rousseau J (2018)	Customizing Functionality in an Electronic Health Record to Capture Value of Provider-Specific Services	Cin: Computers, Informatics, Nursing	✗	No economic analysis
Keller ME, Kelling SE, Cornelius DC, Oni HA, Bright DR (2015)	Enhancing practice efficiency and patient care by sharing electronic health records	Perspectives in Health Information Management	✗	Not provider related

Authors & Year	Title	Journal	Included?	Reason for exclusion
Kelley M, Padula W (2019)	Development of a Machine Learning Algorithm to Predict Future Risk of Patients for high-cost hospital-acquired pressure injuries	Value in Health	✗	No economic analysis
Kosiorek D (2014)	Analyze cost, usability features carefully when considering EHR switch: Use the experience your practice gained during its first EHR implementation to make your new system work for you	Medical Economics	✗	No economic analysis
Kramer H, Lin G, Curtin C, Crowe E, Granderson J (2019)	Building analytics and monitoring-based commissioning: industry practice, costs, and savings	Energy Efficiency	✗	Not health care related
Lal LS, Raju A, Miller L-A, Chen H, Arbuckle R, Sansgiry SS (2011)	Impact of changes in reimbursement policies and institutional practice algorithm for utilization of erythropoietic-stimulating agents on treatment patterns and costs in anemic lymphoma patients	Supportive Care in Cancer	✗	Not provider related
Lee YH (2018)	Efficiency improvement in a busy radiology practice: determination of musculoskeletal magnetic resonance imaging protocol using deep-learning convolutional neural networks	Journal of Digital Imaging	✓	
Li K, Naganawa S, Wang K, et al. (2012)	Study of the cost-benefit analysis of electronic medical record systems in general hospital in China	Journal of Medical Systems	✓	
Mayeda E, Gerland A (2018)	Using analytics to design provider networks for value-based contracts: To build a successful provider network in a value-based world, health care organizations should collect and analyze several key pieces of data	Healthcare Financial Management	✗	No economic analysis
McFarland A (2017)	A cost utility analysis of the clinical algorithm for nasogastric tube placement confirmation in adult hospital patients	Journal of Advanced Nursing	✗	No data or analytics (analogue)
Mercer C, Bell G, Low N, Estcourt C, Brook G, Cassell J (2012)	Quantifying the public health value of provider-led partner notification using an evidence-based algorithm with routinely-collected data	Sexually Transmitted Infections	✗	No data or analytics (analogue)

Authors & Year	Title	Journal	Included?	Reason for exclusion
Mertz L (2014)	Saving Lives and Money with Smarter Hospitals: Streaming analytics, other new tech help to balance costs and benefits	IEEE pulse	✗	Not provider related
Mertz L (2018)	Machine Learning Takes on Health Care: Leonard D'Avolio's Cyft Employs Big Data to Benefit Patients and Providers	IEEE pulse	✗	No economic analysis
Morrissey J (2015)	Re-imaging imaging: Providers looking to analytics tools to cope with value-based care	Health Data Management	✗	No economic analysis
O'Reilly-Shah V, Easton G, Gillespie S (2017)	Assessing the global reach and value of a provider-facing healthcare app using large-scale analytics	BMJ Global Health	✗	No economic analysis
Ogundipe OF, Van den Bergh R, Thierry B, et al. (2019)	Better care for babies: the added value of a modified reverse syphilis testing algorithm for the treatment of congenital syphilis in a maternity Hospital in Central African Republic	BMC pediatrics	✗	No data or analytics (analogue)
Okumura LM, Veroneze I, Bugardt CI, Fragoso MF (2016)	Effects of a computerized provider order entry and a clinical decision support system to improve cefazolin use in surgical prophylaxis: a cost saving analysis	Pharmacy Practice (Granada)	✓	
Patt DA, Nubie M, Kazzaz DR, et al. (2012)	Clinical decision support tools to improve quality and practice efficiency across a large network of oncology practices	Journal of Clinical Oncology	✗	No data or analytics (analogue)
Peck JS, Benneyan JC, Nightingale DJ, Gaehde SA (2014)	Characterizing the value of predictive analytics in facilitating hospital patient flow	IIE Transactions on Healthcare Systems Engineering	✓	
Pyron L, Carter-Templeton H (2019)	Improved Patient Flow and Provider Efficiency After the Implementation of an Electronic Health Record	CIN: Computers, Informatics, Nursing	✓	
Qinglan Y, Yushan Z (2015)	The value and practice of learning analytics in computer assisted language learning	Studies in Literature and Language	✗	Not health care related

Authors & Year	Title	Journal	Included?	Reason for exclusion
Quadros DG, Neville IS, Urena FM, Solla DJF, Paiva WS, Teixeira M (2019)	Safety and Costs Analysis of a Fast-track Algorithm for Early Hospital Discharge After Brain Tumor Surgery	Neurosurgery	✓	
Qutub M, Govindan P, Vattappillil A (2019)	Effectiveness of a Two-Step Testing Algorithm for Reliable and Cost-Effective Detection of Clostridium difficile Infection in a Tertiary Care Hospital in Saudi Arabia	Medical Sciences	✗	No data or analytics (analogue)
Rahmawati SR (2019)	Could We Derive Benefit From Implementing Electronic Medical Records In Hospital?: A Structured Evidence and Narrative Review	ARKESMAS (Arsip Kesehatan Masyarakat)	✓	
Redd TK, Read-Brown S, Choi D, Yackel TR, Tu DC, Chiang MF (2014)	Electronic health record impact on productivity and efficiency in an academic pediatric ophthalmology practice	Journal of American Association for Pediatric Ophthalmology and Strabismus	✓	
Reis ZSN, Maia TA, Marcolino MS, Becerra-Posada F, Novillo-Ortiz D, Ribeiro ALP (2017)	Is there evidence of cost benefits of electronic medical records, standards, or interoperability in hospital information systems? Overview of systematic reviews	JMIR Medical Informatics	✓	
Rivera J, Delaney S (2015)	Using business analytics to improve outcomes: Orlando Health is taking advantage of customized solutions to get its hospital and physician practice revenue cycle systems in synch and strengthen its organization operationally and financially	Healthcare Financial Management	✓	
Rommers MK, Zwaveling J, Guchelaar H-J, Teepe-Twiss IM (2013)	Evaluation of rule effectiveness and positive predictive value of clinical rules in a Dutch clinical decision support system in daily hospital pharmacy practice	Artificial Intelligence in Medicine	✗	No data or analytics (analogue)
Rosenbluth G, Wilson SD, Maselli JH, Auerbach AD (2011)	Analgesic prescribing practices can be improved by low-cost point-of-care decision support	Journal of Pain and Symptom Management	✗	No data or analytics (analogue)

Authors & Year	Title	Journal	Included?	Reason for exclusion
Samir M (2009)	Anemia analyzer: algorithm and reflex testing in clinical practice leading to efficiency and cost savings	Advances in Information Technology and Communication in Health	✗	No data or analytics (analogue)
Schnaus MJ, Michalik M, Skarda P (2017)	Effects of Electronic Medical Record Display on Provider Ordering Behavior: Leveraging the EMR to Improve Quality and Costs	The American Journal of Medicine	✓	
Scholz J, Portela LD, Abe TMO, et al. (2016)	Cost-effectiveness analysis of smoking-cessation treatment using electronic medical records in a cardiovascular hospital	Clinical Trials and Regulatory Science in Cardiology	✗	No data or analytics (analogue)
Schouten P (2013)	Big data in health care: solving provider revenue leakage with advanced analytics	Healthcare Financial Management	✓	
Séroussi B, Soulet A, Spano J-P, et al. (2013)	Which patients may benefit from the use of a decision support system to improve compliance of physician decisions with clinical practice guidelines: a case study with breast cancer involving data mining	Studies in Health Technology and Informatics	✗	No economic analysis
Silow-Carroll S, Edwards JN, Rodin D (2012)	Using electronic health records to improve quality and efficiency: the experiences of leading hospitals	Issue Brief (Commonw Fund)	✓	
Stekel SF, Long Z, Tradup DJ, Hangiandreu NJ (2019)	Use of Image-Based Analytics for Ultrasound Practice Management and Efficiency Improvement	Journal of Digital Imaging	✓	
Stoves J, Connolly J, Cheung CK, et al. (2010)	Electronic consultation as an alternative to hospital referral for patients with chronic kidney disease: a novel application for networked electronic health records to improve the accessibility and efficiency of healthcare	Quality and Safety in Health Care	✓	
Taghavi A, Monem H (2018)	Increasing the Efficiency of Using CCU Beds of Hospitals through Optimization and Combination of Genetic Algorithm and Imperialist Competitive	Journal of Health and Biomedical Informatics	✗	No economic analysis

Authors & Year	Title	Journal	Included?	Reason for exclusion
Terry K (2011)	Rev up your EHR: how to optimize performance; Learn ways to increase revenue, improve practice efficiency and quality	Medical Economics	✗	No economic analysis
Terry K (2014)	Value-based incentives can help practices offset EHR costs	Medical Economics	✓	
Terry K (2014)	Use your EHR system to boost practice revenue	Contemporary OB/GYN	✗	No economic analysis
Teuben M, Löhr N, Jensen KO, et al. (2019)	Improved pre-hospital care efficiency due to the implementation of pre-hospital trauma life support (PHTLS®) algorithms	European Journal of Trauma and Emergency Surgery	✗	No data or analytics (analogue)
Teufel II RJ, Kazley AS, Ebeling MD, Basco Jr WT (2012)	Hospital electronic medical record use and cost of inpatient pediatric care	Academic Pediatrics	✗	No economic analysis
Thompson G, O'Horo JC, Pickering BW, Herasevich V (2015)	Impact of the Electronic Medical Record on Mortality, Length of Stay, and Cost in the Hospital and ICU: A Systematic Review and Metaanalysis	Critical Care Medicine	✓	
Urbinati A, Bogers M, Chiesa V, Frattini F (2018)	How do Provider Companies Create and Capture Value from Big Data Technology: An Exploratory Multiple Case Study Analysis	Academy of Management Global Proceedings	✗	Not health care related
Urbinati A, Bogers M, Chiesa V, Frattini F (2019)	Creating and capturing value from Big Data: A multiple-case study analysis of provider companies	Technovation	✗	Not health care related
Uslu A, Stausberg J (2011)	Value of the electronic medical record for hospital care: A review of the literature	Journal of Healthcare Engineering	✓	
Van der Maas M, Steuten L (2015)	A PCT-algorithm to guide antibiotic therapy in patients hospitalized with COPD exacerbations leads to net cost savings by reducing frequency and duration of antibiotic use as compared to current practice	Value in Health	✗	No data or analytics (analogue)

Authors & Year	Title	Journal	Included?	Reason for exclusion
Verhoye E, Vandecandelaere P, De Beenhouwer H, et al. (2015)	A hospital-level cost-effectiveness analysis model for toxigenic <i>Clostridium difficile</i> detection algorithms	Journal of Hospital Infection	✗	No data or analytics (analogue)
Voermans AM, Mewes JC, Broyles MR, Steuten LM (2019)	Cost-Effectiveness Analysis of a Procalcitonin-Guided Decision Algorithm for Antibiotic Stewardship Using Real-World US Hospital Data	Omics: A Journal of Integrative Biology	✗	No data or analytics (analogue)
Voleti VB, Braunstein AL, Mahabir C, Schrier A, Chiang MF (2011)	Evaluation Of An Academic Eye Clinic'S Practice Efficiency During The Early Transition Period To An Electronic Health Record System	Investigative Ophthalmology & Visual Science	✓	
Wagholikar KB, Hankey RA, Decker LK, et al. (2015)	Evaluation of the effect of decision support on the efficiency of primary care providers in the outpatient practice	Journal of Primary Care & Community Health	✓	
Wang H, Cui Z, Chen Y, Avidan M, Abdallah AB, Kronzer A (2018)	Predicting hospital readmission via cost-sensitive deep learning	IEEE/ACM Transactions on Computational Biology and bioinformatics	✓	
Wilson G, Kishk M (2013)	A decision support model proving 'value for money' selection of elements and components on hospital refurbishments: development of a functioning prototype	Construction Engineering	✗	Not health care related
Wuest TK (2019)	CORR Insights@: How are Electronic Health Records Associated with Provider Productivity and Billing in Orthopaedic Surgery?	Clinical Orthopaedics and Related Research	✗	No economic analysis
Xiao Y, Meng B, Tang T, Wu Y, Xie R (2017)	Research and Practice for Leveraging Big Data in Smart Education: Value and Path	e-Education Research	✗	Not health care related
Zeng Y-c, He T, Li X-h, Li J-q, Xiao F (2012)	Study on the Cost Audit of Electronic Medical Records of 65855 Patients Discharged from the Hospital	Hospital Administration Journal of Chinese People's Liberation Army	✗	No economic analysis

Authors & Year	Title	Journal	Included?	Reason for exclusion
Zhang J, Zheng T, Fang J (2013)	Application Prospect of EPR System in Total Cost Accounting of Hospitals	Chinese Health Economics	✗	No economic analysis
Zimlichman E, Keohane C, Franz C, et al. (2013)	Return on investment for vendor computerized physician order entry in four community hospitals: the importance of decision support	The Joint Commission Journal on Quality and Patient Safety	✓	

Appendix 4: Detailed syntheses of the final 50 studies included in the review

Study	Objective	Findings	Methodology & data	Region	Categorization
Systematic literature search (Google Scholar & PubMed, n=43)					
[20] Highfill, T. (2019): Do hospitals with electronic health records have lower costs? A systematic review and meta-analysis	→ Presents a systematic review and meta-analysis of literature examining the effect of EHR introduction on hospital costs thereby differentiating between “basic” (incl. data repository & information system) and “advanced” (incl. computerized physician order entry & clinical decision support) EHRs	→ Overall, the meta-analysis revealed 1.1% to 13.8% lower costs for hospitals that deployed an EHR (95% CI) → Hospitals with “basic” EHRs were found to have 0.3% to 23.8% lower costs (95% CI) → Hospitals with “advanced” EHRs showed 3% lower costs, however this effect was not statistically significant	Systematic literature review and meta-analysis based on 7 articles with no limitation on publication date	Various	→ Electronic Health Records → Direct positive economic impact
[21] Rahmawati et al. (2018): Could We Derive Benefit From Implementing Electronic Medical Records In Hospital?: A Structured Evidence and Narrative Review	→ Narrative review of the impact of EHR introductions on efficiency and outcomes	→ Overall, the impact of EHR introductions on provider efficiency extracted from the included studies was ambiguous → The authors identified several benefits of EHR introduction including reduced length of stay (LOS) or decreased infection rate → However, studies were partly contradictory especially related to the impact on average LOS with some studies showing increased times	Narrative review including 12 studies from 2008 to 2018 in a qualitative synthesis in accordance with the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement	Various	→ Electronic Health Records → Mixed economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
		→ Identified disadvantages included increased costs per patient accompanied by lower efficiency in medical-surgical settings			
[22] Reis et al. (2017): Is there evidence of cost benefits of electronic medical records, standards, or interoperability in hospital information systems? Overview of systematic reviews	→ Presents an overview of systematic reviews with the primary goal of evaluating impact of EHR, interoperability and standards on cost-effectiveness, as well as, quality of care as secondary goal	<ul style="list-style-type: none"> → The authors identified preliminary benefits of EHRs and related components on the quality of care → Overall, cost-effectiveness could not clearly be examined due to heterogeneous study designs, but mixed effects were identified for EHRs without Health Information Exchange (HIE) 	Overview of systematic reviews through February 2016 including 6 studies in accordance with the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement	Various	<ul style="list-style-type: none"> → Electronic Health Records → Mixed economic impact
[23] Uslu et al. (2011): Value of the electronic medical record for hospital care: A review of the literature	→ Presents a literature review on the impact of EHR on quality of care and hospital costs	<ul style="list-style-type: none"> → 5 studies provided slightly positive indices regarding a positive effect on care outcomes after EHR introduction and 1 found mixed results → The authors stated that 5 studies also provided evidence for a positive impact on cost for care providers mainly linked to time savings required for administrative and archiving work, as well as, savings in nursing costs → 1 study implied negative effects on provider economics → Nevertheless, many of the mentioned studies did not provide actual costs savings, but rather efficiency improvements that could potentially lead to savings 	Literature review based on 7 included studies in the field of interest resulting from a search between 2004 and 2010	Various	<ul style="list-style-type: none"> → Electronic Health Records → Mixed economic impact
[30] Thompson et al. (2015): Impact of the Electronic Medical Record on Mortality, Length of Stay, and Cost in the Hospital and	→ Presents a systematic review and meta-analysis of the effects of health information technology (HIT) on mortality, length	<ul style="list-style-type: none"> → Overall, electronic interventions did not show a substantial effect on mortality, LOS or costs → The only statistically significant effect was the positive impact of surveillance systems on mortality, other effects on quality indicators were not statistically significant 	Systematics review and meta-analysis based on 45 studies through July 2013 in the field of interest of which 26 were included in the quantitative meta-analysis deploying	Various	<ul style="list-style-type: none"> → Electronic Health Records → Mixed economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
ICU: A Systematic Review and Metaanalysis	of stay (LOS) and costs for hospitals	→ Cost effects were considered by 14 studies, however, could not be quantitatively synthesized due to significant heterogeneity, however, 8 of the 14 studies showed a decrease in cost after an electronic intervention	Dersimonian and Laird random effects models		
[31] Choi et al. (2013): Cost-benefit analysis of electronic medical record system at a tertiary care hospital	→ Examines a cost-benefit analysis (CBA) for an EHR implementation at the Samsung Medical Center general hospital	→ Negative 5-year net-present-value (NPV) of \$385,000 and a positive 8-year NPV of \$3,617,000 were determined → The positive 8-year NPV was achieved by fully cutting “legacy” costs like paper records (incl. related FTEs) and by generating additional revenue through medical transcriptions and by repurposing former paper record space into clinical space	Cost-benefit analysis (CBA) based on retrospective financial data of the Samsung Medical Center general hospital and expert interviews to allocate the share of benefits and cost reductions accredited to EHR introduction	South Korea	→ Electronic Health Records → Mixed economic impact
[32] Li et al. (2012): Study of the cost-benefit analysis of electronic medical record systems in general hospital in China	→ Examines the 6-year return on investment (ROI) of an EHR implementation in a Chinese general hospital	→ The EHR installation broke even after 3 years and showed a positive 6-year ROI of \$559,025 → The positive ROI was mainly driven by savings in new record creation, FTE savings, savings related to ADEs, improved charge capture and decreased billing errors	Return on investment calculation based on financial data and expert opinions on potential savings at a 700-bed general hospital with benefits/saving categories including storage requirements, record maintenance, new record creation, charge capture, adverse drug effects (ADE) and others	China	→ Electronic Health Records → Direct positive economic impact
[33] Zimlichman et al. (2013): Return on investment for vendor computerized physician order entry in four community hospitals: the importance of decision support	→ Examines the return on investment (ROI) of a vendor computerized physician order entry (CPOE) on the basis of a reduction in preventable adverse drug effects (ADE)	→ Hospital group A (2 hospitals) had a comparably lower installation cost for the vendor CPOE and was able to break even after 8 years and achieved a 11.3% 10-year ROI → Hospital group B (2 hospitals) with comparably higher installation costs showed a negative 10-year ROI of 3.1% → The authors attributed the rather low ROIs and a long break-even timeline for group A to a lack of clinical decision support tools at all hospitals	10-year cost-benefit analysis including ROI, net cash flow and breakeven points evaluating the introduction of a CPOE at four hospitals with benefits being only based on reductions in ADEs	USA	→ Electronic Health Records → Mixed economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
[34] Jang et al. (2014): Return on investment in electronic health records in primary care practices: a mixed-methods study	→ Examines the return on investment (ROI) of EHR introduction for 17 Canadian primary care clinics	<ul style="list-style-type: none"> → Primary care clinics typically recovered their EHR investment within 6.2 to 17.4 months (95% CI) going along with increased patient volume and practice revenue → More recent EHR systems and those using flow sheets showed shorter break-even timelines → Surveyed physicians stated benefits such as better ability to manage results, faster information retrieval and better patient encounter preparation 	Mixed-methods study determining break-even times based on clinic financial and care data, as well as, physician surveys at 132 community-based, primary care clinics in Canada	Canada	<ul style="list-style-type: none"> → Electronic Health Records → Direct positive economic impact
[35] Adler-Milstein et al. (2013): A survey analysis suggests that electronic health records will yield revenue gains for some practices and losses for many	→ Examines the 5-year return-on-investment (ROI) of EHR implementation for a network of 49 community practices	<ul style="list-style-type: none"> → EHR introduction had a negative 5-year ROI of \$43,743 per physician on average → 27% of practices achieved a positive ROI by fully cutting “legacy” costs like paper records and dictation and also leveraging EHR for revenue generation via increased efficiency and billing 	Cost-benefit analysis (CBA) based on retrospective practice accounting data and a survey completed by practices allocating the share of benefits and cost reductions accredited to EHR introduction	United States of America (USA)	<ul style="list-style-type: none"> → Electronic Health Records → Direct negative economic impact
[36] Encinosa et al. (2013): Will meaningful use electronic medical records reduce hospital costs?	→ Examines the impact of establishing different levels of EHR (Meaningful Use functions 1-5) on Adverse-Drug-Effects and respective costs	→ Adopting all 5 functions reduced ADEs from 3.6% to 1.4% with the potential to save the associated costs of \$4,790 per avoided ADE ($p < 0.01$)	Multivariate logit regression analysis based on Florida inpatient hospitalization data, American Hospital Association Annual Survey data and Medicare Hospital Compare data	USA	<ul style="list-style-type: none"> → Electronic Health Records → Direct positive economic impact
[37] Joseph, M. (2010): Meaningful streamlining: Hybrid practice management/EMR system boosts quality, reduces costs	→ Presents personnel cost savings related to an EHR introduction for the US-based Westmed Medical Group provider network	→ The introduction of an EHR reduced the number of paper record FTEs by 17 FTEs, saving more than \$6 million in 5 years	Qualitative case study of the Westmed Medical Group network	USA	<ul style="list-style-type: none"> → Electronic Health Records → Direct positive economic impact
[39] Silow-Carroll et al. (2012): Using electronic health records to improve quality and efficiency: the experiences of leading hospitals	→ Presents the experiences of 9 hospitals that implemented an EHR in terms of quality of care and efficiency	<ul style="list-style-type: none"> → Time efficiency: Mostly anecdotal information that revealed an ambiguous effect of EHRs on time savings for physicians, however, one hospital reported it was able to reduce or redirect to higher-value activities 190 FTEs since the EHR took over certain tasks → Patient volume: Hospitals reported a positive effect on “throughput”, e.g., the time to 	Qualitative and semi-quantitative case studies of 9 major US-based hospitals (Carilion Roanoke Memorial Hospital, Virginia; Doctors Hospital, Ohio; Geisinger Wyoming Valley Hospital, Pennsylvania; Gundersen Lutheran Medical Center,	USA	<ul style="list-style-type: none"> → Electronic Health Records → Direct positive economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
		<p>assign a bed for a newly admitted patient decreased by 90 minutes at one hospital and by 80% when admitting an emergency department patient</p> <p>→ Redundancies: It was perceived by all hospitals that redundant tests were reduced with one hospital reporting a laboratory test reduction of 18% and a radiology examination decrease of 6.3%</p> <p>→ Billing: One hospital reported it was able to reduce write-offs for care associated to inadequate documentation of the services or required waivers</p> <p>→ Return on investment (ROI): One hospital calculated the ROI of the EHR estimating an annualized benefit of \$50.7 million and breaking even after 5 years</p>	<p>Wisconsin; Metro Health Hospital, Michigan; New York-Presbyterian Hospital, New York; Sentara Norfolk General Hospital, Virginia; VA Central Iowa Health Care System, Iowa; Yale-New Haven Hospital, Connecticut)</p>		
<p>[40] Schnaus et al. (2017): Effects of Electronic Medical Record Display on Provider Ordering Behavior: Leveraging the EMR to Improve Quality and Costs</p>	<p>→ Examines the impact of a temporary change in the preselected type of complete blood count (CBC) test (with vs. without differentials in an EHR’s computerized physician order entry (CPOE) tool (i.e. physicians searching for “complete blood count” in the CPOE tool had the CBC with differentials pre-selected for a certain period of time)</p>	<p>→ Significantly more CBC tests with differentials were ordered in the change period vs. in the time before or after the change period</p> <p>→ Of CBCs ordered, 37.7% included differentials before the change period compared to 50% during the change period ($p < 0.01$)</p> <p>→ Since costs for a CBC without differentials was \$0.80 and \$2.92 with differentials, this temporary change in the tool resulted in an average daily cost increase for CBC testing of \$293.1</p> <p>→ This change could mainly be attributed to a simple change in pre-selection of the CPOE tool since other effects were controlled for</p>	<p>Linear regression statistical analysis for CBCs ordered at the Regions Hospital in Minnesota in 2016 before (June 16 to July 5), during (July 6 to July 28) and after (July 29 to August 20) the change with sample sizes of 13,242, 14,017 and 13,238 respectively; cost data obtained from internal laboratory operations</p>	<p>USA</p>	<p>→ Electronic Health Records → Direct negative economic impact</p>
<p>[41] Terry, K. (2014): Value-based incentives can help practices offset EHR costs</p>	<p>→ Presents two case studies of how EHR systems can support in generating additional revenue from participating in value-based payment or bonus schemes</p>	<p>→ Not having an EHR is seen to come with the “opportunity costs” of not being able to participate in value-based schemes such as accountable care organizations (ACO), patient-centered medical homes or pay-for-performance programs</p>	<p>Qualitative case studies of a 7-doctor nephrology practice and an internal medicine practice</p>	<p>USA</p>	<p>→ Electronic Health Records → Direct positive economic impact</p>

Study	Objective	Findings	Methodology & data	Region	Categorization
		<ul style="list-style-type: none"> → The first case study presents a 7-doctor nephrology practice that is a member of an ACO and participates in the Medicare Shared Savings Program thereby generating additional bonus revenues of an undisclosed number → The second case study presents an internal medicine practice participates in an ACO and collects pay-for-performance payments, also the practice generates some revenue from sharing quality data extracted from the EHR with public registries 			
<p>[42] Dandu et al. (2019): How are Electronic Health Records Associated with Provider Productivity and Billing in Orthopaedic Surgery?</p>	<p>→ Examines the impact of EHR introduction on patient volumes (productivity) and billing in orthopedic surgery</p>	<ul style="list-style-type: none"> → EHR introduction did not lead to higher overall volumes, i.e. productivity in general → Only total knee arthroplasty volumes increased by 4-7 surgeries (95% CI, $p < 0.001$) → EHR introduction did not affect billing 	<p>Retrospective multivariate analysis based on publicly available Medicare Utilization and Payment datasets</p>	<p>USA</p>	<ul style="list-style-type: none"> → Electronic Health Records → Neutral economic impact
<p>[43] Redd et al. (2014): Electronic health record impact on productivity and efficiency in an academic pediatric ophthalmology practice</p>	<p>→ Examines the impact of EHR introduction in a pediatric ophthalmology department on productivity in terms of patient volume and efficiency in terms of charting time and after-hours charting</p>	<ul style="list-style-type: none"> → A non-statistically significant 11% decrease ($p=0.18$) in clinical volume after EHR introduction was identified → Since no data on efficiency before EHR introduction in terms of charting was available, no efficiency impact of EHR could be shown 	<p>Retrospective statistical analysis based on patient volume data of four physicians pre- and post-EHR introduction with charting time and after-hours charting being considered only post-introduction</p>	<p>USA</p>	<ul style="list-style-type: none"> → Electronic Health Records → Neutral economic impact
<p>[44] Voletia et al. (2011): Evaluation Of An Academic Eye Clinic’s Practice Efficiency During The Early Transition Period To An Electronic Health Record System</p>	<p>→ Examines the impact of an EHR introduction on patient volume and visit cycle times at an eye clinic of an academic medical center</p>	<p>→ No statistically significant changes from before to after EHR installation could be observed in patient volume ($p=0.31$) and cycle times ($p=0.92$)</p>	<p>Retrospective statistical comparison of monthly patient visits and patient cycle times before and during the first three months after EHR introduction</p>	<p>USA</p>	<ul style="list-style-type: none"> → Electronic Health Records → Neutral economic impact
<p>[45] Kaneko et al. (2018): Impact of electronic medical records (EMRs) on hospital productivity in Japan</p>	<p>→ Examines the effect of EHR introduction in terms of labor productivity and multi-factor productivity (MFP) differentiating between “early adopter”,</p>	<ul style="list-style-type: none"> → EHR implementation had a significant negative impact on MFP growth only for the “late adopters” (0.31-0.82 OR, 95% CI) → No statistically significant relation was found for labor productivity growth 	<p>Logistic regression analysis of labor productivity and MFP growth based on data between 2006 and 2015 from 658 municipal hospitals in Japan</p>	<p>Japan</p>	<ul style="list-style-type: none"> → Electronic Health Records → Indirect negative economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
	“follower” and “late adopter” hospitals				
[46] De Leon et al. (2010): The business end of health information technology. Can a fully integrated electronic health record increase provider productivity in a large community practice?	→ Examines productivity of a 75-physician practice before and after EHR implementation	<ul style="list-style-type: none"> → Productivity decreases were observed at the time of EHR implementation → Productivity increased by 1.7% per month ($p < 0.001$) per provider after the EHR was fully implemented → The majority of gains could be associated to a newly introduced pay-for-performance program enabled by data capture of the EHR 	Longitudinal mixed model analysis of the productivity of 75 physicians in terms of patient volume at a large urban primary care practice between January 2005 and February 2009 before and after implementing an EHR	USA	<ul style="list-style-type: none"> → Electronic Health Records → Indirect positive economic impact
[47] Kadish et al. (2018): Implementation to Optimization: A Tailored, Data-Driven Approach to Improve Provider Efficiency and Confidence in Use of the Electronic Medical Record	→ Examines the effect of EHR training for physicians on physician confidence with system and efficiency in terms of time in system (TIS)	<ul style="list-style-type: none"> → Physicians reported a significant 36%-point increase in confidence using the EHR system after the training ($p < 0.001$) → Overall efficiency, i.e. TIS, showed only minimal improvements of less than 1 minute per appointment which was not statistically significant ($p = 0.1$) 	Semi-quantitative physician survey analysis to examine physician confidence and statistical comparison of TIS before and after training via paired Wilcoxon test	USA	<ul style="list-style-type: none"> → Electronic Health Records → Neutral economic impact
[48] Chuang et al. (2019): Examine the impact of the implementation of an electronic medical record system on operating theatre efficiency at a teaching hospital in Australia	→ Examines the impact on operating theater efficiency after an EHR introduction in terms of operation sessions starting late, average delay time and cancellations	<ul style="list-style-type: none"> → The EHR implementation resulted in temporarily reduced efficiency, i.e. an increase in delays in theatre start times from 13.2% to 88.0% of sessions during the first month post implementation ($p < 0.0001$) → Efficiency improved post implementation and got back to normal efficiency after 4 months of EHR usage ($p < 0.01$) 	Retrospective statistical analysis of operating theater data between September 2018 and January 2019 at a major acute teaching hospital	Australia	<ul style="list-style-type: none"> → Electronic Health Records → Indirect negative economic impact
[49] Furukawa et al. (2010): Electronic medical records and cost efficiency in hospital medical-surgical units	→ Examines the effect of EHR introduction on the efficiency of medical-surgical units in hospitals	<ul style="list-style-type: none"> → EHR implementation was on average associated with lower efficiency in medical-surgical units → Fully fledged EHR systems incl. computerized physician order entry (CPOE) & clinical decision support (CDS) did not have a significant effect on efficiency 	Stochastic frontier analysis (SFA) based on EHR implementation data from the Healthcare Information and Management Systems Society (HIMSS) databases and on costs and nurse staffing from the Annual Financial Disclosure Reports of the California Office of Statewide Health Planning and Development (OSHPD) of 365 Californian hospitals	USA	<ul style="list-style-type: none"> → Electronic Health Records → Indirect negative economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
[50] Hollenbeck et al. (2017): Electronic medical record adoption: the effect on efficiency, completeness, and accuracy in an academic orthopaedic practice	→ Examines the impact of EHR introduction in the orthopedic department of a hospital on efficiency in terms of patient volume, physicians needed per patient and record completeness	<ul style="list-style-type: none"> → No significant difference in monthly patient volumes was identified ($p=0.075$), however, more physicians were needed per patient resulting in a 19% reduction in volume per physician ($p<0.001$) → EHRs were 1.3 times more likely to include all important medical information → Physician surveys revealed concerns regarding efficiency and increased “off-hours” work for record keeping 	Retrospective comparative study at a 10-surgeon academic medical center based on 60 paper charts, 60 EHRs, billing data and a physician survey to qualitatively assess satisfaction and perceived efficiency	USA	<ul style="list-style-type: none"> → Electronic Health Records → Indirect negative economic impact
[51] Huerta et al. (2012): Electronic health record implementation and hospitals’ total factor productivity	→ Examines the impact of different kinds of EHR introductions (never, incremental, “big-bang”, etc.) on hospital efficiency measured as Total Factor Productivity (TFP)	<ul style="list-style-type: none"> → All kinds of EHR implementation result in lower efficiency of underlying care processes measured as Technological Change (TC) ($p=0.11$) → “Big bang”, i.e. the implementation of a fully-fledged EHR in a relatively short time-period approach, performing the worst → Some approaches were able to reach a slight improvement in overall productivity (TFP), however mainly linked to Technical Efficiency Change (EFFCH) improvements (i.e., physicians worked harder, not smarter) 	Frontier analysis measuring hospitals’ TFP split into Technical efficiency change (EFFCH) and Technological Change (TC) based on American Hospital Association (AHA) Annual Surveys of Hospitals (2006-2008)	USA	<ul style="list-style-type: none"> → Electronic Health Records → Indirect negative economic impact
[53] Furukawa et al. (2011): Electronic medical records and the efficiency of hospital emergency departments	→ Examines the relationship between sophistication of introduced EHR systems (no EHR, minimal EHR, fully functional EHR) and the efficiency of hospital-based emergency departments (ED)	<ul style="list-style-type: none"> → Fully functional EHR systems including computerized physician order entry and decision support, compared to no or only basic EHRs, were associated with lower ED length of stay (-11.4% to -33.4%, 95% CI), lower ED wait times (-19.3% to -108.9%, 90% CI) and lower ED treatment time (-7.1% to -19.1%, 95% CI) → These effects, however, varied significantly by patient acuity level and diagnostic services provided 	Survey-weighted ordinary least squares analysis utilizing US National Hospital Ambulatory Medical Care Survey (NHAMCS) data of 35,849 patients from 364 hospital-based EDs	USA	<ul style="list-style-type: none"> → Electronic Health Records → Indirect positive economic impact
[54] Kazley et al. (2009): Electronic medical record use and efficiency: A DEA and windows analysis of hospitals	→ Examines the relationship between EHR usage and hospital efficiency and efficiency improvement over time for a sample of 4606 non-federal acute care hospitals in the US	<ul style="list-style-type: none"> → A positive relationship between EHR usage and hospital efficiency is observed only for small hospitals (6-100 beds) which are 1.2 to 2.486 times more likely to be more efficient with an EHR (95% CI) → No efficiency increase over time is associated with EHR usage 	Data envelopment analysis for a sample of 4,606 non-federal acute care hospitals determining efficiency and change in efficiency considering non-physician FTEs, beds, capital assets and	USA	<ul style="list-style-type: none"> → Electronic Health Records → Indirect positive economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
[55] Pyron et al. (2019): Improved Patient Flow and Provider Efficiency After the Implementation of an Electronic Health Record	→ Examines the impact of EHR introduction on the efficiency of six urgent care clinics in terms of patient flow and average length of stay (LOS)	→ The EHR introduction had a positive impact on door-to-triage, door-to-provider and door-to-discharge times → Average LOS decreased from 109 minutes before to 73 minutes after EHR introduction	operating expenses as inputs and admissions and outpatient visits as outputs Retrospective longitudinal study based on several sources of data including an online survey, EHR data, paper chart data & direct observations of physicians at a hospital-owned freestanding urgent care system	USA	→ Electronic Health Records → Indirect positive economic impact
[56] Fleddermann et al. (2018): Implementation of best practice alert in an electronic medical record to limit lower-value inpatient echocardiograms	→ Examines the impact of introducing an automatic alert to avoid unnecessary imaging studies, i.e., transthoracic echocardiography (TTE)	→ Over 209 days, the alert triggered 3,226 times with 20% of the respective TTEs being cancelled, saving the costs for 20% of otherwise performed TTEs	Statistical analysis of TTE orders removed following 3,226 alerts over 209 days at Saint Luke’s Mid America Heart Institute	USA	→ Clinical Decision Support → Direct positive economic impact
[57] Okumura et al. (2016): Effects of a computerized provider order entry and a clinical decision support system to improve cefazolin use in surgical prophylaxis: a cost saving analysis	→ Examines the cost savings of implementing a clinical decision support (CDS) algorithm to improve prophylactic cefazolin (antibiotic) usage	→ Following the introduction of a computerized CDS system in 2005 the Defined Daily Doses/100 bed days decreased from 3.3 in 2002 to 2.15 in 2013 with an average yearly decrease of 0.53 (1.26 to -0.2, 95% CI) → Total cost savings were estimated at around \$50,000 between 2005 and 2013	Cross-sectional study based on prophylactic cefazolin usage and costs between 2002 and 2013 determining impact of decision support from 2005 on at a Brazilian university hospital	Brazil	→ Clinical Decision Support → Direct positive economic impact
[59] Quadros et al. (2019): Safety and Costs Analysis of a Fast-track Algorithm for Early Hospital Discharge After Brain Tumor Surgery	→ Examines the impact of introducing a fast-track algorithm to steer decision making on discharges after brain tumor surgery	→ The decision-making algorithm resulted in a significant length of stay reduction of 2 days considering the median ($p < 0.001$); without impacting complication or readmission rates → Significant cost reductions per case where observed post-implementation of \$630 per hospitalization ($p = 0.043$)	Retrospective cohort study based on data from brain tumor resections from a single neurosurgeon in 2017 comparing statistics pre- and post-implementation	Brazil	→ Clinical Decision Support → Direct positive economic impact
[60] Collins et al. (2019): Dysphagia Severity and Decision Making Algorithm Impact on Length of Hospital Stay, Restraint Use and Cost in Stroke Patients	→ Examines the effect of a post-stroke dysphagia (swallowing difficulty) severity and decision-making algorithm on length of stay, restraint use and costs	→ The decision-making algorithm resulted in an earlier insertion of a nasal feeding tube of on average 2.7 days compared to the non-supported regular treatment ($p = 0.146$) → Decreases in nasal tube replacements and repeat x-rays translated to decreased costs	Retrospective statistical analysis of data from 40 stroke patients at a US-based hospital	USA	→ Clinical Decision Support → Direct positive economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
[61] Waghlikar et al. (2015): Evaluation of the effect of decision support on the efficiency of primary care providers in the outpatient practice	→ Examines the impact of a clinical decision support (CDS) tool supporting patient chart review, decisions on preventive services and chronic disease management on the time for physicians to generate care recommendations	→ CDS assistance resulted in statistically significant average time savings of 3 minutes 16 seconds (65%) per patient ($p < 0.0001$)	Statistical comparison of time needed for physicians to arrive at a recommendation for patients (tracked via completion time of a checklist) with or without access to a decision support system for 30 patients of a primary care practice	USA	→ Clinical Decision Support → Indirect positive economic impact
[62] Elkin et al. (2010): The introduction of a diagnostic decision support system (DXplain™) into the workflow of a teaching hospital service can decrease the cost of service for diagnostically challenging Diagnostic Related Groups (DRGs)	→ Examines the impact of a diagnostic decision support system on case costs for diagnostically challenging patients in the General Medicine Department of a hospital	→ After tool implementation costs per case for diagnostically challenging patients decreased by between 3.7-19.5% (95% CI) → The authors hypothesize that the tool aids physicians to consider differential diagnoses potentially guiding them towards the correct diagnosis early on which avoids unnecessary treatments	Retrospective statistical analysis based on financial charges data for 1,173 control group and 564 intervention group cases at a 1,200-bed hospital	USA	→ Clinical Decision Support → Direct positive economic impact
[63] Lee, Y. H. (2018): Efficiency improvement in a busy radiology practice: determination of musculoskeletal magnetic resonance imaging protocol using deep-learning convolutional neural networks	→ Presents the potential utilization of a Deep-Learning Convolutional Neural Network (CNN) to determine Musculoskeletal magnetic resonance imaging (MRI) scanning protocols (i.e., determination of diagnostic performance, image quality, hardware and software and radiologist preferences, etc.)	→ The CNN successfully determined the optimal MRI scanning protocol with a sensitivity of 92.1% and specificity of 95.76% when compared to the radiologist expert opinions → Nevertheless, the authors only hypothesize and do not prove potential efficiency improvements in practice	Application of a CNN to a test set of 5,258 MRI scans determining one of two overarching optimal MRI protocol based on patient ages, gender, referring departments, examinations and other information	South Korea	→ Advanced Analytics → Indirect positive economic impact
[65] Wang et al. (2018): Predicting hospital readmission via cost-sensitive deep learning	→ Presents the utilization of a convolutional neural network (CNN) based on EHR data to predict 30-day, 60-day and 1-year hospital readmissions	→ The developed prediction tool which is also deployed in the hospital achieves a specificity of 89%, 93% and 79% for 30-day, 60-day and 1-year readmissions	Deployment of a CNN learning features from time series of vital signs and other data of real-world EHRs of a large US-based hospital's	USA	→ Advanced Analytics → Indirect positive economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
		→ The study does, however, not elaborate on potential economic impacts for the hospital when deploying the tool	general hospital ward and operating room data		
[66] Almeida et al. (2016): A disruptive Big data approach to leverage the efficiency in management and clinical decision support in a Hospital	→ Presents an analytics platform based on Big Data analysis via Machine Learning analyzing various sources of clinical information incl. EHRs to improve outcomes and efficiency	→ The System showed potential to increase efficiency by predicting 30% of intensive care unit (ICU) admissions and 50% of non-ICU inpatient deaths → Nevertheless, the authors only hypothesize this efficiency improvement potential	Qualitative case study of the São João Hospital Center	Portugal	→ Advanced Analytics → Indirect positive economic impact
[67] Peck et al. (2014): Characterizing the value of predictive analytics in facilitating hospital patient flow	→ Examines the impact of sharing predictions on the patient flow from emergency department (ED) to inpatient units (IU) with physicians by using discrete event simulation predictive analytics	→ Sharing information on crowding levels and total expected bed needs resulted in a statistically significant reduction in boarding time from the ED to IUs between 11.69% and 18.38% (dependent on hospital type) (p<0.05)	Discrete event simulation predictive analytics based on current emergency department information	USA	→ Advanced Analytics → Indirect positive economic impact
[68] Stekel et al. (2019): Use of Image-Based Analytics for Ultrasound Practice Management and Efficiency Improvement	→ Examines the advantages of a business/workflow analytics tool of an ultrasound practice in terms of equipment utilization and potential levers for efficiency improvements	→ Probe utilization data was used to support purchasing decision making resulting in not replacing broken probes and thereby saving \$10,000 → Scan time analysis resulted in a short-list of exams that would benefit the most from efficiency improvements → Physician efficiency analysis and benchmarking was seen valuable for best practice identification	Statistical analysis of an undisclosed number of ultrasound images and related metadata and procedure data such as exam length	USA	→ Business Analytics → Direct positive economic impact
[70] Dulac et al. (2017): A data-driven approach to improving clinical care and reducing costs	→ Presents two examples of how data analytics can reduce costs in health systems → UTMB Health (UTMB) used data analytics to uncover root causes of high preventable complication and readmission rates which implied penalty payment	→ UTMB was able to reduce penalty payment reductions to 0% by identifying imprecise EHR documentation and coding for two key obstetrical preventable complications and for a misinterpreted readmission reason → FA realized that best-performing physicians had \$1,232 lower costs for each heart failure case treated compared to lowest performers; Based on these findings a new program to potentially achieve best-performer efficiency was introduced	Qualitative case studies of UTMB Health, Texas and Franciscan Alliance, Indiana	USA	→ Business Analytics → Direct positive economic impact (UTMB) → Indirect positive economic impact (FA)

Study	Objective	Findings	Methodology & data	Region	Categorization
	<p>reductions totaling 3.5% of all payments</p> <p>→ Franciscan Alliance (FA) used data analytics to identify best-and worst-performing physicians to align performances, improve quality and save costs</p>				
[71] Rivera et al. (2015): Using business analytics to improve outcomes	<p>→ Presents the impact of several business analytics applications in the fields of physician performance and billing analytics at the Orlando Health Physician Group</p>	<p>→ Physician performance analytics: At the group, total contribution margins are calculated for every single provider to allow for benchmarking, target setting and tracking, however, an actual cost/efficiency-impact was not considered by the authors</p> <p>→ Billing analytics: By prescreening patients for potential payment defaults, around \$14 million per year are saved in bad debt write-offs according to the group</p>	Qualitative case study of the Orlando Health Physician Group	USA	<p>→ Business Analytics</p> <p>→ Direct positive economic impact</p>
[72] Schouten, P. (2013): Big data in health care: solving provider revenue leakage with advanced analytics	<p>→ Presents the impact of a pattern-based business analytics solution to address revenue leakage problems of a health system</p>	<p>→ The health system reported to increase the probability of detecting missed charges and decrease audit-related costs</p> <p>→ Overall, 2% of outpatient revenue that had previously gone unbilled was identified and audit costs were reduced by 75%</p> <p>→ The author claims that based on industry average, hospitals deploying analytics solutions are able to increase operating income by 10%</p>	Qualitative case study of a large US-based health system	USA	<p>→ Business Analytics</p> <p>→ Direct positive economic impact</p>
[73] Stoves et al. (2010): Electronic consultation as an alternative to hospital referral for patients with chronic kidney disease: a novel application for networked electronic health records to improve the accessibility and efficiency of healthcare	<p>→ Examines the advantages of an electronic medical round in the field of chronic kidney care connecting general practitioners (GP) with nephrologists in the UK</p>	<p>→ Electronic consultations between GPs and nephrologists resulted in an increase of 34%-points of referrals being considered as appropriate compared to paper-based communication (based on expert opinion) and in 78%-points fewer referrals to the hospital</p> <p>→ Physician and nephrologist interviews and questionnaires revealed perceived efficiency improvements following the introduction</p>	Quantitative comparison of patterns and quality between paper-based and electronic referrals based on 12-month referral data from 85 practices; Qualitative analysis of physician experiences in terms of efficiency and quality based on phone interviews and questionnaires	United Kingdom (UK)	<p>→ Telemedicine</p> <p>→ Indirect positive economic impact</p>

Study	Objective	Findings	Methodology & data	Region	Categorization
Targeted supplementary literature search (n=7)					
[5] Bright et al. (2012): Effect of clinical decision-support systems: a systematic review	→ Presents a systematic review and meta-analysis of the effects of clinical decision-support (CDS) systems on clinical outcomes, care processes, workload and efficiency, patient satisfaction, costs and provider use	<ul style="list-style-type: none"> → The authors observed limited evidence for benefits of CDS for clinical, economic, workload and efficiency outcomes → Significant positive impact could be shown for process measures such as better choices in the preventive care services, appropriate clinical studies or treatments ordered/prescribed → Modest positive impact could be shown for effects on morbidity with potential chain-effects for mortality → Modest evidence for a positive impact on costs was shown based on 22 studies 	Systematic review and meta-analysis based on a Medline search for studies between 1976 and January 2011 including 148 unique studies	Various	<ul style="list-style-type: none"> → Clinical Decision Support → Direct positive economic impact
[38] Zlabek et al. (2011): Early cost and safety benefits of an inpatient electronic health record	→ Examines the effect of EHR and computerized physician order entry (CPOE) implementation on quality, cost and safety of care	<ul style="list-style-type: none"> → Surrogates for quality were length of stay (LOS), 30-day readmissions, case mix and risk-adjusted mortality → Surrogates for costs were laboratory tests, radiology examinations, transcription costs and paper consumption → No significant effect of the EHR or CPOE was observed on the quality surrogates → The number of laboratory tests showed no significant change right after the EHR introduction, however, decreased by 18% from pre-EHR to 9 months post-CPOE introduction (p<0.001) → A similar pattern was observed for the number of radiology examinations with a 6.3% decrease after CPOE introduction (p<0.009) → Monthly transcription costs decreased by 74.6% right after EHR introduction resulting in \$667,896 savings in the year after EHR introduction (p<0.001) → Paper savings totaled \$30,531 in the year after EHR introduction (p<0.001) 	Pre-post statistical analysis based on data collected from 1 year before to 1 year after EHR introduction (CPOE system was introduced 3 months after EHR introduction) at the 325-bed Gundersen Lutheran Medical Center	USA	<ul style="list-style-type: none"> → Electronic Health Records → Direct positive economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
[52] McDowell et al. (2017): Effect of the implementation of a new electronic health record system on surgical case turnover time	→ Examines the impact of an EHR introduction on the efficiency of the operating room in terms of surgical case turnover time (TOT) at a US-based hospital	→ EHR implementation led to a significant efficiency decrease in the operating room persisting over a 5-month time period → TOT increased on average by 10 min (63 vs 53, $p < 0.001$) in the first month after implementation, which slightly improved in the second (59 vs. 53, $p < 0.001$) and remained at the pre-implementation baseline starting 5 months after EHR implementation	Statistical pre-post analysis of mean TOTs covering 25,499 cases divided into a pre- and post-implementation group	USA	→ Electronic Health Records → Indirect negative economic impact
[58] Levick et al. (2013): Reducing unnecessary testing in a CPOE system through implementation of a targeted CDS intervention	→ Examines the impact of introducing a clinical decision support (CDS) intervention, i.e. an alert for B-Type Natriuretic Peptide (BNP) testing, in a computerized physician order entry (CPOE) system, on test volume and costs	→ The introduction of the CDS alert resulted in a significant reduction of tests of 21% relative to the mean, ultimately saving an estimated \$92,000 per year	Multiple regression analysis based on a sample of 41,306 patients with at least one BNP test at the provider network between January 2008 and September 2011	USA	→ Clinical Decision Support → Direct positive economic impact
[64] Trivedi et al. (2018): Automatic determination of the need for intravenous contrast in musculoskeletal MRI examinations using IBM Watson's natural language processing algorithm	→ Examines the potential of using the IBM Watson Natural Language Processing (NLP) algorithm to automatically assign usage of intravenous contrast for musculoskeletal magnetic resonance imaging (MRI) during protocol creation based on free-text EHR information	→ Watson correctly assigned 129 of 140 "with contrast" (WC) protocols achieving a sensitivity of 0.743, a specificity of 0.921, a positive predictive value of 0.904 and an overall accuracy of 0.832 → The authors hypothesize that the utilization of this decision-support tool may increase efficiency for radiologist, however, do not provide any quantitative proof	Application of 8 traditional machine learning models and IBM Watson's deep learning-based NLP model to a dataset of 1,520 MRI exams (1,240 training set, 280 test set)	USA	→ Advanced Analytics → Indirect positive economic impact
[69] Swedberg, C. (2013): RFID boosts medical equipment usage at UK hospital	→ Presents the effect of introducing a radio-frequency identification (RFID) system to track loaned medical equipment on equipment utilization and lending costs	→ Equipment utilization rates increased from 5% to 40% reducing the need to rent or purchase equipment saving an estimated \$200,000 per year	Qualitative case study of a UK-based 1,100-bed hospital	UK	→ Business Analytics → Direct positive economic impact
[74] Heidbuchel et al. (2015): EuroEco (European Health Economic Trial on Home	Examines differences in costs and financial impact between remote and in-office follow-ups (FU) for	→ Remote FUs resulted in fewer in-person visits (3.79 +/-1.67 vs. 5.53 +/-2.32; $p < 0.001$), more non-office-based contacts (1.95 +/-3.29 vs. 1.01 +/-2.64; $p < 0.001$), more internet	Randomized, non-blinded, parallel-design trial in 17 provider centers from six European countries (Belgium,	Europe	→ Telemedicine → Neutral economic impact

Study	Objective	Findings	Methodology & data	Region	Categorization
Monitoring in ICD Patients): a provider perspective in five European countries on costs and net financial impact of follow-up with or without remote monitoring	implantable cardiac defibrillators (ICD) for providers, as well as, for health care payers	<p>sessions (11.02 +/-15.28 vs. 0.06 +/-0.31; $p < 0.001$), as well as, fewer hospitalizations and shorter length-of-stay (last 2 not statistically significant)</p> <p>→ On average, the total cost and net financial impact for providers did not show differences between remote and in-office FUs (Mean (95% CI): €204 (169–238) vs. €213 (182–243), not significant)</p> <p>→ Importantly, however, regional heterogeneity could be observed where providers in countries with remote FU reimbursement in place showed maintained or increased profit, whereas in other countries less profit was achieved</p>	Finland, Germany, UK, Spain & Netherlands) covering 242 patients completing the study		

Appendix 5: Long-list of attributes and attribute levels and exclusion process to arrive at short list

Attributes	Attribute levels
1 Provider	<ul style="list-style-type: none"> – Modality manufacturer – RIS/PACS software provider – AI-software startup – <i>University hospital</i>
2 Application	<ul style="list-style-type: none"> – Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI – Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation – Presorting of mammographic screening reports into “100% normal” (BI-RADS 1&2) and “suspicious” incl. automatic lesion marking – <i>Automatic detection and marking of carcinoma of the prostate in MRI scans incl. contouring for potential biopsy</i> – <i>Automatic morphometry in MRI brain scans incl. volumetry and lesion detection</i> – <i>Probability of COVID-19 infection (in %) based on lung CT scan</i>
3 <i>Automatic differential diagnosis proposal?</i>	<ul style="list-style-type: none"> – <i>Yes</i> – <i>No</i>
4 <i>Automatic report creation?</i>	<ul style="list-style-type: none"> – <i>Yes</i> – <i>No</i>
5 Quality	<ul style="list-style-type: none"> – <i>Worse</i> – <i>Same</i> – <i>Better</i>
6 Time savings	<ul style="list-style-type: none"> – Low – Medium – High
7 Pricing	<ul style="list-style-type: none"> – €3 per study – €6 per study – €9 per study

Excluded attributes/levels

2/3D indicates two/three-dimensional; AI, Artificial Intelligence; BI-RADS, Breast Imaging Reporting and Data System; CT, Computed Tomography; MRI, Magnetic Resonance Imaging; PACS, Picture Archiving and Communication System; RIS, Radiology Information System

Appendix 6: Experimental design and efficiency

Choice set	Attributes				
	1	2	3	4	5
1	2	2	1	2	6
	3	1	2	3	3
2	1	3	1	2	3
	2	2	2	1	9
3	1	2	1	1	3
	3	1	2	2	6
4	3	3	1	1	9
	1	2	2	3	6
5	3	2	1	3	3
	1	3	2	2	9
6	2	3	2	3	9
	3	1	1	1	6
7	1	1	1	3	9
	3	2	2	2	3
8	2	3	1	3	6
	1	2	2	2	9
9	2	1	2	1	3
	3	2	1	3	9
10	1	3	2	1	6
	2	1	1	2	3

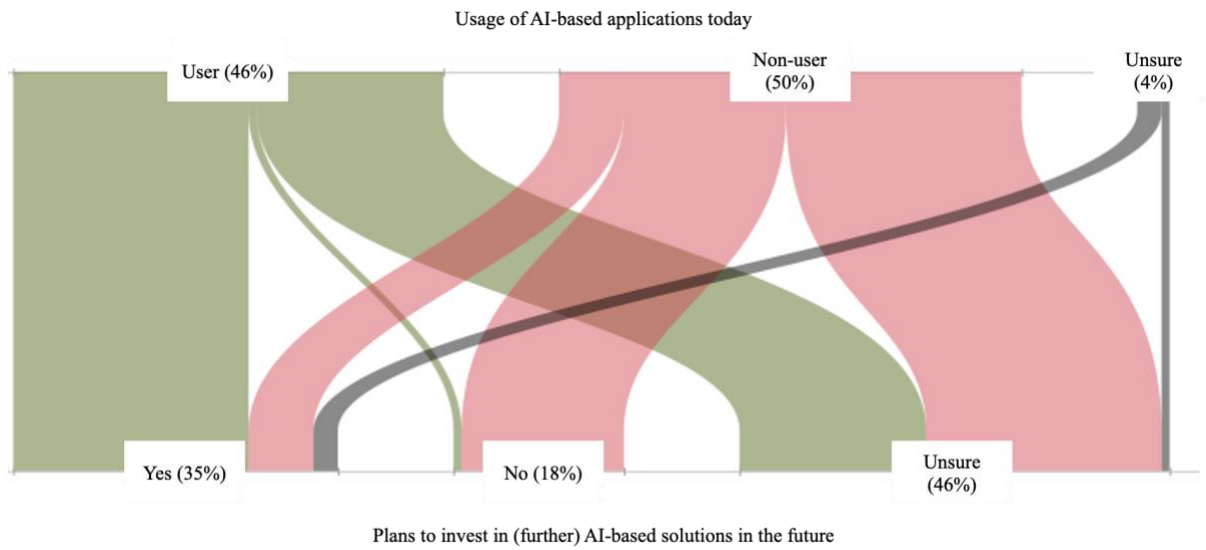
D-efficiency: 92.35%

Appendix 7: Overview of sample frame characteristics

Sample & sample frame characteristics		% sample	% sample frame
Gender	Male	78%	66%
	Female	21%	33%
Age	Mean	51	52.4
Job position	Total outpatient	74%	48%
	Total inpatient	25%	46%
	Employed in public authority	1%	1%
	Other	0%	5%
Specializations	Pediatric radiology	1%	2%
	Neuroradiology	7%	7%

Source: Ärztstatistik zum 31. Dezember 2020, Bundesärztekammer (retrieved from: https://www.bundesaerztekammer.de/fileadmin/user_upload/downloads/pdf-Ordner/Statistik_2020/2020-Statistik.pdf)

Appendix 8: The relationship between current AI usage and plans for (further) investments in AI



AI indicates Artificial Intelligence; Note: figures rounded

Appendix 9: Conditional logit estimations for simple model (model I) and models incorporating subject-related interactions (models II-IV)

n=114		Model I (simple model)		Model II		Model III		Model IV	
Variable	$\hat{\beta}$ (SE)	<i>p-value</i> (LogW)	$\hat{\beta}$ (SE)	<i>p-value</i> (LogW)	$\hat{\beta}$ (SE)	<i>p-value</i> (LogW)	$\hat{\beta}$ (SE)	<i>p-value</i> (LogW)	
Provider		0.1404 (0.853)		0.1354 (0.868)		0.1275 (0.894)		0.1398 (0.855)	
L1: Modality manufacturer	-0.0585 (0.0603)		-0.0569 (0.0607)		-0.0589 (0.0608)		-0.0573 (0.0613)		
L2: RIS/PACS provider	-0.0615 (0.0631)		-0.0652 (0.0636)		-0.0653 (0.0637)		-0.0647 (0.0641)		
L3: AI-software startup	0.12 (0.0608)		0.1221 (0.0613)		0.1242 (0.0614)		0.122 (0.0617)		
Application		<0.0001 (11.578)		0.0013 (2.889)		0.0014 (2.852)		<0.0001 (4.586)	
L1: Diagnostics (routine diagnostics)	0.2984 (0.0622)		0.2909 (0.2433)		0.2886 (0.2387)		0.1655 (0.2519)		
L2: Process efficiency (scan time reduction)	-0.3896 (0.0579)		-0.7046 (0.2504)		-0.6696 (0.238)		-0.8704 (0.2511)		
L3: Screening support (mammography)	0.0911 (0.0642)		0.4136 (0.2434)		0.381 (0.2413)		0.7049 (0.254)		
Quality		<0.0001 (9.727)		0.0524 (1.281)		0.0521 (1.283)		0.0519 (1.285)	
L1: Same	-0.2421 (0.039)		-0.3084 (0.1583)		-0.3033 (0.153)		-0.3032 (0.1531)		

	L2: Better	0.2421 (0.039)		0.3084 (0.1583)		0.3033 (0.153)		0.3032 (0.1531)	
Time savings			<0.0001 (13.702)		<0.0001 (14.064)		<0.0001 (14.127)		<0.0001 (14.449)
	L1: Low	-0.4339 (0.0637)		-0.4414 (0.0643)		-0.4427 (0.0644)		-0.451 (0.0649)	
	L2: Medium	0.039 (0.0584)		0.0382 (0.0589)		0.0382 (0.059)		0.0398 (0.0594)	
	L3: High	0.3949 (0.0587)		0.4031 (0.0592)		0.4045 (0.0593)		0.4113 (0.0598)	
Price	Price per study	-0.1607 (0.0176)	<0.0001 (20.895)	-0.1634 (0.0178)	<0.0001 (21.275)	-0.1593 (0.0178)	<0.0001 (21.185)	-0.1618 (0.018)	<0.0001 (20.554)
No-choice	No-choice	-1.4499 (0.1198)	<0.0001 (33.422)	-1.4611 (0.1209)	<0.0001 (33.361)	-1.4762 (0.1214)	<0.0001 (33.885)	-1.4851 (0.1222)	<0.0001 (33.926)
Subject-related interactions	Gender[M]* Application[Diagnostics]			-0.0899 (0.246)	0.0014 (2.862)	-0.0903 (0.2414)	0.0014 (2.850)	-0.0783 (0.2417)	0.001 (3.009)
	Gender[M]* Application[Process]			0.3435 (0.2523)		0.306 (0.2402)		0.3241 (0.2403)	
	Gender[M]* Application[Screening]			-0.2536 (0.2453)		-0.2157 (0.2434)		-0.2458 (0.244)	
	Gender[F]* Quality[Better]			0.1605 (0.1663)	0.0161 (1.793)	0.1571 (0.1611)	0.021 (1.679)	0.1585 (0.1613)	0.0205 (1.689)
	Budget responsibility[Y]* Price					-0.0347 (0.0105)	0.001 (3.005)	-0.0366 (0.0106)	0.0005 (3.278)
	Specialization[Mammo- graphy]*Application [Screening]							0.3873 (0.0932)	<0.0001 (4.068)

Model fit	AICc	2197.69	2186.10	2177.31	2162.70
	BIC	2242.88	2261.25	2257.44	2252.79
	-2LogLikelihood	2179.53	2155.67	2144.82	2126.10
	LogLikelihood	-1089.77	-1077.84	-1072.41	-1063.05

Appendix 10: Overview of single outcome indicators considered for calculation of consolidated O/E values for elective and emergency care

Consolidated O/E ratio	Averaged input indicators for consolidated O/E ratio
O/E ratio emergency care	Stroke (ICD: I21 & I22) <ul style="list-style-type: none"> - 30-day risk-adjusted standardized mortality rate Myocardial infarction (heart attack) (ICD: I61, I63 & I64) <ul style="list-style-type: none"> - 30-day risk-adjusted standardized mortality rate
O/E ratio elective care	Hip replacement surgery due to coxarthrosis (OPS: 5-820.0/8/9/x) <ul style="list-style-type: none"> - 90-day risk-adjusted standardized mortality rate - Risk-adjusted revision surgery within 365 days - Risk-adjusted surgical complications within 90/365 days - Risk-adjusted femoral fracture within 90 days

Appendix 11: Original DCE survey instrument in German

Fragebogen

1 Start

Umfrage zur Künstlichen Intelligenz (KI) in der Radiologie

Liebe Teilnehmerin, lieber Teilnehmer,

die **Künstliche Intelligenz**, oder kurz KI, findet langsam, aber stetig ihren Platz in unserem Alltag und auch unserem Gesundheitswesen. Speziell in der Radiologie konnten in letzter Zeit viele Erfolge vermeldet werden.

Sie als **Radiologin oder Radiologe** wissen am besten, wo und wie KI am besten Ihre täglichen Abläufe unterstützen könnte. Fakt ist, dass Sie in naher Zukunft aus einer Auswahl an kommerzialisierten KI-basierten Assistenzprogrammen auswählen können.

Interessanterweise werden die Präferenzen von Ärztinnen und Ärzten bisher wenig in die öffentliche Diskussion eingebunden. Diese Umfrage soll dies ändern und befasst sich daher mit der folgenden Frage:

„Wie werden KI-basierte Assistenzsysteme von Radiologinnen und Radiologen wahrgenommen und welche Eigenschaften sind besonders wichtig bei der Auswahl eines solchen Systems?“

Als kleines **Dankeschön** stellen wir Ihnen am Ende der Umfrage **eine Übersicht der aktuell in Deutschland verfügbaren Assistenzsysteme** auf KI-Basis in der Radiologie zur Verfügung. Außerdem können Sie gerne Ihre E-Mail Adresse hinterlassen, um einen Ergebnisbericht nach Abschluss des Projektes zu erhalten. **Selbstverständlich werden Ihre Angaben streng vertraulich behandelt, bleiben anonym und werden nicht für kommerzielle Zwecke genutzt.**

Wie läuft diese Umfrage ab?

Diese Umfrage wird **ca. 10-15 Min.** Ihrer Zeit in Anspruch nehmen und umfasst 2 Teile:

1. Fragen zu Ihrer Person, Ihrem Berufsalltag & bisheriger Erfahrung mit KI
2. Aufgabe zur Bestimmung Ihrer Präferenzen bezüglich KI in der Radiologie

Wer führt diese Umfrage durch?

Dieses Forschungsprojekt wird vom Lehrstuhl für Wirtschafts- und Sozialpolitik der **WHU – Otto Beisheim School of Management** mit Unterstützung der radiologischen Abteilungen des **Johanniter Krankenhauses in Bonn** (Prof. Dr. med. K. Wilhelm) und des **Uniklinikums Aachen** (PD Dr. med. Peter Isfort) durchgeführt. Bei Fragen und Anmerkungen können Sie jederzeit per Mail (philip.wedel@whu.edu) Kontakt aufnehmen.

Herzlichen Dank für Ihre Zeit!

2 Teil 1: Allgemeine Fragen

Geschlecht

- Weiblich
- Männlich
- Divers

Alter

Wo üben Sie hauptsächlich Ihre Tätigkeit aus?

- Krankenhaus
- Universitätskrankenhaus

- Radiologische Praxis
- Medizinisches Versorgungszentrum (MVZ)
- Behörde/Körperschaft (z.B. Bundeswehr, Gesundheitsamt, etc.)
- Sonstiges

In welcher Position üben Sie hauptsächlich Ihre Tätigkeit aus?

- Selbstständig niedergelassen
- Chefarzt/-ärztin im Krankenhaus
- Facharzt/-ärztin im Krankenhaus
- Assistenzarzt/-ärztin im Krankenhaus
- Angestellt in Praxis/MVZ
- Angestellt in Behörde/Körperschaft
- Ruhestand

Wie viele Befunde erstellen Sie selbstständig durchschnittlich pro Tag (grober Durchschnitt)?**Wie viele Befunde validieren/vidieren Sie durchschnittlich pro Tag (grober Durchschnitt)?****Haben Sie einen besonderen Schwerpunkt?**

Als Schwerpunkt gilt, wenn über 70% der Arbeitszeit auf diesen Bereich verwendet wird.

- Kein Schwerpunkt, der über 70% Arbeitszeit einnimmt
- Neuroradiologie
- Kinderradiologie
- Interventionelle Radiologie
- Mammadiagnostik
- Muskuloskelettale Radiologie
- Onkologische Diagnostik
- Konventionelle Radiologie (Röntgen)
- Sonstiges

Wie schätzen Sie folgende Aussagen zur Digitalisierung ein?

Stimme stark zu Stimme zu Weder noch Stimme nicht zu Stimme überhaupt nicht zu

In meinem Privatleben bin ich technikbegeistert.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ich informiere mich regelmäßig über technische Neuerungen in meinem Berufsfeld.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Mein Arbeitsumfeld und entsprechende Prozesse sind sehr digitalisiert.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Die Vielzahl und Varietät der digitalen Anwendungen in der Radiologie sind zunehmend schwieriger zu überblicken.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

3 Teil 1: Fragen zu KI

Wie viele Jahre sind Sie als Facharzt/-ärztin der Radiologie tätig?

- 1-3
- 4-6
- 7-9
- 10-12
- 13+

Im wievielten Lehrjahr der radiologischen Facharztausbildung befinden Sie sich?

- 1-2
- 3-4
- 5-6
- 6+
- Keine radiologische Facharztausbildung

Wie schätzen Sie die folgenden Aussagen zum Thema Künstliche Intelligenz (KI) ein?

	Stimme stark zu	Stimme zu	Weder noch	Stimme nicht zu	Stimme gar nicht zu
Ich folge der öffentlichen Diskussion zum Thema KI.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

KI ersetzt RadiologInnen in der Zukunft.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
KI ergänzt RadiologInnen in der Zukunft.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
KI kann die Qualität in der Radiologie verbessern.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
KI kann die Effizienz in der Radiologie verbessern.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
KI kann in der Radiologie Kosten einsparen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ich vertraue KI in der Radiologie.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ich sehe Weiterbildungsbedarf in Sachen KI in der Radiologie.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
PatientInnen werden in 5 Jahren radiologische Einrichtungen bevorzugen, die zusätzlich auf KI-Unterstützung setzen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
PatientInnen werden in 10 Jahren radiologische Einrichtungen bevorzugen, die zusätzlich auf KI-Unterstützung setzen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Wie schätzen Sie die folgenden Aussagen zu KI-Angeboten für die Radiologie ein?

	Stimme stark zu	Stimme zu	Weder noch	Stimme nicht zu	Stimme gar nicht zu
Wir bekommen zunehmend Angebote für KI-basierte Lösungen von diversen Anbietern.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Wir holen Angebote für KI-basierte Lösungen zunehmend selbst ein.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Das Preisniveau für KI in der Radiologie ist angemessen.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ich fühle mich gut informiert bezüglich der derzeit am Markt					

erhältlichen KI-basierten Assistenzprogramme.

Wir entwickeln selbst KI-Anwendungen, um Prozesse zu beschleunigen oder die Diagnostik zu verbessern.

Wir entwickeln selbst KI-Anwendungen im Rahmen unserer Forschungsagenda.

Nutzen Sie in Ihrer Tätigkeit als Radiologe bzw. Radiologin bereits KI Anwendungen?

- Ja
- Nein
- Unsicher

Welche Eigenschaften von KI-basierten Assistenzsystemen sind Ihnen am wichtigsten?

Verschieben Sie die blauen Boxen von links nach rechts in Ihre gewählte Reihenfolge. Die für Sie wichtigste Eigenschaft steht auf der rechten Seite an oberster Stelle. (Auf kleinen Bildschirmen, z.B. Smartphones, bilden Sie eine Reihenfolge durch klicken auf die blauen Boxen; "1" entspricht hier der für Sie wichtigsten Eigenschaft.)

1 2 3 4 5 6 7

Das System spart mir Zeit in der Diagnostik/Befundung.

Das System verkürzt den Scan-Vorgang.

Das System verbessert die Bildqualität.

Das System spart mir Kosten.

Ich kann den Einsatz des Systems über EBM/GOÄ abrechnen.

Das System

diagnostiziert besser

als der Mensch.

Das System ist als
Medizinprodukt

zugelassen.

4 Teil 1: Fragen zur Nutzung von KI

Sie haben angegeben, dass Sie bereits KI-Lösungen nutzen. In welchen Bereichen nutzen Sie KI?

- Unterstützung/Beschleunigung von Diagnostik
- Prognostizierung von Krankheitsverläufen
- Erstellung von Befunden
- Verbesserung der Bildqualität
- Verkürzung des Scanvorgangs
- Ersetzen/reduzieren von Kontrastmittel
- Praxis/Stations-Management (z.b. Abrechnungsoptimierung, Prozessoptimierung)
- Sonstiges

Von welchen Anbietern nutzen Sie KI-basierte Anwendungen?

- Philips
- Siemens Healthineers
- GE
- Andere Modalitätenhersteller
- RIS/PACS-Softwareanbieter
- KI-Software Startups
- Eigenentwicklungen
- Sonstige
- Unsicher

Planen Sie in den nächsten 2 Jahren (weitere) KI-basierte Assistenzprogramme einzuführen?

- Ja

- Nein
- Unsicher

5 Teil 2: Einführung

Stellen Sie sich nun bitte folgendes Szenario vor:

Von verschiedenen Anbietern werden Ihnen KI-basierte Assistenzprogramme angeboten. Die verschiedenen Angebote unterscheiden sich in ihrer Anwendung, weiteren Parametern und im Preis. Sie wollen nun das beste Angebot für Ihre Praxis/Station wählen.

Auf den folgenden 10 Seiten werden jeweils 2 Angebote für diese Assistenzprogramme beschrieben. Außerdem können Sie sich immer gegen die dargestellten Angebote entscheiden.

WICHTIG: Stellen Sie sich auf jeder dieser Seiten vor, dass Sie nur die jeweiligen zwei Angebote zur Auswahl hätten. Nehmen Sie bitte an, dass Sie nicht gewählte Alternativen auf keinem anderen Wege nutzen könnten. Auch nicht, wenn Sie eine ähnliche Lösung bereits in Ihrer Station/Praxis nutzen. Für die Studie ist es von besonderer Bedeutung, dass Sie alle Wahlvorgänge abschließen.

6 Teil 2: DCE CS 1

Auswahl 1/10

	Angebot 1	Angebot 2
Anbieter:	RIS/PACS-Softwareanbieter	KI-Software Startup
Anwendung:	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation	Automatische Kennzeichnung von Lungenherden in CT Thorax und Leber- & Nierenherden in MR Abdomen
Qualität:	Gleich: Bildqualität so gut wie bisher	Besser: Erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen
Zeitersparnis:	Mittel: MR Scanprozess 30% schneller	Hoch: Diagnostikprozess 50% schneller
Preis:	6 € pro Studie	3 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem RIS/PACS-Softwareanbieter (z.B. AGFA/Dedalus, Medavis, etc.) entwickeltes Assistenzprogramm, welches die Scan-Zeit für MR-Aufnahmen des Abdomens bei gleichbleibender Bildqualität um 30% verkürzt. Pro Studie kostet der Einsatz des Systems 6€.

Angebot 2 ist ein von einem KI-Software Startup entwickeltes Programm, welches Sie bei der Diagnostik in den beschriebenen Bereichen unterstützt (Die Kennzeichnung wird in Ihr bestehendes PACS integriert). Das System erkennt Auffälligkeiten, die Sie

auch bei langer Betrachtung nicht erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 50% schneller abschließen können. Für den Einsatz werden 3€ pro Studie berechnet.

7 Teil 2: DCE CS 2

Auswahl 2/10

	Angebot 1	Angebot 2
Anbieter:	Modalitätenhersteller	RIS/PACS-Softwareanbieter
Anwendung:	Vor-Sortierung von Mammographie-Screening Befunden in „100% unauffällig“ (BI-RADS 1&2) und „auffällig“ inkl. automatischer Markierung von Läsionen	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation
Qualität:	Gleich: Erkennt Auffälligkeiten, die Sie auch erkennen	Besser: Höhere Bildqualität
Zeitersparnis:	Mittel: Diagnostikprozess 30% schneller	Gering: MR Scanprozess 10% schneller
Preis:	3 € pro Studie	9 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem Modalitätenhersteller (z.B. Siemens, Philips, GE etc.) entwickeltes Assistenzprogramm, welches Mammographie-Scans im Rahmen des Brustkrebs-Screenings automatisch vorsortiert in "100% unauffällig" (BI-RADS 1&2) und "auffällig". Das System erkennt alle Auffälligkeiten, die Sie auch erkennen würden und beschleunigt Ihren Diagnostikprozess um 30%. Pro Studie (umfasst beide Mammae) kostet der Einsatz des Systems 3€.

Angebot 2 ist ein von einem RIS/PACS Softwareanbieter (z.B. AGFA/Dedalus, Medvals, etc.) entwickeltes Programm, welches die Scan-Zeit für MR-Aufnahmen des Abdomens bei höherer Bildqualität um 10% verkürzt. Für den Einsatz werden 9€ pro Studie berechnet.

8 Teil 2: DCE CS 3

Auswahl 3/10

	Angebot 1	Angebot 2
Anbieter:	Modalitätenhersteller	KI-Software Startup
Anwendung:	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation	Automatische Kennzeichnung von Lungenherden in CT Thorax und Leber- & Nierenherden in MR Abdomen
Qualität:	Gleich: Bildqualität so gut wie bisher	Besser: Erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen
Zeitersparnis:	Gering: MR Scanprozess 10% schneller	Mittel: Diagnostikprozess 30% schneller
Preis:	3 € pro Studie	6 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem Modalitätenhersteller (z.B. Siemens, Phillips, GE etc.) entwickeltes Assistenzprogramm, welches die Scanzeit für MR-Aufnahmen des Abdomens bei gleichbleibender Bildqualität um 10% verkürzt. Pro Studie kostet der Einsatz des Systems 3€.

Angebot 2 ist ein von einem KI-Software Startup entwickeltes Programm, welches Sie bei der Diagnostik in den beschriebenen Bereichen unterstützt (Die Kennzeichnung wird in Ihr bestehendes PACS integriert). Das System erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 30% schneller abschließen können. Für den Einsatz werden 6€ pro Studie berechnet.

9 Teil 2: DCE CS 4

Auswahl 4/10

	Angebot 1	Angebot 2
Anbieter:	KI-Software Startup	Modalitätenhersteller
Anwendung:	Vor-Sortierung von Mammographie-Screening Befunden in „100% unauffällig“ (BI-RADS 1&2) und „auffällig“ inkl. automatischer Markierung von Läsionen	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation
Qualität:	Gleich: Erkennt Auffälligkeiten, die Sie auch erkennen	Besser: Höhere Bildqualität
Zeitersparnis:	Gering: Diagnostikprozess 10% schneller	Hoch: MR Scanprozess 50% schneller
Preis:	9 € pro Studie	6 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem KI-Software Startup entwickeltes Assistenzprogramm, welches Mammographie-Scans im Rahmen des Brustkrebs-Screenings automatisch vorsortiert in "100% unauffällig" (BI-RADS 1&2) und "auffällig". Das System erkennt alle Auffälligkeiten, die Sie auch erkennen würden und beschleunigt Ihren Diagnostikprozess um 10%. Pro Studie (umfasst beide Mammae) kostet der Einsatz des Systems 9€.

Angebot 2 ist ein von einem Modalitätenhersteller (z.B. Siemens, Philips, GE etc.) entwickeltes Programm, welches die Scan-Zeit für MR-Aufnahmen des Abdomens bei besserer Bildqualität um 50% verkürzt. Für den Einsatz werden 6€ pro Studie berechnet.

10 Teil 2: DCE CS 5

Auswahl 5/10

	Angebot 1	Angebot 2
Anbieter:	KI-Software Startup	Modalitätenhersteller
Anwendung:	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation	Vor-Sortierung von Mammographie-Screening Befunden in „100% unauffällig“ (BI-RADS 1&2) und „auffällig“ inkl. automatischer Markierung von Läsionen
Qualität:	Gleich: Bildqualität so gut wie bisher	Besser: Erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen
Zeitersparnis:	Hoch: MR Scanprozess 50% schneller	Mittel: Diagnostikprozess 30% schneller
Preis:	3 € pro Studie	9 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem KI-Software Startup entwickeltes Assistenzprogramm, welches die Scanzeit für MR-Aufnahmen des Abdomens bei gleichbleibender Bildqualität um 50% verkürzt. Pro Studie kostet der Einsatz des Systems 3€.

Angebot 2 ist ein von einem Modalitätenhersteller (z.B. Siemens, Philips, GE etc.) entwickeltes Programm, welches Mammographie-Scans im Rahmen des Brustkrebs-Screenings automatisch vorsortiert in "100% unauffällig" (BI-RADS 1&2) und "auffällig". Das System erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 30% schneller abschließen können. Für den Einsatz werden 9€ pro Studie (umfasst beide Mammæ) berechnet.

11 Teil 2: DCE CS 6

Auswahl 6/10

	Angebot 1	Angebot 2
Anbieter:	RIS/PACS-Softwareanbieter	KI-Software Startup
Anwendung:	Vor-Sortierung von Mammographie-Screening Befunden in „100% unauffällig“ (BI-RADS 1&2) und „auffällig“ inkl. automatischer Markierung von Läsionen	Automatische Kennzeichnung von Lungenherden in CT Thorax und Leber- & Nierenherden in MR Abdomen
Qualität:	Besser: Erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen	Gleich: Erkennt Auffälligkeiten, die Sie auch erkennen
Zeitersparnis:	Hoch: Diagnostikprozess 50% schneller	Gering: Diagnostikprozess 10% schneller
Preis:	9 € pro Studie	6 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem RIS/PACS-Softwareanbieter (z.B. AGFA/Dedalus, Medavis, etc.) entwickeltes Assistenzprogramm, welches Mammographie-Scans im Rahmen des Brustkrebs-Screenings automatisch vorsortiert in "100% unauffällig" (BI-RADS 1&2) und "auffällig". Das System erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 50% schneller abschließen können. Pro Studie (umfasst beide Mammae) kostet der Einsatz des Systems 9€.

Angebot 2 ist ein von einem KI-Software Startup entwickeltes Programm, welches Sie bei der Diagnostik in den beschriebenen Bereichen unterstützt (Die Kennzeichnung wird in Ihr bestehendes PACS integriert). Das System erkennt Auffälligkeiten, die Sie auch erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 10% schneller abschließen können. Für den Einsatz werden 6€ pro Studie berechnet.

12 Teil 2: DCE CS 7

Auswahl 7/10

	Angebot 1	Angebot 2
Anbieter:	Modalitätenhersteller	KI-Software Startup
Anwendung:	Automatische Kennzeichnung von Lungenherden in CT Thorax und Leber- & Nierenherden in MR Abdomen	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation
Qualität:	Gleich: Erkennt Auffälligkeiten, die Sie auch erkennen	Besser: Höhere Bildqualität
Zeitersparnis:	Hoch: Diagnostikprozess 50% schneller	Mittel: MR Scanprozess 30% schneller
Preis:	9 € pro Studie	3 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem Modalitätenhersteller (z.B. Siemens, Philips, GE etc.) entwickeltes Assistenzprogramm, welches Sie bei der Diagnostik in den beschriebenen Bereichen unterstützt (Die Kennzeichnung wird in Ihr bestehendes PACS integriert). Das System erkennt Auffälligkeiten, die Sie auch erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 50% schneller abschließen können. Pro Studie kostet der Einsatz des Systems 9€.

Angebot 2 ist ein von einem KI-Software Startup entwickeltes Programm, welches die Scan-Zeit für MR-Aufnahmen des Abdomens bei besserer Bildqualität um 30% verkürzt. Für den Einsatz werden 3€ pro Studie berechnet.

13 Teil 2: DCE CS 8

Auswahl 8/10

	Angebot 1	Angebot 2
Anbieter:	RIS/PACS-Softwareanbieter	Modalitätenhersteller
Anwendung:	Vor-Sortierung von Mammographie-Screening Befunden in „100% unauffällig“ (BI-RADS 1&2) und „auffällig“ inkl. automatischer Markierung von Läsionen	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation
Qualität:	Gleich: Erkennt Auffälligkeiten, die Sie auch erkennen	Besser: Höhere Bildqualität
Zeitersparnis:	Hoch: Diagnostikprozess 50% schneller	Mittel: MR Scanprozess 30% schneller
Preis:	6 € pro Studie	9 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem RIS/PACS-Softwareanbieter (z.B. AGFA/Dedalus, Medavis, etc.) entwickeltes Assistenzprogramm, welches Mammographie-Scans im Rahmen des Brustkrebs-Screenings automatisch vorsortiert in "100% unauffällig" (BI-RADS 1&2) und "auffällig". Das System erkennt alle Auffälligkeiten, die Sie auch erkennen würden und beschleunigt Ihren Diagnostikprozess um 50%. Pro Studie (umfasst beide Mammae) kostet der Einsatz des Systems 6€.

Angebot 2 ist ein von einem Modalitätenhersteller (z.B. Siemens, Philips, GE etc.) entwickeltes Programm, welches die Scan-Zeit für MR-Aufnahmen des Abdomens bei höherer Bildqualität um 30% verkürzt. Für den Einsatz werden 9€ pro Studie berechnet.

14 Teil 2: DCE CS 9

Auswahl 9/10

	Angebot 1	Angebot 2
Anbieter:	RIS/PACS-Softwareanbieter	KI-Software Startup
Anwendung:	Automatische Kennzeichnung von Lungenherden in CT Thorax und Leber- & Nierenherden in MR Abdomen	Verringerung der Scan-Zeit von 2D & 3D Sequenzen im MR Abdomen über KI-basierte Datenmanipulation
Qualität:	Besser: Erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen	Gleich: Bildqualität so gut wie bisher
Zeitersparnis:	Gering: Diagnostikprozess 10% schneller	Hoch: MR Scanprozess 50% schneller
Preis:	3 € pro Studie	9 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem RIS/PACS-Softwareanbieter (z.B. AGFA/Dedalus, Medavis, etc.) entwickeltes Assistenzprogramm, welches Sie bei der Diagnostik in den beschriebenen Bereichen unterstützt (Die Kennzeichnung wird in Ihr bestehendes PACS integriert). Das System erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 10% schneller abschließen können. Pro Studie kostet der Einsatz des Systems 3€. Angebot 2 ist ein von einem KI-Software Startup entwickeltes Programm, welches die Scan-Zeit für MR-Aufnahmen des Abdomens bei gleichbleibender Bildqualität um 50% verkürzt. Für den Einsatz werden 9€ pro Studie berechnet.

15 Teil 2: DCE CS 10

Auswahl 10/10

	Angebot 1	Angebot 2
Anbieter:	Modalitätenhersteller	RIS/PACS-Softwareanbieter
Anwendung:	Vor-Sortierung von Mammographie-Screening Befunden in „100% unauffällig“ (BI-RADS 1&2) und „auffällig“ inkl. automatischer Markierung von Läsionen	Automatische Kennzeichnung von Lungenherden in CT Thorax und Leber- & Nierenherden in MR Abdomen
Qualität:	Besser: Erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen	Gleich: Erkennt Auffälligkeiten, die Sie auch erkennen
Zeitersparnis:	Gering: Diagnostikprozess 10% schneller	Mittel: Diagnostikprozess 30% schneller
Preis:	6 € pro Studie	3 € pro Studie

Für welches Angebot entscheiden Sie sich?

- Angebot 1
- Angebot 2
- Keines dieser Angebote

Lesehilfe (falls benötigt):

Angebot 1 ist ein von einem Modalitätenhersteller (z.B. Siemens, Philips, GE etc.) entwickeltes Assistenzprogramm, welches Mammographie-Scans im Rahmen des Brustkrebs-Screenings automatisch vorsortiert in "100% unauffällig" (BI-RADS 1&2) und "auffällig". Das System erkennt Auffälligkeiten, die Sie auch bei langer Betrachtung nicht erkennen würden und beschleunigt Ihren Diagnostikprozess um 10%. Pro Studie (umfasst beide Mammae) kostet der Einsatz des Systems 6€.

Angebot 2 ist ein von einem RIS/PACS-Softwareanbieter (z.B. AGFA/Dedalus, Medavis, etc.) entwickeltes Programm, welches Sie bei der Diagnostik in den beschriebenen Bereichen unterstützt (Die Kennzeichnung wird in Ihr bestehendes PACS integriert). Das System erkennt alle Auffälligkeiten, die Sie auch erkennen würden und tut dies so schnell, dass Sie den Diagnostikprozess 30% schneller abschließen können. Für den Einsatz werden 3€ pro Studie berechnet.

16 Dankeschön

Liebe Teilnehmerin, lieber Teilnehmer,

ganz herzlichen Dank für Ihre Zeit. Ihre Antworten können als wichtige Anhaltspunkte für gesundheitspolitische Entscheidungen und die Entwicklung von tatsächlich nachgefragten Assistenzsystemen genutzt werden.

Wie versprochen können Sie sich auf der nächsten Seite eine aktuelle Übersicht der prominentesten KI-Lösungen in der Radiologie herunterladen.

Falls Sie an einem Ergebnisreport interessiert sind, hinterlassen Sie hier gerne Ihre Mail-Adresse.

Um die Umfrage abzuschließen, klicken Sie bitte auf "Weiter".

17 Ende

Die Umfrage wurde erfolgreich abgeschlossen. Klicken Sie [hier](#) für den Download einer Übersicht von kommerziellen KI-basierten Assistenzsystemen in der Radiologie. Bei Rückfragen und Anmerkungen können Sie sich gerne bei uns melden: philip.wedel@whu.edu.

Appendix 12: English translation of DCE survey instrument

1 Start

Survey on Artificial Intelligence (AI) in radiology

Dear participant,
Artificial Intelligence, or AI, slowly but steadily finds its place in our everyday lives, as well as, in healthcare. Especially in radiology quite a few successes were achieved in the last couple of years.

You, being a radiologist yourself knows best in which situations and how AI can best assist your daily work. As a matter of fact, in the near future you will most likely be able to choose from a variety of AI-based assistance tools.

Interestingly, physicians' preferences are rarely considered in public discussions. This survey attempts to change this and concerns the following question:

„How do radiologists perceive AI-based applications and which features are considered important when choosing such a tool?“

As an appreciation of your time we provide an overview of all currently available AI-based radiology applications in Germany. Furthermore, feel free to leave your mail address to receive information on the results of the study attached to this survey. Self evidently, all answers are treated confidentially and are not used for commercial purposes.

How is this survey structured?

This survey will take approx. 10-15 min. of your time and is composed of 2 parts:

1. Questions regarding you as a person, your work environment & existing experience with AI
2. Task to determine your preferences regarding AI-based assistance tools in radiology

Who is conducting this survey?

This research study is conducted by BLINDED. In case of questions or comments, feel free to reach out via mail: BLINDED

Thank you very much for your time!

2 Part 1: General questions

Gender

- Female
- Male
- Diverse

Age

Where do you practice your job

- Hospital
- University hospital
- Radiology practice
- Medical Services Center (MSC)
- Public authority
- Other

In which position do you practice your job?

- Self-employed in practice
- Chief physician in hospital
- Consulting physician in hospital
- Resident physician in hospital
- Employed by practice/MSc
- Employed by public authority
- Retired

How many reports do you autonomously create per day (rough average)?

How many reports do you validate per day (rough average)?

Do you have a specialization?

Specialization here means, that more than 70% of your time is spent on this area.

- No specialization covering more than 70% of my time
- Neuroradiology
- Pediatric radiology
- Interventional radiology
- Mamma (breast) diagnostics
- Musculoskeletal diagnostics
- Oncological diagnostics
- Conventional radiology (x-ray)
- Other

How do you assess the following statements regarding digitalization?

	Strongly agree	Agree	Neither	Disagree	Strongly disagree
I am technophile in my private life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I keep myself regularly informed about technical novelties regarding my job.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My work environment and respective processes are digitalized.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

The amount and variety of digital applications in radiology is increasingly difficult to grasp.

3 Part 1: AI-related questions

How many years of work experience as a fully trained radiologist do you have?

- 1-3
- 4-6
- 7-9
- 10-12
- 13+

In which year of your residency are you currently?

- 1-2
- 3-4
- 5-6
- 6+
- No residency in radiology

How do you assess the following statements regarding AI?

	Strongly agree	Agree	Neither	Disagree	Strongly disagree
I follow the public discussion regarding AI.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
AI will replace radiologists in the future.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
AI complements radiologists in the future.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
AI can improve quality in radiology.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
AI can improve efficiency in radiology.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
AI can save costs in radiology.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I trust AI in radiology.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I see the need for further education on AI in radiology.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

In 5 years, patients will prefer radiologic institutions that additionally rely in AI-based support.

In 10 years, patients will prefer radiologic institutions that additionally rely in AI-based support.

How do you assess the following statements regarding the AI-based offering in radiology?

	Strongly agree	Agree	Neither	Disagree	Strongly disagree
We increasingly receive offers for AI-based applications from various providers.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
We increasingly ask for offers for AI-based applications ourselves.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The pricing for AI in radiology is appropriate.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel well informed regarding the commercially available AI-based applications in radiology.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
We ourselves develop AI to support diagnostics or improve process efficiency.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
We ourselves develop AI because of our research agenda.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Do you currently utilize AI-based applications as a radiologist?

- Yes
- No
- Unsure

Which features of AI-based assistance tools are most important for you?

Verschieben Sie die blauen Boxen von links nach rechts in Ihre gewählte Reihenfolge. Die für Sie wichtigste Eigenschaft steht auf der rechten Seite an oberster Stelle. (Auf kleinen Bildschirmen, z.B. Smartphones, bilden Sie eine Reihenfolge durch klicken auf die blauen Boxen; "1" entspricht hier der für Sie wichtigsten Eigenschaft.)

	1	2	3	4	5	6	7
The application saves time in diagnostics.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The application shortens scan times.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The application improves scan image quality.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The application saves costs.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I get reimbursed for using the application.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The application diagnoses better than human radiologists.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The application is approved as a medical device.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

4 Part 1: AI usage questions

You indicated that you are currently using AI. In which areas is this the case?

- Supporting/speeding up diagnostics
- Prognosis of disease progression
- Creation of reports
- Improvement of image quality
- Shortening of scan times
- Replacing/reducing contrast agents
- Practice/ward process management
- Other

Which providers of AI-based applications do you utilize?

- Philips
- Siemens Healthineers
- GE
- Other modality/equipment manufacturer
- RIS/PACS-software provider
- AI-software startup
- Own development
- Other
- Unsure

Do you plan to invest in (further) AI-based assistance tools in the next 2 years?

- Yes
- No
- Unsure

5 Part 2: Introduction

Please imagine the following scenario:

Several providers are offering different AI-based assistance tools. The offers differ regarding their general application type, other parameters and in price. Now, you want to choose the best offer for your *practice/department*.

On the following 10 pages you have the choice between 2 differing tool options. Furthermore, you can always decide against adopting one of the two displayed offers.

IMPORTANT: Please imagine that there are no alternative tool options than the ones displayed on each of the 10 pages. Please assume that you are not able to adopt options you did not choose any other way, even if you are currently using a similar tool in your practice/department. It is of utmost importance for this study that you complete all 10 choice sets.

6 Part 2: DCE CS 1

Choice 1/10

	Offer 1	Offer 2
Provider:	RIS/PACS software provider	AI software startup
Application:	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI
Quality:	Same: Same image quality	Better: Detects anomalies you would not detect even with long inspection
Time savings:	Medium: MRI scan process 30% faster	High: Diagnostics process 50% faster
Price	6 € per study	3 € per study

Which offer do you prefer?

- Offer 1
- Offer 2
- None of these

Interpretation (if needed):

Offer 1 comprises an assistance tool provided by a RIS/PACS-software provider (e.g., AGFA/Dedalus, Medavis, etc.) which cuts scan times for MRI scans of the abdomen by 30% at same image quality. The application of the tool is priced at 6€ per study. Offer 2 comprises an assistance tool provided by an AI-software startup which supports routine diagnostics in the mentioned areas (the markings are integrated in your existing PACS software). The system detects anomalies that you would not detect even after long examination and does this at a speed that cuts your diagnostics process time by 50%. The application is priced at 3€ per study.

7 Part 2: DCE CS 2

Choice 2/10

	Offer 1	Offer 2
Provider:	Modality provider	RIS/PACS software provider
Application:	Presorting of mammographic screening reports into "100% normal" (BI-RADS 1&2) and "suspicious" incl. automatic lesion marking	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation
Quality:	Same: Detects anomalies you would detect, too	Better: Higher image quality
Time savings:	Medium: Diagnostics process 30% faster	Low: MRI scan process 10% faster
Price:	3 € per study	9 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

8 Part 2: DCE CS 3

Choice 3/10

	Offer 1	Offer 2
Provider:	Modality provider	AI software startup
Application:	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI
Quality:	Same: Same image quality	Better: Detects anomalies you would not detect even with long inspection
Time savings:	Low: MRI scan process 10% faster	Medium: Diagnostics process 30% faster
Price:	3 € per study	6 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

9 Part 2: DCE CS 4

Choice 4/10

	Offer 1	Offer 2
Provider:	AI software startup	Modality provider
Application:	Presorting of mammographic screening reports into "100% normal" (BI-RADS 1&2) and "suspicious" incl. automatic lesion marking	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation
Quality:	Same: Detects anomalies you would detect, too	Better: Higher image quality
Time savings:	Low: Diagnostics process 10% faster	High: MRI scan process 50% faster
Price:	9 € per study	6 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

10 Part 2: DCE CS 5

Choice 5/10

	Offer 1	Offer 2
Provider:	AI software startup	Modality provider
Application:	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation	Presorting of mammographic screening reports into "100% normal" (BI-RADS 1&2) and "suspicious" incl. automatic lesion marking
Quality:	Same: Same image quality	Better: Detects anomalies you would not detect even with long inspection
Time savings:	High: MRI scan process 50% faster	Medium: Diagnostics process 30% faster
Price:	3 € per study	9 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

11 Part 2: DCE CS 6

Choice 6/10

	Offer 1	Offer 2
Provider:	RIS/PACS-SoftwareProvider	AI software startup
Application:	Presorting of mammographic screening reports into "100% normal" (BI-RADS 1&2) and "suspicious" incl. automatic lesion marking	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI
Quality:	Better: Detects anomalies you would not detect even with long inspection	Same: Detects anomalies you would detect, too
Time savings:	High: MRI scan process 50% faster	Low: Diagnostics process 10% faster
Price:	9 € per study	6 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

12 Part 2: DCE CS 7

Choice 7/10

	Offer 1	Offer 2
Provider:	Modality provider	AI software startup
Application:	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation
Quality:	Same: Detects anomalies you would detect, too	Better: Higher image quality
Time savings:	High: MRI scan process 50% faster	Medium: MRI scan process 30% faster
Price:	9 € per study	3 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

13 Part 2: DCE CS 8

Choice 8/10

	Offer 1	Offer 2
Provider:	RIS/PACS-SoftwareProvider	Modality provider
Application:	Presorting of mammographic screening reports into "100% normal" (BI-RADS 1&2) and "suspicious" incl. automatic lesion marking	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation
Quality:	Same: Detects anomalies you would detect, too	Better: Higher image quality
Time savings:	High: MRI scan process 50% faster	Medium: MRI scan process 30% faster
Price:	6 € per study	9 € per study

Which offer do you pick?

- Offer 1
- Offer 2 Noen
- of these

14 Part 2: DCE CS 9

Choice 9/10

	Offer 1	Offer 2
Provider:	RIS/PACS-SoftwareProvider	AI software startup
Application:	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI	Reduction of scan times for 2D & 3D abdominal MRI sequences via AI-based data manipulation
Quality:	Better: Detects anomalies you would not detect even with long inspection	Same: Same image quality
Time savings:	Low: Diagnostics process 10% faster	High: MRI scan process 50% faster
Price:	3 € per study	9 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

15 Part 2: DCE CS 10

Choice 10/10

	Offer 1	Offer 2
Provider:	Modality provider	RIS/PACS-SoftwareProvider
Application:	Presorting of mammographic screening reports into "100% normal" (BI-RADS 1&2) and "suspicious" incl. automatic lesion marking	Automatic marking of lung lesions in thoracic CT and liver and kidney lesions in abdominal MRI
Quality:	Better: Detects anomalies you would not detect even with long inspection	Same: Detects anomalies you would detect, too
Time savings:	Low: Diagnostics process 10% faster	Medium: Diagnostics process 30% faster
Price:	6 € per study	3 € per study

Which offer do you pick?

- Offer 1
- Offer 2 None
- of these

16 Thank you

Dear participant,
 thank you very much for your time. Your answers can provide valuable insights for future public health decisions and the development of actually preferred assistance tools.
 As promised, you find an overview of currently available commercial AI-based assistance tools on the following page.

Please leave your mail address if you are interested in a results report.

To finish the survey, please click on "Next".

17 End

The survey was completed successfully. Click here for the promised AI-based tool overview. Feel free to reach out in case of questions and comments: BLINDED