

# **The perspective of IT decision makers on factors influencing adoption and implementation of AI-technologies in German Hospitals: Descriptive Analysis**

Lina Weinert, Julia Müller, Laura Svensson, Oliver Heinze

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# The perspective of IT decision makers on factors influencing adoption and implementation of AI-technologies in German Hospitals: Descriptive Analysis

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## Abstract

**Background:** New AI tools are being developed at a high speed. Yet, strategies and practical experiences surrounding the adoption and implementation of AI in health care are lacking. This is likely due to AI's high implementation complexity, legacy IT infrastructure and unclear business cases, thus complicating AI adoption. Research has recently started to identify factors influencing organizations' readiness for AI.

**Objective:** Our study aimed to investigate the factors influencing AI readiness as well as possible barriers to AI adoption and implementation in German hospitals. We also tried to assess the status quo concerning the dissemination of AI tools in German hospitals. We focused on IT decision makers which is a seldom studied but highly relevant group.

**Methods:** We created an online survey based on recent AI readiness and implementation literature. The survey was pretested. Possible participants were identified through a publicly accessible database and contacted via e-mail or via invitational leaflets sent by mail, in some cases accompanied by a telephonic pre-notification. Survey responses were analyzed through descriptive statistical methods.

**Results:** Overall, we contacted 609 possible participants and our database recorded 40 fully completed surveys. Most participants agreed or rather agreed with the statement that AI will be relevant in the future, both in Germany (37/40, 92,5%) and in their own hospital (36/40, 89,5%). Participants were asked whether their hospital used or planned using AI technologies. 65% (26/40) answered this question with "yes". Most AI technologies were used or planned in patient care, followed by biomedical research, administration, and logistics and central purchasing. The most important barriers to AI were lacking resources (staff, knowledge, financial). Relevant possible opportunities of using AI were increases in efficiency due to time saving effects, competitive advantages, and increases in quality of care. Most AI tools in use or in planning were developed with external partners.

**Conclusions:** Few tools have been implemented in routine care and many hospitals do not use or do not plan on using AI in the future. This can likely be explained by missing or unclear business cases or needed modern IT infrastructure to integrate AI tools in a usable manner, hence complicating decision making and resource attribution. Since most AI technologies already in use were developed in cooperation with external partners, these relationships should be fostered. IT decision makers in hospitals should assess their hospital's readiness for AI individually with a focus on resources. Further research should continue to monitor the dissemination of AI tools and AI readiness factors to see if improvements can be made over time, especially in regards to governmentally supported investments in AI technologies that could alleviate financial burdens. Qualitative studies with hospital IT decision makers should be conducted to explore the reasons for slow AI adoption in more detail.

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## Original Manuscript

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## Abstract

**Background:** New AI tools are being developed at a high speed. Yet, strategies and practical experiences surrounding the adoption and implementation of AI in health care are lacking. This is likely due to AI's high implementation complexity, legacy IT infrastructure and unclear business cases, thus complicating AI adoption. Research has recently started to identify factors influencing organisations' readiness for AI.

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**Conclusions:** Few tools have been implemented in routine care and many hospitals do not use or do not plan on using AI in the future. This can likely be explained by missing or unclear business cases or needed modern IT infrastructure to integrate AI tools in a usable manner, hence complicating decision making and resource attribution. Since most AI technologies already in use were developed in cooperation with external partners, these relationships should be fostered. IT decision makers in hospitals should assess their hospital's readiness for AI individually with a focus on resources. Further research should continue to monitor the dissemination of AI tools and AI readiness factors to see if improvements can be made over time, especially in regards to governmentally supported investments in AI technologies that could alleviate financial burdens. Qualitative studies with hospital IT decision makers should be conducted to explore the reasons for slow AI adoption in more detail.

**Keywords:** artificial intelligence; AI readiness; implementation; decision making; descriptive analysis; quantitative study

## Background

In recent years, Artificial Intelligence (AI) in medicine has gained significant attention, with innovative technologies promising better quality of diagnosis [1–3], treatment [1], advancements in personalized medicine [1,4] and improvements in workflow [5] while having the potential for saving costs and time [1,6]. The use of AI could free health care workers from repetitive, tedious tasks and enable them to allocate their attention and time more effectively [7]. At the same time, fears surrounding AI in health care persist. Common fears are possible job losses due to automation and negative effects on the patient-physician relationship [2,8,9].

There are different relevant subcategories of AI, such as machine learning or deep learning, with different implications for professional users and health care organizations. However, in this paper, we will focus on the general concept of AI in hospitals.

The transfer of new and innovative technologies into practice is usually associated with barriers and requires employees' and institutions' ability to adapt to change [10,11]. Recently, existing frameworks and learnings on the dissemination of innovative technologies have been applied to AI [12]. Three main components can be outlined: (1) adoption, which entails the decision to use an innovation [13], (2) readiness, encompassing the assessment of the conditions needed to engage in an activity [14], and (3) implementation, describing an innovation's transfer into practice [12].

While new AI technologies are being developed at a high speed, strategies and practical experiences surrounding the adoption and implementation of AI in health care are lacking [15,16]. This is partly due to AI's high implementation complexity, as it is neither easy-to-use nor easy-to-deploy [14,17]. Furthermore, AI is also hard to understand, as the workings and results of automated algorithms are sometimes non-transparent and pose a "black box", hence lowering trust and discouraging decision makers and users [4,18,19].

In order to inform and help organizations with AI adoption, Jöhnk et al. [12] developed a model focussing on organizational (AI) readiness. They described AI readiness both as a predecessor and constant influence on AI adoption and implementation. The authors identified 18 organizational readiness factors in five categories (strategic alignment, resources, knowledge, culture, and data) and point out that these factors continuously foster AI adoption [12]. Awareness of these factors can improve the adoption and implementation outcomes, because a higher level of organizational readiness is believed to increase the success of innovation adoption while lowering the risk of failure [18,20]. For example, knowledge and awareness of AI were shown to be prerequisites for successful AI adoption [12,21,22].

Challenges to AI readiness can be observed on the technological, organizational, and environmental level, following the Technological-organizational-environmental framework (TOE) by DePietro et al. [23] and its extension to AI by Pumplun et al. [21]. Observed technological challenges often stem from data accessibility issues due to AI's need for extensive data bases and the adjacent data privacy considerations [21,24]. Environmental challenges include questions about consumer/patient trust in AI, regulatory acceptance and in some cases the employees' council [6,21,25]. Concerning organizational challenges, lack of (top) managerial support has been identified as very relevant [14]. A further challenge is the need for highly skilled and trained staff, e.g., data scientists, which is a very sought-after group of professionals [12,14]. Financial aspects, such as unclear reimbursement processes for health care delivered by AI, and liability issues contribute to hesitancy in AI adoption and implementation [1].

This hesitancy and slow uptake were shown in a recent systematic review by Yin et al. [5]. The authors report on real-life implementations of AI in healthcare. Their search retrieved 51 real-life clinical implementations of AI worldwide, with most studies conducted in the US. The most common applications of AI tools were in the field of decision support. The technologies mainly focused on specific diseases such as sepsis, breast cancer, and diabetic retinopathy [5]. Diverging



outcome measures and studies with low-quality were prevalent in the review, making it difficult for decision makers to compare and evaluate AI effectiveness, advantages, and disadvantages. Furthermore, in the papers they found, outcome evaluation and acceptance measures only included patients and health care workers [5]. Their search strategy retrieved only one paper from Germany, which is in contrast with the German Government's AI strategy [26] and recent political efforts to increase the use of AI in hospitals [27]. Hence, we identified a need to investigate the current spread of AI technologies in hospitals and their stage of development as well as AI readiness factors in Germany. We recognized hospitals' Chief Information Officers (CIOs) as important intermediaries, since their position is linked to the clinical implementation of AI as well as to developers, tech companies, and regulatory authorities. To the authors' knowledge, no other study surveyed this group so far.

## Aims

This study presents the first large-scale, web-based survey of the status quo concerning the adoption and implementation of AI technologies in German hospitals. We further aimed to gain insights into the number, type, and developmental stage of AI-technologies currently in use. In addition to the literature on AI readiness and adoption, we tried to examine the applicability of existent AI readiness factors to the German health care sector.

## Methods

### Study Design

A quantitative study design was chosen to obtain a general overview of the situation in Germany. Data were collected through an anonymous online questionnaire. We invited CIOs and people in comparable positions from randomly selected German Hospitals. Anonymity was ensured throughout the entire study. The study was approved by the Ethics Committee of the Heidelberg University Hospital (S-490/2020). The study was reported according to the CHERRIES checklist for quantitative research [28].

### Instrument development and design

Informed by an extensive literature review and guided by Pumplun et al.'s [21] extended TOE framework as well as the organizational AI readiness model by Jöhnk et al. [12], LW, JM, and LS developed the survey. Afterwards, the survey was pre-tested with six researchers from the field of medical informatics utilizing a cognitive pretesting method [29]. Pretest participants suggested changes in question wording and order. These suggestions were implemented, and the final survey was created.

The final survey did not include randomized or alternated items. Adaptive questioning was used to reduce the length of the questionnaire. On average, the 10-page-questionnaire contained 6,3 items per page. Possible answers were either presented on a 5-point-Likert-Scale or as "yes or no", with "I don't know" and "prefer not to say" as alternative options. Few questions asked for further elaboration of answers in open text formats. Automatic checks for completeness were performed and participants had to choose an answer for every question. Cookies were used to assign unique user IDs. Participants were offered an option to go back and modify their answers. They were also able to leave the survey and continue later. IP addresses of participants were neither saved nor checked.

The questionnaire focused on participants' professional opinions on AI in hospitals. In addition, it included items on their practical experiences, perceived barriers, opportunities, and needed resources for the implementation of AI in their hospital. Besides these questions, the questionnaire also asked for the participants' sociodemographic data, hospital size, and hospital ownership (private, public, or non-profit). A translated, English version of the survey can be found in Attachment 1. REDCap

(Research Electronic Data Capture) [30,31], hosted at the Heidelberg University Hospital, was used for study data collection and management. REDCap is a secure, web-based software platform designed to support data capture for research studies [30,31].

## Data collection and analysis

From a publicly available database of hospitals in Germany, we randomly selected a number of hospitals to include in our study, aiming for equal, realistic representation of hospital sizes (measured through number of hospital beds) in each sample. In total, we reached out to 609 possible participants in four rounds of recruitment. Initially, participants were invited via e-mail to participate in the study. The e-mails contained a link to access the open survey and information about the study (e.g., purpose of the study, length of questionnaire, data protection guidelines, investigators). Because participation in this study was voluntary and anonymous, we regarded survey completion as consent for study participation and data usage.

In round three of recruitment, to increase the number of participants, we employed telephonic pre-notifications when an office telephone number was publicly available. In round four of recruitment, we designed invitational leaflets which were sent via mail. The leaflets encompassed a short informational text and a QR-Code leading to the open survey. For each round, we sent two reminders via e-mail. Our survey was not advertised elsewhere, as we wanted to include only members of our specific target group in the sample. No incentives were offered for study participants.

Data were collected from October 2020 to February 2021. After completion, all data were exported from REDCap to SPSS statistical software (version 27, IBM). All data were checked for plausibility and analyzed by LW. Descriptive analyses were conducted. For open item responses, recurring keywords and phrases were paraphrased and summarized.

## Results

Our database recorded 50 participants. 10 surveys were terminated early, usually in the first third of the survey. 40 surveys were fully completed and included in the analysis, which results in a response rate of 6,2%. Timeframes were analyzed, but no unusual timeframes were observed. No statistical corrections were performed.

## Demographic characteristics

40 fully completed surveys were included in the analysis. Most participants were between 46 and 55 years old ( $n=23$ ) and 82,5% (33/40) of the participants were male. Twenty-six out of 40 participants said they were CIOs or leaders of their institution's Information Technology (IT) department. Other commonly mentioned professions were "IT department employee" ( $n=7$ ) or "research associate" ( $n=4$ ). Overall, 75% (30/40) of participants worked in a public hospital, 20% (8/40) in a non-profit hospital and 5% (2/40) in a private hospital. 37,5% (15/40) of the participants were employed by an academic hospital. Table 1 provides information on the participant characteristics.

Tab. 1: Participant characteristics (N=40)

<i>Characteristic</i>	<i>n (%)</i>
<b>Gender, n (%)</b>	
Female	5 (12,5)
Male	33 (82,5)
Prefer not to say	2 (5)
<b>Age group in years, n (%)</b>	
26-35	2 (5)
35-45	8 (20)
46-55	23 (57,5)

56-65	5 (12,5)
Over 65	2 (5)
<b>Hospital ownership, n (%)</b>	
Public	30 (75)
Non-profit	8 (20)
Private	2 (5)
<b>Academic affiliation, n (%)</b>	
academic	15 (37,5)
non-academic	25 (62,5)
<b>Number of beds in hospital, n (%)</b>	
1-199	3 (7,5)
200-399	5 (12,5)
400-599	7 (17,5)
600-799	4 (10)
>800	21 (52,5)
<b>Position*, n</b>	
Chief Information Officer/leader of the IT Department	26
Chief Data Officer	1
Chief Medical Officer	1
IT Department Employee	7
Research Associate	4
Data Scientist	3
No answer	1
other	3
*selection of multiple items possible	

## Participants' professional opinions and assessments

Most participants were either undecided or said they rather disagreed with the statement that AI is relevant for the current healthcare provision in their hospital and in Germany. However, most participants agreed or rather agreed that AI will be relevant in the future, both in Germany (37/40, 92,5%) and in their own hospital (36/40, 89,5%). This fits well with most participants fully agreeing or rather agreeing that AI plays a role in their hospital's strategy (22/40, 55%). On the topic of information about the possible application of AI in hospitals, participants were more undecided, with 20 (49,5%) out of 40 saying they are well informed or rather well informed, 15 (37,5%) who are undecided, and 5 (12,5%) who were rather uninformed. Overall, participants were rather optimistic about the use of AI technologies in their hospital. 14 (35%) rather agreed their hospital was ready for AI, 14 (35%) were undecided, 7 (17,5%) said they were rather not ready and only 4 (10%) stated their hospital was not ready at all. One participant did not answer this question.

### AI technologies in use or in planning

The next section of the questionnaire focused on AI tools and technologies. In the first subcategory, participants were asked whether their hospital used or planned using AI technologies. 65% (26/40) answered this question with "yes". Most AI technologies were used or planned in patient care, followed by biomedical research, administration, and logistics and central purchasing. Other areas mentioned by participants in free text were marketing, malware detection, and pathology. Participants were presented with a list of common AI technologies when they had answered with

“yes” to the first question in this subcategory (please see Attachment 1 for the full list of technologies). For every listed AI technology, they could categorize their hospital’s current stance on this technology. The options were “in planning”, “in research and developmental stage”, “implementation phase”, “routine care”, and “not applicable”. The most commonly chosen technologies overall were speech recognition and text analysis systems (20/40, 50%, assigned one of the stances other than “not applicable”), systems for picture recognition (17/40, 42,5%), and robotics and autonomous systems (17/40, 42,5%). Sensorics and communication systems were least picked (10/40, 25%). Most technologies were in the planning phase.

Concerning these technologies’ integration into the overarching system architecture, 11,5% were integrated, 38,5% were not integrated but integration was planned, 23,1% were partly integrated, and 26,9% were not integrated. In free text, participants provided reasons for the lacking integration which included missing interfaces, costs, missing standards for interfaces, processes and organization, unfavorable cost-benefit relationship, missing evaluation and overall concepts, and immaturity of the AI technology. Participants stated that most AI technologies were developed with industry partners (60,5%) and with university-based research partners (23,7%). Only 7,9% of AI technologies were developed within the participants’ own institutions.

### Barriers to AI use

The second subcategory encompassed questions about perceived barriers to the use of AI. Through a matrix design, we presented participants with a list of known barriers compiled from literature. The barrier most participants (36/40, 90%) agreed or partly agreed with was “lacking resources (staff, knowledge, financial)”. Other relevant barriers were “lacking compatibility/interoperability with existing IT infrastructure” (33/40, 83%) and “quality of data” (30/40, 75%). Participants also disagreed or rather disagreed with some of the barriers derived from literature. Here, the barriers with the least agreement were “leadership acceptance” (4/40, 10%, agreed or rather agreed with the statement) and “patient acceptance” (4/40, 10%). Other barriers with low agreement were “user (e.g., doctors, nurses) acceptance” (9/40, 23%) and “corporate culture” (13/40, 33%). In free text, some participants described further barriers. These contained immaturity of available AI technologies, fear of high expenses in the training and learning phase of AI, and the AI producers’ cloud strategies.

Tab. 2: Perceived barriers to implementation and use of AI (n=40)

Ranking	Barrier	Responses of “agree” or “rather agree”, n (%)
1	Lacking resources (staff, knowledge, financial)	36 (90%)
2	Lacking compatibility/interoperability with existing IT infrastructure	33 (83%)
3	Quality of data	30 (75%)
4	Availability of data	26 (65%)
5	Ethical aspects (e.g., liability issues)	24 (60%)
6	Product range on the market	23 (58%)
7	Data protection	22 (55%)
7	Quantity of data	22 (55%)
8	Legal regulations	19 (48%)
9	Consent of the employees’ council	15 (38%)
10	Corporate culture	13 (33%)
11	User (e.g., doctors, nurses, administration) acceptance	9 (23%)
12	Leadership acceptance	4 (10%)
12	Patient acceptance	4 (10%)

### Possible opportunities associated with AI

In the third subcategory, participants were asked about positive prospects possibly associated with AI. Then, they had to state their agreement with these opportunities on a 5-point-Likert-Scale. The opportunity with the highest agreement was “increase in efficiency due to time saving effects” (29/40, 73% agreed or rather agreement with the statement). The other statements also yielded high agreement rates. The opportunity participants agreed with least was “financial savings”. Only 40% (16/40) said they agreed or rather agreed with the statement that AI could lead to financial savings in their hospital, while 40% disagreed or rather disagreed. Overall, this subcategory led to homogenous results. No further opportunities were raised in free text.

Tab. 3: Perceived opportunities associated with the implementation and use of AI (n=40)

<i>Ranking</i>	<i>Opportunity</i>	<i>Responses of “agree” or “rather agree”, n (%)</i>
1	Increase in efficiency due to time saving effects	29 (73%)
2	Competitive advantage	27 (69%)
3	Increase in quality of care	25 (66%)
4	Easing the workload of employees	21 (53%)
5	Financial savings	16 (40%)

### Resources and requirements for AI use in hospitals

For the fourth subcategory, we focused on resources needed for the use of AI technologies in hospitals. Again, participants were presented with a list of known critical resources for AI implementation and they had to indicate their level of agreement with these findings from literature. The resource most people needed was “staffing resources” (35/40, 90% agreed or rather agreed with the statement). The resource with the least relevance was “organizational frameworks” (25/40, 64%). As seen with other subcategories before, the distribution of answers was homogeneous.

Tab. 4: Resources needed for use and implementation of AI (n=40)

<i>Ranking</i>	<i>Resource</i>	<i>Responses of “agree” or “rather agree”, n (%)</i>
1	Staffing resources	35 (90%)
2	Time	34 (87%)
3	Knowledge	33 (85%)
4	Financial resources	32 (84%)
5	Technical resources	31 (79%)
6	Data base	27 (69%)
7	Organizational frameworks	25 (64%)

The next item asked participants in a yes or no format whether their hospital needed to fulfil any further requirements or resources besides the ones already mentioned. 40% answered with “yes” and provided explanations in free text. Here, organizational aspects were most common, e.g. competencies and responsibilities, workflow, and legal issues. Technical aspects were described in detail, such as lacking hard- and software, interoperability, difficulties with data transfer from old to new systems, need for additional modules for data capture and Wi-Fi availability and speed.

### Market supply

Considering the tech industry and their offerings on the market, participants were highly undecided. 58% (23/40) said they did not know if supply met demand for AI technologies in their hospital. Only 7% (3/40) stated that offerings on the market were sufficient.



## Discussion

### Principal findings

This study produced insights into the current and planned dissemination of AI tools as well as perceived barriers and opportunities for their use in 40 hospitals in Germany. We designed an online survey based on existent literature on implementation of AI in hospitals. Our participants were mainly from an IT background, with 28 decision makers in leadership positions. Two thirds of participants said they used or planned to use AI tools in their institution. Speech recognition and text analysis systems, systems for picture recognition, and robotics and autonomous systems were the tools or systems most commonly used or in planning. The results show that most participants recognize the implementation of AI in hospitals as a relevant, forthcoming part of their IT strategy. However, lacking resources and compatibility/interoperability with existing IT infrastructure were identified as barriers. Staffing resources, time, knowledge, financial resources, and technical resources needed for the implementation of AI were all highly relevant resources. A possible increase in efficiency due to time saving effects, competitive advantage, and increase in quality of care were seen as the most important opportunities associated with AI use.

### AI in hospital strategies

AI Readiness as a concept has been described and explored recently [12,21]. “Strategic alignment” was identified as one of five key aspects of organizational AI readiness. Our survey included a question addressing whether AI was part of the participants’ hospital IT strategy. To this question, 55% (22/40) agreed or rather agreed that AI was part of their strategy. Also, most participants agreed or rather agreed that AI will be relevant in the future, both in Germany (37/40, 92,5%) and in their own hospital (36/40, 89,5%). However, this also means that there are decision-makers who recognize the relevance of AI in the future but do not consider it a part of their hospitals’ strategy. Firstly, this could be due to the complexity of AI implementation, e.g. uncertainties surrounding the workings of the technology, acceptance of the technology and an unclear regulatory situation [1,14,16,17,25,32]. Secondly, a hesitancy to include AI in a hospital’s IT strategy could be explained by high costs and unclear reimbursement schemes [1]. In our study, 84% (32/40) participants agreed that their institution lacked financial resources and 94% (36/40) said a lack in resources overall is a barrier for AI implementation. At the same time, only 40% (16/40) agreed with the statement that AI holds a potential for financial savings. This paints a picture of AI as a resource-intensive technology with limited financial rewards. While there are both expectations and observations of AI as a possible tool to save cost and generate high revenue [1,6,25], e.g. through higher efficiency, high-quality evidence analysing the cost and benefits of AI implementation in hospitals is missing [7]. Hence, decision makers lack evidence and information and the business case for AI in hospitals remains unclear [16,25], which in turn inhibits organizational AI readiness [12].

In order to compensate for financial burden due to investments in digital technologies, the German Government recently introduced a new law, the “hospital future act” (Krankenhauszukunftsgesetz – KHZG). Through this law, hospitals trying to implement digital technologies, including decision support systems, can apply for financial support to facilitate necessary acquisitions [27]. The law went into effect during our data collection period, thus we can not report on possible impacts of this law. But since financial aspects were reported as a relevant barrier in our study, it could be of interest for future research to evaluate the effects of the new law.

### AI Acceptability

Regarding further barriers to the implementation of AI, “soft” factors such as users’, patients’ and leadership’s acceptance were seen as less relevant barriers by the participants in our survey. This impression might be caused by limited contact of IT department members to users, leadership, and especially patients. Acceptance issues might also become more obvious to decision makers over time, since most participants in our study have not implemented AI in their hospital yet. It is nonetheless important to consider the evidence that acceptability is a relevant antecedent of AI

adoption and implementation. For example, one paper reviewing nine studies on the acceptance of AI in healthcare came to the conclusion that consumers have a robust reluctance towards medical care delivered by AI compared to human providers [33]. In another study, only 3% of patients found that possible negative aspects of AI outweighed potential benefits [34]. Overall, there is mixed evidence on patients' acceptance of AI in the medical context and further research is needed [5]. Leadership acceptance and support have been identified as important antecedents for AI implementation [12,21]. The acceptance of AI users, such as physicians and hospital employees, has also been identified as relevant in other studies [9,35]. Following the technology acceptance model (TAM), perceived ease of use and usefulness can positively impact favourable attitudes towards a new technology, which in turn improves the acceptability and use [10,36]. Hence, IT decision makers should not underestimate the issue of AI acceptability and should take the fears and perceptions surrounding AI from outside their department seriously when planning to implement new AI technology.

### **Possible Mismatch in Supply and Demand**

Another finding in our study was the result that only 7% (3/40) of participants said that supply of applicable AI solutions on the tech market was sufficient for their needs. Another 58% (23/40) reported that they were unsure. One reason could be that we did not reach the right people in the institution, and they were thus unable to assess the tech market. Further possibilities could be that our participants have not spent time researching the offerings on the tech market. This could be especially true for those who are not using or planning on using AI tools. Yet, it could also be possible that the offerings on the market do not fit with the requirements of their potential clients. This result could be of value for tech companies trying to reach decision makers in hospitals. The finding is especially important considering that only 7,9% of AI tools were developed within the hospitals in our survey. Hence, partnerships for the development of AI tools are common and should be fostered.

### **Strengths and Limitations**

Our study investigated the status quo of AI technologies in German hospitals and the applicability of AI readiness factors derived from literature. We surveyed hospital CIOs, a group we identified as important intermediaries for digital innovation adoption and implementation. While other studies about the perceptions, barriers, and issues surrounding AI questioned AI users (e.g., physicians/health professionals), patients, or other stakeholders [34,37–39], we focused on the seldom studied group of IT decision makers. This presents a strength of our study design and furthers the holistic discussion about real-world implementation of AI and AI readiness.

Due to technical limitations, we are not able to report the number of unique site visitors. This impedes the calculation of correct survey response rates. Although we employed various different recruitment methods (e-mail, letter, telephone calls) over a prolonged period of time, our sample size remained small in comparison to the number of hospitals in Germany (1914 hospitals in the year 2019 [32]). The small number of respondents may be explained by a general lack of interest in the survey's topic [40]. At the same time, the people who chose to participate in the survey might have a stronger interest or profound experiences with AI. We tried to minimize this effect by pointing out in the invitations that no knowledge or experiences with AI are necessary for participation. Yet, there is a risk of non-response bias present in our study.

Considering the demographics of the survey respondents, the sample is very homogenous as most participants were male, middle-aged, and worked in larger hospitals. However, this distribution was to be expected and represents the composition of IT departments in Germany [41].

Because AI is a new and complex technology, it is possible that our participants misunderstood some questions or falsely claimed they used AI in their hospital. We managed this risk by including explanatory text in our survey, conducting pretests, and by choosing participants who are supposed to

be experts on a related field. Still, this risk has to be kept in mind when comparing our results.

## Conclusion

The presented study paints a mixed picture of the status quo of AI in German hospitals. In our sample, few tools have been implemented in routine care and many hospitals do not use or do not plan on using AI in the future. This can likely be explained by missing or unclear business cases, hence complicating decision making and resource attribution. We also observed a mismatch or lacking information about AI offerings in the tech market. This is another important aspect to be monitored since most AI technologies already in use were developed in cooperation with external partners. Thus, these relationships should be fostered. IT decision makers in hospitals should assess their hospital's readiness for AI individually with a focus on resources. Further research should continue to monitor the dissemination of AI tools and AI readiness factors to see if improvements can be made over time, especially in regards to governmentally supported investments in AI technologies that could alleviate the financial burden. Qualitative studies with hospital IT decision makers should be conducted to explore the reasons for slow AI adoption in more detail. The results of our study may infer that AI adoption is not only a topic solely for the IT department but also for the whole hospital as an enterprise including management, medical staff and business in terms of an important building block of the digital transformation.

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## Authors' Contributions

LW drafted and prepared the original manuscript. OH was the overall principal investigator of the study. LW and JM were responsible for study design and study protocol. LW, JM, LS, and OH contributed to concept and design of the study and to the preparation of the manuscript. LW, JM, and LS constructed and tested the survey design and the quantitative data collection tool. LW analyzed survey data. LW interpreted and phrased results from quantitative data. All authors provided substantial comments and approved the final version of the manuscript.

## Conflict of Interest

The authors declare to have no conflict of interest.

## Abbreviations

AI:	Artificial Intelligence
CIO:	Chief Information Officer
IT:	Information Technology
KHZG:	Krankenhauszukunftsgesetz (hospital future act)
REDCap:	Research Electronic Data Capture
TOE:	Technological-organizational-environmental framework

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## Supplementary Files

## Multimedia Appendixes

Translated survey.

URL: <http://asset.jmir.pub/assets/af9292592cdc707a955ad9a972eabfb8.docx>