Managing Artificial Intelligence Applications in Healthcare: Promoting Information Processing among Stakeholders

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Abstract

AI applications hold great potential for improving healthcare. However, successfully operating AI is a complex endeavor requiring organizations to establish adequate management approaches. Managing AI applications requires functioning information exchange between a diverse set of stakeholders. Lacking information processing among stakeholders increases task uncertainty, hampering the operation of AI applications. Existing research lacks an understanding of holistic AI management approaches. To shed light on AI management in healthcare, we conducted a multi-perspective literature analysis followed by an interview study. Based on the organizational information processing theory, this paper investigates AI management in healthcare from an organizational perspective. As a result, we develop the AI application management model (AIAMA) that illustrates the managerial factors of AI management in healthcare and its interrelations. Furthermore, we provide managerial practices that improve information processing among stakeholders. We contribute to the academic discourse by providing a conceptual framework that increases the theoretical understanding of AI's management factors and understanding of management interrelations. Moreover, we contribute to practice by providing management practices that promote information processing and decrease task uncertainty when managing AI applications in healthcare.

Keywords: Artificial intelligence; Healthcare; Managing AI; Management model; Information processing

1 Introduction

Artificial intelligence (AI) applications are increasingly enhancing today's capabilities in healthcare by superior performance in disease detection, disease treatment, and medical decision-making (Rajpurkar et al., 2022; Yu et al., 2018). While these advancements technologically allow for remarkable improvements for, among others, patients and clinicians (Deo, 2015; Jiang et al., 2017; Rajpurkar et al., 2022), they also pressure hospitals to establish adequate organizational structures for successfully operating AI applications (Sun & Medaglia, 2019).

Compared to previous information technology, operating AI applications in healthcare requires novel forms of management in terms of coordination and control. This is because AI applications are becoming increasingly autonomous as their learning capabilities improve (Berente et al., 2021). Moreover, AI applications are becoming increasingly opaque and intelligible only to selected stakeholders (Berente et al., 2021). For instance, drifts within the abstract computerized AI model or the real-world environment may change the behavior of AI applications, however often remaining undisclosed to relevant stakeholders such as the product owner. The constant shift of AI's internal facets and external environment, thus, requires novel forms of coordination and control (Benbya et al., 2019; Faraj et al., 2018; Jöhnk et al., 2021). To coordinate and control, decision-makers must ensure having all relevant information at hand to make informed decisions since information is the "*knowledge for the purpose of taking effective action*" (Mason & Mitroff, 1973, p. 475). However, the information exchange concerning AI applications among the relevant stakeholders often hampers due to prevailing competence heterogeneity and siloed organizational structures within hospitals. In healthcare, operating AI technologies is a multiparty process that requires deep expertise and coordination between multiple domains (Higgins & Madai, 2020). The diverse nature of AI stakeholders complicates the manager's coordination and control tasks as each stakeholder has different AI competencies, understanding, and information needs. Exemplary information needs of patients arise from their ethical requirements concerning transparency, fairness, and privacy. The insufficient satisfaction of information needs can lead to distrust among patients and induce rejection of AI operations in healthcare. Another example is the information needs of developers to ensure adequate application quality. Not all information can be gathered through technical AI monitoring, requiring active engagement with patients and medical staff to obtain information on operational quality. Often, such communication does not exist once the AI application is in use—as long as there are no major incidents. Consequently, the insufficient satisfaction of information needs leads to information gaps and high levels of task uncertainty, bearing a risk for AI applications' inefficient and potentially harmful operation. AI management must take measures to promote information processing between the patient, medical staff, developers, and other stakeholders. However, the tasks of AI management are often not well understood by decision-makers. Successfully operating AI applications raises new challenges across hospitals, demanding careful management and the introduction of sound management practices to improve information processing among stakeholders

(Shaw et al., 2019; Yu & Kohane, 2019). AI managers must "*communicate, lead, coordinate, and control organizational efforts to […] realize their goals, while at the same time, avoiding the negative consequences*" (Berente et al., 2021, p. 1434). Accordingly, managing AI applications is about establishing adequate communication and coordination among stakeholders. In doing so, promoting information processing capabilities and solving information gaps among the diverse stakeholder types is a key task for AI managers to reduce the postulated task uncertainty. Despite its importance, both practitioners and researchers are still struggling to cope with the management of AI applications in production (Ananny & Crawford, 2018; Diakopoulos, 2015; Dwivedi et al., 2019) and are failing to develop adequate, holistic managerial practices promoting information processing.

Although remarkable research on AI application management has been brought forth (Li et al., 2021; Sturm et al., 2021; Teodorescu et al., 2021), existing research predominantly conceptualizes individual management factors (i.e., describing *what* to manage) rather than holistically capturing them and investigating their inherent relations. Related work also lacks a managerial understanding of domain-specific management (e.g., operationalizing management models) and concrete practices for improving communication and coordination in AI management. Existing AI management approaches, such as MLOps, are promising yet focus on technical facets instead of holistic management (see Kreuzberger et al., 2022). Following calls for research by scholars (Baier et al., 2019; Collins et al., 2021; Topol, 2019) and renowned journals (Benbya et al., 2019; Berente et al., 2019; Buxmann et al., 2019; Dwivedi et al., 2019) on the management of AI applications in organizations, we ask:

What are the factors of managing AI applications in healthcare and how are they related?
What management practices improve information processing among stakeholders in AI management?

To answer our research questions, we studied the management of AI applications in healthcare following a prescriptive two-step research approach consisting of a literature review and a subsequent interview study through the theoretical lens of the organizational information processing theory (OIPT) (Galbraith, 1974; Haußmann et al., 2012). We set out with a multi-perspective literature search to identify, analyze, and structure the management factors that represent abstractions of core AI management tasks and managerial interrelations. Furthermore, we derived practices that improve information processing among the stakeholders, facilitating AI application management. Consequently, we considered relevant perspectives from healthcare, AI, and digital technology management research and triangulated them, as recommended by Flick (2010). Then, we iteratively developed the comprehensive AI application management (AIAMA) model that theorizes the management factors and managerial interrelations. The management practices further theorize the managerial interrelations promoting information processing between the management factors. After that, we conducted 11 expert interviews to further refine the AIAMA model and enhance underlying management practices with expert knowledge from research and practice.

We contribute to the academic discourse and practice in three ways: First, we develop a theoretical model that holistically conceptualizes the various management factors of AI management and depicts their interrelations from an information processing perspective. Second, we contribute to the organizational information processing theory by deriving management practices that represent instantiations of OIPT strategies for improving information processing and reducing task uncertainty. Third, we contribute to practice by providing management practices that practitioners can adopt to improve coordination and communication in AI management by facilitating information processing. Therefore, all stakeholders associated with operating and managing an AI application in healthcare (e.g., physician practices, hospitals, healthcare providers, and researchers) will benefit from the paper's results.

2 Theoretical Foundations

2.1 Conceptual foundations of AI application management

From a technical perspective, current AI applications mostly rely on machine learning (ML) technology and vastly differ from other software applications used in healthcare, changing the way organizations must manage such systems. For instance, reconfigurations in operations (e.g., data adaptions, feature updates) occur continually and are data-driven rather than code-based (Baier et al., 2019). Moreover, AI applications can change their own rules depending on the given input without direct human intervention (Ågerfalk, 2020). When bringing these attributes of AI applications into a practical perspective, the successful and safe operation requires intensive contextual consideration since AI technology may not work in the same way in different fields (Ågerfalk, 2020). Accordingly, considering the contextual environment of the healthcare domain is critical for the successful management of AI applications. The system dynamics of AI applications lead to immense practical implications as AI operations increasingly affect critical organizational processes such as AI-enabled health monitoring (Hummer et al., 2019).

Fostering comprehensive and context-aware digital technology management – in terms of dedicated AI management – can help lever AI applications' full potential. Existing research from the computer science domain has widely addressed technical AI application management, focusing on model and pipeline management along the AI lifecycle (e.g., Hummer et al., 2019; Kreuzberger et al., 2022). Overall, the theoretical work from the computer science domain is based on the assumption that AI management is a matter of technical problem-solving in terms of pipeline management and architectural performance optimization. However, we argue that the theoretical scope of the computer science domain is too short-sighted. Relevant questions concerning, for instance, trust, accountability, robustness, and model fairness remain out of sight, leaving responsible roles increasingly struggling to cope with AI applications' specialties (Ananny & Crawford, 2018; Lämmermann et al., 2022; Teodorescu et al., 2021). In the information systems (IS) domain, which naturally aims to take a robust socio-technical perspective on the management of information technology, recent research has brought forth relevant theoretical groundwork on the management of AI. Relevant work expands the technical view and incorporates behavioral, organizational, and human dimensions into the academic discourse (e.g., Berente et al., 2021; Fügener et al., 2021; Li et al., 2021; Teodorescu et al., 2021). One major theoretical advancement is the recognition of AI as a continuously evolving frontier of computational advances requiring AI management beyond technical perspectives only (Berente et al., 2021). In line with our view considering AI as a moving target, we adopt the definition of AI from Berente et al. (2021), referring to AI as "*the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems*" as our operational definition for our research. The dynamics and continuous change around AI and its technical specialties pose significant consequences for managers and differ from other information technology (Berente et al., 2021). Many of the tasks that AI managers have are socio-technical and closely related to the AI stakeholder's requirements (Berente et al., 2021). The role of AI management is to shape the organization's AI-related endeavor in a thoughtful way by controlling and coordinating the tasks of other stakeholders in the organization (Berente et al., 2021; Drucker & Maciariello, 2008).

While significant research on AI application management exists (Li et al., 2021; Sturm et al., 2021; Teodorescu et al., 2021), most studies tend to focus on individual management factors (i.e., detailing what to manage) instead of offering a comprehensive view that holistically captures them and examines their interrelations. Furthermore, existing literature often falls short in offering a managerial perspective on domain-specific management and tangible practices to enhance communication and coordination in AI management. However, we argue that establishing sound practices that promote information processing is essential for fostering AI management. Many AI challenges are to be solved by collaborative actions across different departments and between people with highly specialized professional qualifications. This collaboration requires mutual understanding and efficient information exchange while overcoming information gaps. Providing a theoretical understanding of how organizations can establish effective information exchange among the stakeholders along with their complex and specialized tasks and background is key for the successful management of AI applications. Practices for promoting information flow among the stakeholders are insufficiently recognized by existing AI management theory, although it is critical for AI management. A well-functioning information exchange enables the AI management to have all the information at hand to make informed decisions and coordinate solutions for operational problems.

2.2 Specialties of AI operations in healthcare

To develop a theoretical understanding of AI management that promotes information processing for successfully operating AI applications, we have chosen the healthcare field as our research context. The healthcare domain is a promising but challenging application domain for AI, offering significant use cases such as disease diagnosis, patient monitoring, genome analysis, and advanced decision support. (European Commission, 2021). Although organizations are increasingly adopting AI applications, adoption is still often limited to specific departments, teams, and application areas (European Commission, 2021). Moreover, in healthcare, AI implementations often fail to produce the desired results. Often, technology-related stakeholders (e.g., AI developers, software vendors) are held responsible for the failure (Lebcir et al., 2021). However, studies suggest that only 20% of failures account for technical factors, while the majority of failures are rooted in socio-technical issues (Harrison et al., 2007; Lebcir et al., 2021; Lluch, 2011; Wears & Berg, 2005). Accordingly, the healthcare domain offers suitable domain constraints to study the management of AI applications from an IS perspective. Therefore, gaining a deeper theoretical understanding of the healthcare domain is crucial.

The healthcare system's primary goals are, among others, improving the experience of care, improving health, reducing per capita costs, and improving healthcare providers' work processes (Higgins & Madai, 2020; Kelly et al., 2019). However, not all stakeholders in healthcare prioritize these goals and their accompanying challenges equally (Shaw et al., 2019; Sun & Medaglia, 2019). Healthcare organizations vary in shape and size, and the organizational scope when deploying AI applications may not be limited to a single organization – several organizations may affect an AI application, occupying different roles according to their competencies. Our research focuses on healthcare organizations of medium to large size that have the primary purpose of delivering medical care to patients (i.e., hospitals, medical centers) and are likely having inter-organizational relationships with other organizations (e.g., regulatory agencies, IT providers, software vendors, etc.). We have such a specific focus since those healthcare organizations are most likely to source, develop, deploy, and use AI applications across various medical use cases.

Deploying and operating AI applications in hospitals redefines previous medical processes as well as the roles of related stakeholders such as doctors, patients, and IT staff (Jha & Topol, 2016; Levy, 2018). Using AI applications in healthcare, thus, requires a clear definition of responsibilities in case of errors and how the AI application should be integrated into the process (Kohli et al., 2017; Reddy et al., 2019). For instance, the decision-supporting output of AI applications can be prone to errors, potentially fatally impacting patient health, which is why AI-enabled medical devices demand profound process safety and monitoring (Yu et al., 2018). In healthcare, the operation of AI applications can also bring the dark sides of AI to light. AI can lead to enormous individual, organizational, and societal risks (Alt, 2018). One significant risks in the healthcare domain are privacy issues associated with AI (Cheng et al., 2022), as AI mostly relies on machine learning approaches requiring vast amounts of medical data, which is considered highly personal information. Furthermore, particularly driven by the COVID pandemic, AI has the potential to significantly change work environments and workflow procedures, affecting workforce behavior and perceptions (Cheng et al., 2022; Danaher, 2019). Thus, AI-enabled medical devices' potential impact on patient health has led to strong regulations and the highest quality requirements for any activity directly or indirectly related to a patient's health. Healthcare-related approaches for managing AI applications and considering the potential dark effects of AI are still limited. Particularly, the current discourse around responsible AI in healthcare underpins the relevance of ethical and robust AI management (Kumar et al., 2021; Trocin et al., 2021). Most AI applications process highly sensitive health data of patients and produce output that may be used as a basis for far-reaching medical decisions. Consequently, AI applications have high stakes in ethically difficult situations, requiring high standards of patient-centricity and responsible use (Kumar et al., 2021). The responsible operation of AI applications in healthcare poses various difficulties in real-world environments requiring dedicated AI management. By establishing responsible AI applications, AI managers should not only focus on economic and medical values but also on social, ethical, and legal implications (e.g., achieving patient transparency, providing assurance for safety, establishing risk management assessments, etc.) (Kumar et al., 2021).

2.3 Organizational Information Processing Theory

Since functioning information exchange between stakeholders is critical for AI management as well as its operationalization in organizational structures, we recognize the need for further theoretical grounding with existing research theories to increase understanding of relevant constructs and alignment. Therefore, we analyzed existing theories from relevant management research streams such as organization theory (e.g., Daft, 2010; Daft & Lengel, 1986), contingency theory (e.g., Fiedler, 1964; Galbraith, 1973, 1974; Weill & Olson, 1989), control theory (e.g., Kirsch, 1996), stakeholder theory (e.g., Donaldson & Preston, 1995; Freeman, 1984), that enable us to conceptualize the information exchange between individuals in and across organizations. In doing so, we identified a suitable theoretical fit with the organizational information processing theory (OIPT), which theorizes the relationship between an organization's design, information paths, information processing capacity, and the complexity of its tasks. The OIPT was initially developed by Jay R. Galbraith (Galbraith, 1973, 1974) and has found wide adoption and advancement in the context of information technology use by several scholars afterward (e.g., Cooper & Wolfe, 2005; Fairbank et al., 2006; Haußmann et al., 2012; Premkumar et al., 2005).

The basic assumption of the OIPT is that an organization's design is significantly determined by the uncertainty concerning the tasks that an organization must perform (Galbraith, 1973). In our context, the information paths around the AI application determine the uncertainty regarding the management task. The uncertainty here refers to "the difference between the amount of information required to perform the task and the amount of information already possessed by the organization" (Galbraith, 1973, p. 5). It is caused by the increasing complexity within organizations (Haußmann et al., 2012). One primary reason for increasing complexity within organizations is the decomposition of tasks (Galbraith, 1973; Haußmann et al., 2012). To reduce task uncertainty, the structure of an organization should be tailored to fit the specific needs of the environment in which it operates. Organizations should be designed to optimize the flow of information and decision-making processes within the organization, either by reducing task complexity or improving the capacity to process information (Galbraith, 1973, 1974). Therefore, the design of an organization (e.g., design of information paths, team and department structures, etc.) should be based on the demands of the environment, the capabilities of the people within the organization, and the technologies available to the organization (Galbraith, 1973). According to Galbraith (1974, p. 28), three fundamental strategies can reduce task uncertainty: (1) "increase their ability to preplan [tasks]", (2) "increase their flexibility to adapt to their inability to preplan, or (3) "to decrease the level of performance required for continued viability".

While the OIPT from Galbraith (1973; Galbraith) offers a powerful mechanistic model to derive strategies to reduce uncertainty, the original theory had several limitations, which is why it has been further advanced over the past decades by several scholars. According to Haußmann et al. (2012), major limitations were, among others, the lack of considering individual information restrictions among stakeholders (e.g., Zmud, 1979), interpersonal characteristics (e.g., Bensaou & Venkatraman, 1995; Burke et al., 2001), inter-organizational relations (e.g., Fairbank et al., 2006). Consequently, subsequent studies (Burke et al., 2001; cf., Cooper & Wolfe, 2005; Daft & Lengel, 1986) successively advance the original theoretical framework from Galbraith (1973, 1974) and incorporate external environment, interdepartmental relations, and technology as sources of uncertainty and equivocality. One relevant resulting advancement is the recognition that task uncertainty is not the only constraint to be reduced but also equivocality, which is defined as "ambiguity, the existence of multiple and conflicting interpretations about an organizational situation" (Daft & Lengel, 1986, p. 556). Overall, Haußmann et al. (2012) propose an adapted framework of the OIPT, considering the limitations of previous scholars and incorporating helpful advancements (see Figure 1).

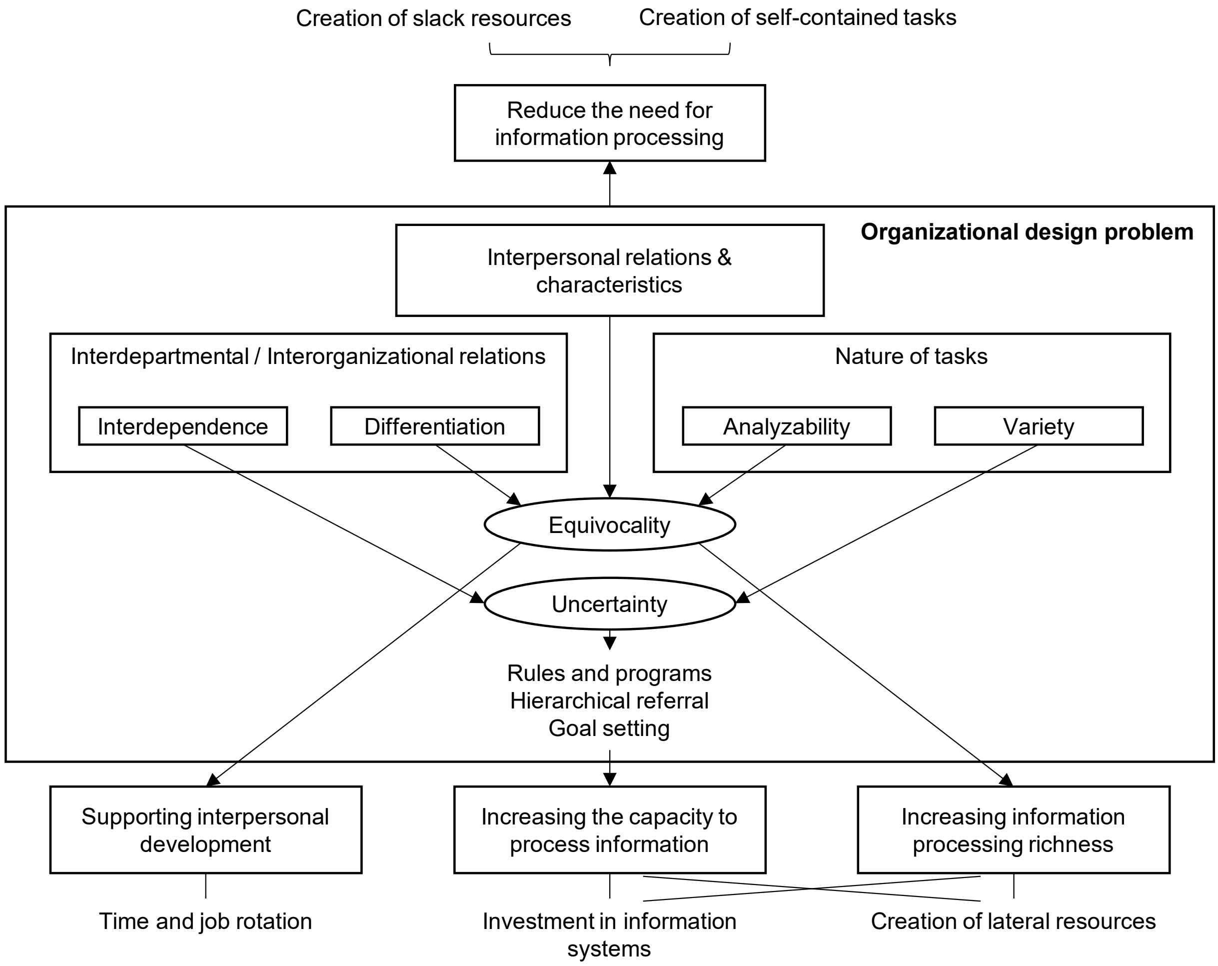

Figure 1. Organizational information processing model (adapted from Haußmann et al. (2012))

The adapted OIPT framework from Haußmann et al. (2012) recognizes the three major reasons for equivocality and uncertainty (i.e., (1) interpersonal relations and characteristics, (2) interdepartmental/inter-organizational relations, (3) nature of tasks). To reduce uncertainty and equivocality, Haußmann et al. (2012) recommend increasing the capacity of process information. Moreover, organizations may promote interpersonal development and increase information processing richness (e.g., by introducing particular expert and lateral management roles) (Cooper & Wolfe, 2005).

Considering the theoretical concepts provided by the OIPT, their adoption and operationalization can improve AI management by promoting information processing capabilities among the many stakeholders. According to Galbraith (1973), larger organizations – such as hospitals – typically employ a number of specialist groups (i.e., physicians, ethicists, health IT specialists, AI specialists, legal counsels, etc.) and resources to provide a certain output. Due to the complex nature of global tasks, hospitals must subdivide their global tasks into many specialist subtasks. This also applies to the global task of operating and managing AI applications in healthcare due to the various specialized subtasks, such as quality assurance, monitoring, model retraining, data cleansing, legal assessments, employee training, risk management, etc., that must be performed by specialist groups. Galbraith (1973, p. 28) states that such subdivision of tasks can impede information processing since task executors (i.e., AI stakeholders) “cannot communicate with all the roles with whom they are interdependent”, which in turn leads to task uncertainty among the task executors. Following Galbraith (1973, p. 28), the solution is to “create mechanisms that permit coordinated action across large numbers of interdependent roles”. In the context of our research, we apply the OIPT as a theoretical foundation to derive management practices in healthcare AI management in healthcare for several reasons. We justify the suitability of the OIPT as follows: First, we argue that the use of AI as an information technology induces novel forms of uncertainty within an organization (Morton & Hu, 2008). AI technology can automate tasks and processes within an organization, and the design of a healthcare organization requires adjustments to accommodate the use of AI. For instance, an organization may need to rethink its decision-making processes and information flow among stakeholders to incorporate AI-powered tools and systems. Particularly, healthcare organizations have many siloed teams and competencies within their organizational boundaries and across, impeding information processing and, therefore, AI management. Second, our research goal is to derive practices for the operationalization of AI management. Based on the proposed strategies of the OIPT, we aim to develop concrete practices for AI management that improve information processing. In doing so, the OIPT, which naturally relies on contingency theory, carries a helpful basis. We use the OIPT as a theoretical foundation to support theory building toward the organizational embedding of AI management.

3 Research Method

To answer our research question, we studied the management of AI applications in healthcare through the theoretical lens of the organizational information processing theory (OIPT). The OIPT allows us to investigate AI management in healthcare from an information processing perspective. We focus on such a perspective because AI application management in healthcare is a multi-party process constantly requiring the interaction between various specialized inter- and intra-organizational teams. Our research method relies on a prescriptive two-step research approach consisting of a literature review and a subsequent interview study. This approach is commonly used in qualitative research studies (e.g., Baier et al., 2019; Benner et al., 2022; Gimpel et al., 2018), capture existing theoretical knowledge (i.e., literature), which is then extended, validated, and triangulated through firsthand experience from experts (i.e., interview study).

The goal of developing a theoretical model such as the AIAMA model is to provide an “underlying structure, the scaffolding or frame” (Merriam & Tisdell, 2016, p. 85) for AI management theory. Therefore, theoretical models should have a high level of abstraction, offering high-level constructs and relationships to capture certain phenomena (Merton, 1968; Ostrom, 2005; van de Ven, 2007). Such frameworks can support the systematic expansion of the organizational AI management theory and prevent fragmentation within the research stream, particularly when existing research is still scarce (Hou et al., 2008; Kuhn, 1970).

The development of the AIAMA model is based on three concepts that build the conceptual foundation of our management model: First, lack of communication and information exchange are the sources of task uncertainty (Berente et al., 2021), leading to information processing issues among stakeholders and impeding the management of AI applications. Accordingly, promoting communication and coordination are the core tasks of AI management (Berente et al., 2021), which our AI management model must consider. Second, the management factors—theoretical constructs representing abstractions of core AI management tasks—are complex socio-technical constructs requiring close collaboration and information exchange between the different stakeholder types (Bosse et al., 2023). Third, since healthcare organizations have varying organizational structures and technology capabilities, we argue that the AIAMA model must be independent of the functional structure of a healthcare organization's stakeholders. For instance, hospitals may have their own AI development staff within their organization, but not necessarily. It is also possible that some AI developers belong to an external AI application studio that has been contracted. Accordingly, we bound our model theorizing independent from inter- or intra-organizational structures.

For the initial model development, we set out with a multi-perspective literature analysis and synthesis focusing on AI management factors and AI management practices in healthcare. Following thorough literature coding based on Gioia et al. (2013), we derived an initial set of AI management factors and management practices (see Section 3.1 for more details). After deriving the initial set of management factors and management practices from the literature, we conducted the design process in the second stage, developing the model's fundamental concepts and features. We determined the model's poles representing the overarching AI management functions, which incorporate the respective management factors. We complemented our model by illustrating the interrelations between the management factors through management cycles. These management practices are subsumed under managerial cycles that foster information processing and facilitate AI management. After each design activity, we applied the model to exemplary use cases, demonstrating its problem-solving capabilities. In total, we executed 16 process iterations – consisting of design, demonstration, and evaluation activities – until our model met our expectations. The initial design iterations (i.e., iterations 1 to 5) focused on developing the model's overall structure and general entities (i.e., management factors). During iterations 6 to 9, we focused on incorporating the management practices linking the management factors (i.e., managerial cycles). During iterations 10 and 11, we presented the model to scholars, and feedback was solicited. Then, we incorporated the scholars' feedback, specified the integration management, and introduced the integration management cycle. We then conducted a qualitative interview study with domain experts to validate, enhance, and refine our model with respect to management factors and management practices. For validating the model abstraction during the interview, we used the criteria proposed by March and Smith (1995, p. 261) and asked the experts for feedback on the model's "*fidelity with real-world phenomena, completeness, level of detail, robustness, and internal consistency*". During the interview study and the model application, we only made minor adaptions regarding the model's presentation (i.e., iterations 12 to 15). After the interview study and the model application, in iteration 16, we made minor adaptions concerning the naming of the model constructs based on reviewers' feedback and refined one management factor in terms of increased patient focus.

3.1 Literature analysis

We followed the recommendations of Vom Brocke et al. (2009) and Webster and Watson (2002) to conduct an interdisciplinary literature analysis. We approached our research from three perspectives (i.e., AI operations, the healthcare domain, and digital technology management) and triangulated the various topics for greater validity (Flick, 2010). The triangulation particularly allows us to derive management factors and practices from the healthcare management domain and digital technology management that also apply to managing AI applications in healthcare. We created three search strings, thoughtfully combining the scope of managing AI applications in healthcare, as presented in Table 1 below.

Table 1. The search strings of the literature review

#	OR		OR		OR		OR	
1	[TOPIC] application product service software technology	**AND**	[TOPIC] healthcare health care medicine health IT health informatics digital health	**AND**	[TOPIC] manag* guid* capability*	**AND**	[TOPIC] artificial intelligence machine learning	**Results: 2,784 Relevant: 21**
2	[TOPIC] deploy* manag* implement* guid*	**AND**	[TOPIC] information system* digital technolog* information technology	**AND**	[TOPIC] impact* challeng* opportunit* consider*	**AND**	[TOPIC] healthcare health care health IT medicine digital health	**Results: 1,102 Relevant: 8**
3	[TITLE] deploy* manag* implement*	**AND**	[TITLE] artificial intelligence machine learning	**AND**	[TOPIC] impact* challeng* opportunit* performance			**Results: 221 Relevant: 3**

We started with search string 1, exploring the literature on AI application management in healthcare using a keyword search in the publication databases Pubmed, Web of Science, and AISeL. In line with our research scope, we deliberately excluded papers focusing on the use of AI applications in management instead of addressing the de facto management of AI applications. After removing duplicates and screening titles and abstracts, we found 21 relevant papers. Considering the triangulation from digital technology management and healthcare management, we extended the literature search by two distinct search strings. Accordingly, we introduced a second keyword combination, targeting how healthcare organizations can manage digital technologies going beyond AI. Due to the broad scope of our query, we set the restriction that the paper must explicitly target management approaches for digital technologies in healthcare. After removing duplicates and screening titles and abstracts, we identified eight relevant papers that addressed digital technology management in healthcare. Search string 3 targeted research into general AI management, going beyond the healthcare domain. Avoiding dilution by healthcare-related results in search string 3, we specified our query, conducting only a partial title search, refraining from using Pubmed, since we sought to explicitly focus on AI management in nonhealthcare fields. In doing so, we excluded papers from our review if they had solely dealt with the AI application in an experimental environment without respect to real-world relationships. We considered three papers to be relevant. Drawing on the initial body of 32 scientific papers from our three searches, we followed Webster and Watson (2002), conducting a thorough forward and backward search, enriching our initial results with publications we missed in our keyword search, leading to another eight papers.

We then analyzed the literature for AI management factors and practices. In doing so, we followed the guidelines on qualitative content analysis of Krippendorff (2013) for guidance on coder qualification, preparation, and reliability and Gioia et al. (2013) for guidance on achieving scientific rigor in our coding procedures. For the coding, we used the knowledge organization module of the software *Citavi 6*, which is a reference management and knowledge organization software that allows users to analyze and categorize content from text-based content (e.g., research manuscripts, interview transcripts, etc.). Following Gioia et al. (2013), we set out to read through our literature carefully and highlight any specific ideas, concepts, or statements that contributed to answering our research question. Accordingly, content considered relevant were statements on management tasks, management activities, procedures for establishing effective information processing among stakeholders, as well as associated hindrances and solution approaches. Based on the identified statements, we labeled these statements with descriptive codes (i.e., open codes), capturing the main theme of each statement. We conducted three iterative coding stages: Initially, we worked independently to establish open codes grounded in our data, iteratively leading to the formation of first-order concepts. Subsequently, in the second stage, we grouped and consolidated these first-order concepts to formulate more abstract second-order themes. Lastly, we refined these second-order themes to derive overarching aggregate dimensions. After each stage, the literature analysis was discussed among the research team. For greater transparency in our literature analysis, we enclosed the concept matrix and the coding scheme derived based on the literature review in Appendix A and Appendix B (Gioia et al., 2013; Webster & Watson, 2002). The concept matrix depicts which papers included empirical data on which concept. The coding scheme illustrates an overview of our first-level concepts, second-order themes, and aggregate dimensions. Based on our literature review, we iteratively derived 41 first-order codes depicting the management of AI applications in healthcare. We then grouped the first-order concepts into higher-level categories. Considering the nature of the codes and themes, we recognized two aggregate dimensions emerging: Management factors describing *what* to manage and management practices describing *how* to manage with respect to improving information processing among stakeholders in AI management.

3.2 Qualitative interview study

In the qualitative interview study (Myers & Newman, 2007), we followed a purposive sampling approach to ensure the insights' interdisciplinariness (Etikan et al., 2016). We interviewed 11 experts from either a technical, medical, regulatory, or organizational perspective on operating AI applications in healthcare (see Table 2). The experts were acquired through both the authors' extensive personal or professional networks and research conferences on the topic of AI in healthcare. To ensure adequate interviewee expertise related to our research goal, the experts were required to have (1) an in-depth understanding of AI management, (2) work or conduct research in the context of real-world health AI applications, (3) and have minimum professional experience of 3 years in the field. Moreover, we ensured the expert sample was homogenously distributed across the different stakeholder disciplines. We conducted semi-structured interviews using an online conferencing tool. Each interview took between 45 and 60 minutes.

Table 2. An overview of the interviewees

Expert	Industry	Position	Organization	Background	Work experience	Country
A	Health AI	Software Developer	Research institution	Medical informatics (M.Sc.)	3- 5 years	Germany
B	Regulatory	Managing Partner, Professor of Law	Law firm and research institution	Attorney and professor, medical law (PhD in law)	> 20 years	Germany
C	Medical technology	ML Researcher	Startup	Computer science (PhD in engineering)	5 –10 years	Germany
D	Medicine	Chief Physician	Hospital	Radiology (M.D. and reader)	10 – 15 years	Germany
E	Medical technology	Data Scientist	Startup	Chemistry (PhD in theoretical physics)	10 – 15 years	Germany
F	Health AI	AI Consultant	Enterprise	Service management and engineering (M.Sc.)	3-5 years	Germany
G	Medicine	Senior Physician, AI Researcher	Hospital	Radiology (M.D.)	10 – 15 years	Germany
H	Medicine	AI Researcher, Chief Strategic Officer	Hospital research institution and startup	Medicine (M.D, PhD in medical neuroscience, MA in medical ethics)	10 – 15 years	Germany
I	Health insurance	Digital Care Manager	Statutory health insurer	Economics (PhD in public economics)	5 – 10 years	Germany
J	Health AI	Director Medical Data Science	Enterprise	Bioinformatics (PhD in data mining and ML)	5 – 10 years	Germany
K	Information systems	Professor of Digital Management	Research institution	Digital management (PhD in information systems)	15 – 20 years	Germany

The purpose of the interview study was threefold: First, we aimed to validate the existing body of AI management factors and practices from a practitioner's perspective. Second, we aimed to expand the management factors and management practices not covered by existing literature. Third, we aimed to gain feedback on the AIAMA model in order to make refinements and increase its validity. The interview guide of our semi-structured interviews was structured as follows: (1) introduction, (2) general statements on operating and managing AI applications, (3) model presentation and theoretical validation, (4) construct-specific questions, (5) interview closure. We enclosed the interview guide in Appendix E.

After transcribing the interviews manually, we coded the interview transcripts drawing on the existing coding derived from the literature-based coding. To analyze our interviews, we imported the interview transcripts as PDF files into *Citavi 6*. For the analysis, we applied the same criteria as in the literature-based coding. Throughout the interview analysis, the first-order codes and second-order themes were continually revised. While one author initially conducted the interview coding, a second author revisited the coding results. During the coding procedures, the research team conducted three coding workshops to increase coding validity and objectivity. As a result, we expanded our set to 47 first-order concepts through our interview analysis. While assigning the first-order concepts to the existing second-order themes, no additional second-order themes or aggregated dimensions emerged. Instead, we could assign all additionally derived first-order concepts to existing second-order themes. As a result, our coding scheme consists of 12 second-order (i.e., nine higher-level management factors, three levels of management-practices) themes. For further details on the final coding scheme, please refer to Appendix C.

Based on the qualitative interview study, we were able to further expand our understanding of management factors and management practices. Furthermore, we were able to validate and refine our theoretical model. After explaining the AIAMA model's features during the interview, all experts could immediately apply the model to their self-selected AI applications and illustrate their AI management. All the experts found the model expressive and informative and had no difficulties with comprehension. During the validation, each of our experts could match their AI management to the respective constructs of the AIAMA model. The model offered a valuable basis for the interview partners to discuss the management of AI applications in healthcare. Further, we refined the AIAMA model's presentation based on the experts' feedback.

After 11 expert interviews, we arrived at consistent results regarding the body of AI management factors and practices and the refinement of our model. Therefore, we deemed no further contribution through additional interviews since theoretical saturation on the constructs captured by the model had been reached (Marshall et al., 2013).

3.3 Model application

After the interview study, once we achieved a mature state of the AIAMA model, we applied the AIAMA model and gathered further insights into the AI management practices from an organizational perspective by analyzing their information processing across the AI management functions. For this purpose, we used the AIAMA model to analyze the information processing of exemplary management tasks underlying the respective management factors. The modeling of the management factors within the AIAMA model was conducted as part of a research workshop among the author team to reduce subjectivity and achieve scientific objectivity. We initially determined the management tasks' functional root cause (root cause), the organizational location where they become apparent (occurrence), and, thus, where they can be solved (solution). After that, we determined the task uncertainties and resulting information processing that the stakeholders within the affected management factors have. Thus, we analyze the respective management factors that are required to provide the information needed to solve the AI task (information provider). For more details, please refer to Appendix E. In the appendix, we summarize the characterization of each management task concerning root causes, occurrence, solution, and the information provider (see Table 4, Appendix E). In Figure 5, we visualize the model application, exemplified by a typical AI management task of managing the incorporation of updated medical practices (see Figure 7, Appendix E). In summary, applying the AIAMA model allowed us to validate its applicability and elaborate on three focal. Moreover, the model application increases the comprehensibility of the AIAMA model. In doing so, we show how the theoretical model relates to the problem at hand and how it can be used to explain the underlying mechanisms.

4 Results

4.1 AI management factors for setting the managerial scope

Based on the literature review and interview study, we identified 32 different management factors of AI management. The management factors are theoretical constructs that constantly raise management tasks that require information processing in order to solve them. Based on the second-order themes of our coding scheme, we further cluster the management factors and organize them along four overarching management functions, as depicted in Figure 2.

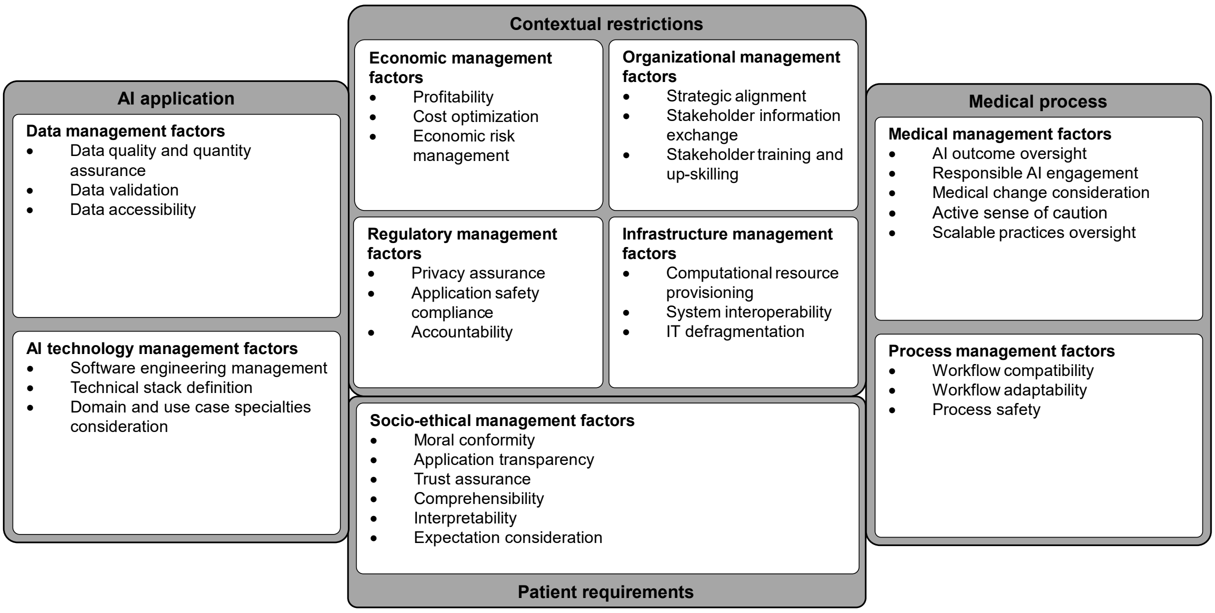

Figure 2. Management factors of AI applications in healthcare

Each management factor consists of several management tasks that can arise when environmental factors or the AI application are subject to change. The management constructs serve as abstract concepts inductively summarizing observations from reality into researchable objects and explaining the activities of AI application management (Bhattacherjee, 2012; Cronbach & Meehl, 1955). Within each of the constructs of the management factors, AI management tasks can arise.

4.2 AI management practices for improved information processing

We combine the insights from the literature review, the interview study, and the AIAMA model application to synthesize managerial practices. Both empirical sources provide valuable information on the design of roles, organizational capabilities, and operational practices in AI application management. We derive managerial requirements along three levels, i.e., organization-, role-, and task-level, which cover a wide scope.

Managerial practices for AI management in healthcare		
Organization-level	*Role-level*	*Task-level*
Interorganizational collaboration	Multi-skilling of roles and patient education	Standardization of technology stack and processes
Strategic goal alignment & communication	Clear ownership for management factors	Performance and quality monitoring with ongoing vigilance
Cross-functional information exchange	Integrating roles with managerial oversight	Disclosure of technical details and configurations
Closed feedback cycles	Explainability and interpretability consideration	Active awareness for tasks
Organizational knowledge management and documentation	Proactive task information sharing between roles	Satisfaction of information needs before task execution

Figure 3. Managerial practices for AI application management in healthcare

Organization-level:

The proposed management practices improve information processing among the stakeholders at an organizational-level. Interorganizational collaboration facilitates the pooling of diverse insights and knowledge, allowing for a more comprehensive understanding of AI-related issues. In doing so, the experts particularly advocate for close collaboration with the IT department (experts D, H). According to expert H, AI deployment and operation have many interdependencies with healthcare organizations' numerous IT systems (e.g., data from an IT system as the input for an AI application). The practice of strategic goal alignment and communication ensures that all stakeholders are aligned in their objectives, leading to cohesive and synergized efforts. Cross-functional information exchange promotes a multidisciplinary approach, harnessing expertise from various fields, thereby enriching the quality and depth of information available. For instance, experts C and J argue for the design of agile processes and activities (e.g., Scrum) to foster creativity and pragmatic solutions against arising management issues. Closed feedback cycles ensure that insights are not only gathered but also acted upon, enabling continuous improvement and adaptive strategies. In that sense, expert J argues for organizational measures promoting the sharing of feedback and promoting a learning environment with closed feedback cycles. Lastly, organizational knowledge management and documentation guarantee that critical information is systematically captured, stored, and easily retrievable, making the entire AI management more informed and efficient. To avoid role conflicts and communicaion inefficiencies in advance, knowledge sharing can contribute to reciprocal understanding (experts F, J).

Role-level:

The management of AI applications through dedicated management practices at the role-level is paramount for improving information processing. The proposed practices significantly contribute to this. Promoting the multi-skilling of management roles ensures that stakeholders are well-informed, fostering a holistic understanding of the management task. Establishing clear ownership for management factors streamlines responsibility and enhances accountability, ensuring that every facet of the AI management factors is considered. Another pivotal aspect is the establishing of integrating roles with managerial oversight ensuring the optimization of information flow. Several experts (i.e., experts C, D, G, H, J) explicitly advocated for a managerial oversight role that actively performs higher-level management and coordinates the respective departments. Creating such an integrating entity has several positive implications for practice: First, organizations can better keep track of the actions taken within the respective departments and ensure the persuasion of the same goal across numerous complex processes (expert C). Second, as AI applications' adoption increases, we expect to have more than a single AI application to manage in the future. Accordingly, it can be beneficial to healthcare organizations to channel actions into higher-level management and utilize the synergies of critical resources (expert G). However, AI application management should focus on impartially mediating the department's requirements instead of managing from an economic perspective (expert C). Otherwise, it can worsen the collaboration between the departments. We observed that various management tasks could benefit from integrating management roles. Depending on the type of AI application and underlying organizational structure, the managerial roles' profiles may vary significantly. Furthermore, the management roles should increasingly manage the explainability and interpretability of the AI application in order to ensure that AI outcomes are transparent and easily comprehensible by the patient. This not only fosters trust but also reduces information ambiguity. Lastly, proactive task information sharing between roles facilitates timely communication and collaborative decision-making, which are essential for the agile and effective management of AI applications in the healthcare domain. To operationalize role-level management practices, expert H refers to two roles: The chief AI officer (CAIO) and the product owner (PO). The CAIO should be responsible for the overall deployment and operation of AI applications within the organization and drive the realization of new AI application projects. Therefore, the CAIO should have an interdisciplinary specialist background (i.e., knowledge in computer science, medicine, and management) and mediate between the specialized departments in case of opposing goals. It also can be recognized as the operationalization of managerial oversight. Once the AI application is in use, the responsibility shifts from the CAIO to the PO. The PO is responsible for proper operation and stays watchful for arising errors and problems (i.e., vigilance). Like the CAIO, the PO should also be multi-skilled, including a thorough understanding of the underlying use case and related processes. Both roles could also be responsible for integrating management, aligning the different management cycles, and enabling coordination.

Task-level:

Complementing the organizational and role-level practices, we further identified managerial practices on a task level. Standardizing the underlying technologies, managerial tasks, and activities can increase process efficiency and allow organizations to better exploit shared resources (experts G and K). Moreover, it is beneficial to disclose technical details and configurations as it increases transparency and trust among the stakeholders, therefore contributing to information sharing. Emphasizing active awareness for tasks ensures that all stakeholders are continuously aware of potential managerial issues resulting in management tasks. Lastly, by ensuring that all information needs are satisfied prior to task execution, the process eliminates potential information bottlenecks, ensuring that decisions are made based on complete and up-to-date data. Furthermore, various experts identified a lack of quantifiable measures in the management of AI applications, arguing for more dedicated performance and quality monitoring (e.g., experts K, E, and J). In other industries, management commonly uses key performance indicators and performance measures to support managerial decision-making. However, in AI application management, adopting adequate measures beyond algorithm-related parameters is still in its infancy, inhibiting proper decision-making. Accordingly, we argue for a thorough application of quantifiable metrics and measures to facilitate managerial decision-making. In this regard, expert H further emphasizes the need for vigilance practices. Although algorithms may be readily developed for deployment, there is a chance that the management requires adaptive measures due to changes in the environment, the algorithm, or the underlying data. In this context, vigilance practices could be adapted from the pharma industry, which has developed comprehensive approaches for the continuous monitoring of drugs in the market.

4.3 Toward the AI application management (AIAMA) model

Based on the management factors and the management practices, we iteratively developed the AIAMA model. Since our first model concept considers the AI management factors as the main source of task uncertainty and equivocality leading to information processing issues among stakeholders (i.e., guiding concept 1), we rely on the management factors from Figure 2 as our model's main building blocks. Building the basis of our AIAMA model, we adopted the management factors and transformed them into our model (i.e., describing *what* to manage), as presented in Figure 4. Each factor consists of *several* dynamic *constructs* that can evolve via system changes. In the model, the constructs serve as abstract concepts inductively summarizing observations from reality into researchable objects and explaining the factors of AI application management (Bhattacherjee, 2012; Cronbach & Meehl, 1955).

Since AI management is a complex multiparty process involving many stakeholders and frequent information exchange across functional spheres, we integrate the information processing concepts of the organizational information processing theory (OIPT) into our model since efficient and functioning information exchange among stakeholders is considered crucial for successful AI management. The OIPT originally provides a mechanistic model of information processing and theoretical foundations on how organizations can promote information processing through organizational design and management approaches (Haußmann et al., 2012). In our model, we integrate the concept of *information processing* through distinct management cycles, enabling coordination and control of the AI management task arising. Following the OIPT, management tasks arising or occurring in the management factors result in information processing needs. Accordingly, promoting information processing contributes to satisfying the information processing needs in order to complete the AI management tasks within the AI management factors.

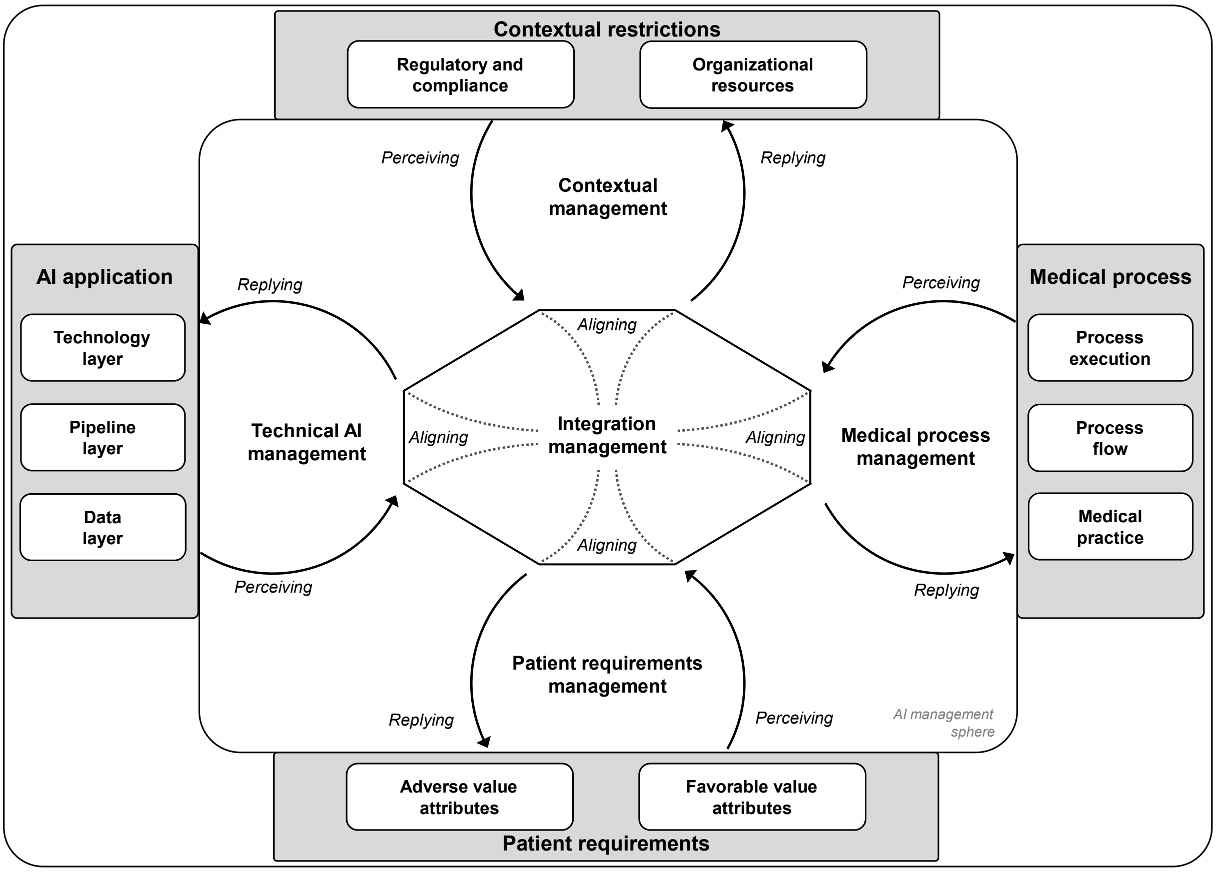

Figure 4. The AI Application Management (AIAMA) model

4.3.1 Management factors guiding the model's management functions

The management functions of the AIAMA model are abstract constructs describing the managerial scope of the underlying management factors that constantly raise management tasks and require management. In the following, we elaborate on each management function in detail.

The management function *AI application* defines the deployed AI technology and consists of three layers. Its subordinate *technology layer* describes how an organization deploys an AI application within its use case. It specifies the AI's general application approach (e.g., type of underlying algorithm). Moreover, the technology layer defines, for instance, the technology stack of the AI application. The *pipeline layer* refers to the technical design of the AI application (i.e., transforming input data into output). We follow Hummer et al.'s (2019, p. 116) description of AI pipelines as "*a series of tasks that generate, monitor, and continuously improves AI models.*" Accordingly, AI pipelines characterize the set of statistical methods and specify performance and quality measures. The *data layer* defines the data required to develop, test, and validate the AI model. It determines data acquisition, quality, protection, and privacy. In the drug treatment planning example, the AI application may require a reliable dataset comprising medication plans and their various medicinal effects.

The management function *contextual restrictions* capture the general space of action of the AI application as a health information system (Cresswell & Sheikh, 2013; Oliveira & Martins, 2011). The underlying construct of *regulatory and compliance* refers to legal restrictions, such as laws on data protection or safety requirements (He et al., 2019; Kelly et al., 2019). The *organizational resources* describe a system's shape regarding financial, human, information, and infrastructural resources (Sun & Medaglia, 2019). For instance, it illustrates the organizational strategies, the AI expertise level, and medical hardware affected by a deployed AI application.

The management function *medical process* captured the process-related considerations and requirements from the AI application's underlying use case. The subordinate construct *process execution* describes the sum of actions in the process that a deployed AI application may affect. It, thus, includes the requirements of medical staff concerning the execution of AI-related tasks and their interaction with the AI application. The underlying construct *process flow* refers to the logical connection of activities specifying how activities are carried out to obtain the desired outcome (e.g., procedural timing of AI decision in decision support). The third construct, *medical practice*, describes procedures and knowledge used to obtain a predefined process outcome (e.g., guidelines, instructions, and advice on how to carry out activities).

The management function *patient requirements* capture the patients' value attributes and requirements towards the AI application; we divide these into *favorable* and *adverse value attributes*. While favorable value attributes enable value creation (e.g., interaction requirements, explainability, safety expectations), adverse value refers to attributes whose existence hinders value creation (e.g., errors and workflow disruption by an AI application) (Higgins & Madai, 2020; Reimer et al., 2020). Particularly in the healthcare domain, the operation of responsible and patient-centric AI applications is crucial, which is why patient requirements must be closely considered by AI management, for instance, through adequate risk mitigation approaches (Kumar et al., 2021).

4.3.2 Management practices guiding the model's management cycles

The model's inner body depicts the de facto AI application management, which we recognize as a set of permanent management practices due to both the nature of AI as a moving target and continuous environmental change (Berente et al., 2021). In the AIAMA model, the managerial practices are represented by five management cycles: *technical AI management*, *contextual management*, *medical process management*, *patient requirements management,* and *integration management.* The first four management cycles comprise management activities that can mitigate and regulate the management tasks arising in the constructs outside the management factors. The integration management cycle focuses on coordinating and controlling the various management factors and ensuring managerial alignment. Supporting that view, Expert D argues for dedicated integration management because "*there is a lot of specialized knowledge [among stakeholders with] few overlapping points, […], which still need this central cycle in terms of integration management*". Accordingly, it connects the four factor management cycles and guides information processing. Although each of the model's factor management cycles targets a dedicated management topic, the cycles should not be understood as separate organizational entities. Instead, the cycles refer to the specific functions that AI application management should – integratively – operationalize within organizational structures.

Describing the interactions between the management dimensions and the integration management sphere, we draw on the theory of dynamic capabilities, which addresses how organizations can cope with changing environments (Barreto, 2010). We model the management cycles as a sequence of three phases: *perceiving*, *aligning*, and *replying*. AI application management is a dynamic multiparty process that continually copes with system change, requiring constant control and improvement (Berente et al., 2021). In our model, the *perceiving* phase refers to managerial practices aiming to perceive construct change (i.e., the requirement to manage). Perceiving can happen either trigger-based, relying on predefined criteria for known changes, or can be individually assessed for extraordinary changes (e.g., data drift incidents, infrastructural change, patient requirement drift, updated medical procedures). Expert H points out that clear responsibilities are essential within the management functions to correctly perceive the ambiguous or abnormal behavior of the AI application. Through *aligning*, management assesses a construct's changes, derives the management task, and develops actions to align these to the system's overall goals. Thus, aligning represents the intersection of the integration management cycles and the other four management cycles, allowing one to propagate information and trigger actions through the AI application management functions (e.g., problem analysis, risk assessments, information forwarding, decision-making, resource allocation). Complementing the management cycle sequences, the *replying* phase refers to managerial practices that change the outer management functions based on decisions made in the previous aligning phase (e.g., data rebalancing, model reconfiguration, process redesign, stakeholder upskilling, and information communication).

The cycle of *technical AI management* controls the implications that target the AI-related architecture and data. Technical AI management should ensure an AI application's technical fitness and should take adequate measures to improve, if necessary. *Contextual management* ensures that a deployed AI application complies with environmental restrictions from a regulatory (e.g., legal regulation) and an organizational (e.g., resources) perspective. In healthcare, *process management* targets implications from the medical process and requires deep medical knowledge. Process management should determine the medical requirements for operating AI applications and should ensure that an application's underlying medical considerations comply with official medical guidelines. *Patient requirements management* comprises managerial activities concerning patient requirements. This includes monitoring patient values (i.e., ethical conformity, transparency requirements, explainability, etc.) as well as strategy development and operationalization to actively shape value attributes.

The integrating management cycle integrates the numerous managerial activities from the four factor management cycles and provides the required capacities for the overarching AI application management. Accordingly, integration management connects the four perspectives, allowing construct change to propagate through the management system and induce responses along different cycles. Integration management works in two ways: Option 1 is the supervised connection of the four factor cycles, enabling the coordination of relatively complex and manifold challenges. However, some challenges may not require extensive aligning, benefiting from rapid and direct propagation between the cycles instead. Accordingly, in option 2, the integration management should enable direct communication between the factor cycles, supporting autonomous coordination and information exchange.

4.4 Observations from applying the AIAMA model in healthcare

To further increase our understanding of the interrelations of the management factors, we applied the AIAMA model to 34 management tasks derived from both literature and expert interviews. We model the tasks in our model since they induce management activities requiring information processing among stakeholders, as proposed by the AIAMA model. In doing so, we studied how the AIAMA model as an organizational management approach is capable of mitigating and solving the different AI management tasks. In doing so, we studied the AI management tasks' root cause, in which factors the task occur, where it is to be solved, and the information processing needs (see Table 4 in Appendix E). By modeling the 34 management tasks, we observed three focal patterns concerning information processing during AI management practices.

Firstly, we observed that the tasks' area of occurrence (i.e., the location where the management tasks are perceived) often deviated from the construct where the tasks are to be solved. This phenomenon is highly relevant for AI management because the divergence between the constructs, where the tasks occur, and where they are to be solved requires the collaboration between different management factors and, accordingly, stakeholders with different competencies and information needs. For instance, perceiving a decrease in application performance by software engineers in the application layer may require a management response in the process layer, ensuring that the physician acquires the input data properly. If the software engineer does not understand the underlying medical process, the definition of adequate responses will hamper and lead to erroneous AI applications and inefficient management (Higgins & Madai, 2020). The deviation between the area of occurrence and solution leads to a high degree of uncertainty (i.e., information mismatch), requiring information processing capabilities that exchange information across the model's management factors. However, the exchange of information is mainly hampered because the factors rely on different expertise. Consequently, integration management must translate the information (processing needs) between the model's management factors.

Secondly, we could observe that management tasks that affect patient requirements (e.g., lack of transparency) often require considering two management factors: the predominantly technical factor of *AI application* and the healthcare-specific factor of *medical process*. That outlines that patient requirements must not be targeted isolatedly from one factor only. Instead, the solution requires an integrated approach of both management factors for managing patient requirement tasks. For instance, when a patient raises privacy concerns about the deployed AI application, it may not be sufficient to decrease the patient's distrust by a clarifying conversation between the doctor and the patient during medical consultation. Instead, the AI application management should take the patient's concerns more seriously and implement a trustworthy privacy-enabling AI pipeline design (e.g., providing privacy-preserving features for patients). As the development of a coordinated solution (i.e., management) from different factors is a non-trivial task, integration management particularly acts as a facilitator and superior management entity, aligning the different management cycles and setting the goals and requirements for challenge mitigation measures.

Thirdly, we observed a difference between the top-bottom and left-right management functions. Problems and solutions are often located along the model's left-right continuum (i.e., AI application and medical process). In contrast, the top-bottom continuum (i.e., patient requirements and contextual restrictions) acts more as boundaries to be considered when managing a particular problem. Accordingly, functions on the left-right continuum are usually the ones to be changed through management responses, while north-south factors are usually regarded as immutable, only finding boundary-spanning consideration. For instance, when facing patient distrust regarding deployed AI applications, it can hardly be solved by changing the patient's satisfaction requirements without inducing a change in the AI application or medical process, which in turn requires setting up mitigating information processes among the different constructs and stakeholders. Instead, AI application management practices must focus on indirectly restoring patient trust by deploying an explainable and transparent AI application while ensuring proper process consideration (Challen et al., 2019; Reimer et al., 2020; Yu et al., 2018).

5 Discussion

Our work provides novel insights into the management of AI applications in healthcare by elaborating on the information processing of the various stakeholders that influence the AI application's operation. Our results demonstrate the relevance of efficient information processing among stakeholders to establish dedicated AI application management. In line with previous research, our findings support the socio-technical perspectives from IS research (e.g., Berente et al., 2021), arguing that technical management approaches are insufficient for successfully operating AI applications in real-world settings. As our results show, many management tasks require integrated management through both technical and non-technical management cycles. Accordingly, the AIAMA model captures five overarching management factors, of which only one factor refers to technical management, while management factors are non-technical, underpinning the role of a socio-technical view on AI application management in practice. Nonetheless, existing technical AI management approaches, such as MLOps (Kreuzberger et al., 2022), provide reliable practices for AI management by mitigating technical risks and shortcomings. Based on the AIAMA model, we derive five major research propositions (*Pn*), aligning the model's constructs and mechanisms as well as guiding future research endeavors.

P1: Patient-centricity should play a salient role in all management functions of AI management to improve patient-centricity.

In line with previous research on AI management and responsible AI in healthcare (e.g., Kumar et al., 2021; Trocin et al., 2021), the AIAMA model emphasizes the relevance of fostering ethical and social management practices, including the active consideration of patients' accountability, privacy, and transparency requirements in a structured manner by dedicated AI management approaches. Accordingly, the patient requirements play a salient role within the AIAMA model compared to other stakeholder groups. Recognizing the patients' outstanding role is vital for AI management approaches in healthcare since patients are no inherent part of the AI-operating and AI-managing organizations. Therefore, their requirements regarding the AI application may be easily overlooked by the lack of information paths from patients to AI management. AI management must increase patient awareness and establish dedicated vigilance through dedicated consideration of patient requirements to contribute to more patient-centric AI applications and ethical conformity. In doing so, striving for patient-centricity must not fall to the patient requirement management alone but to the technical AI, contextual, and medical process management.

P2: Integration management must provide differentiated information based on stakeholders' individual information needs.

Concerning our findings on the opaque cause-and-effect relations of AI management problems combined with the information asymmetries among the heterogeneous stakeholder groups, the AIAMA model depicts the amplifying management complexity of AI management in healthcare. The information needed to overcome the stakeholders' individual task uncertainty varies across the different stakeholder types. Accordingly, the information required to overcome task uncertainty is not unified across the respective stakeholders. Instead, the integration management must synthesize differentiated information for each stakeholder type.

P3: All stakeholders must acquire mutual knowledge about the other stakeholders' interpretations of AI management situations to decrease equivocality.

The AIAMA model further shows that the solution to a managerial problem often differs from the location where the management problem initially becomes apparent (i.e., area of occurrence). This amplifies the risk that stakeholders perceiving a change in a management factor may assess it as noncritical for their own AI management function at first glance, therefore not forwarding the perceived change to the integration management for further assessment. However, the perceived management problem may be critical to the management factors of other stakeholders within the AIAMA model without becoming visible there. The reasons are primarily expertise asymmetries among stakeholders, leading to interpretation asymmetries. Therefore, it is crucial that the integration management not only possesses the capability to assess the consequences of a perceived change but also qualifies each stakeholder to estimate the interpretations of the perceived change of other stakeholders of the AI management. Otherwise, valuable information may seep away in case of mismatches due to failed perceiving activities.

P4: Superior management roles for integration management reduce conflicts of interest, improving the timely formulation of management responses.

The AIAMA model's factor management cycles are usually run by specialized stakeholders possessing individual interests. Mitigating arising management problems often requires the integration management to make trade-offs between the regularly conflicting stakeholder interests. The AIAMA model indicates that an integration management role with hierarchical superiority, possessing ultimate decision power without prejudices, can facilitate the agreement on a specific management response. Such dedicated integrative roles not only promote information processing but also mediate the different stakeholder attitudes and bridge information gaps to reduce task uncertainty.

P5: Integration management leverages the management of several AI applications within the same organizational sphere by channeling information vertically and horizontally.

The AIAMA model comprises the AI management functions and cycles for managing a single AI application in healthcare. The number of AI applications is continuously increasing in larger healthcare organizations such as hospitals. Operating several AI applications with different stakeholders from varying forms may complicate information exchange both horizontally (i.e., between the stakeholders from different AI applications) and vertically (i.e., between the management levels). Integration management can serve as a channel to integrate information from various AI applications across the organizational sphere as well as aggregate management implications to the executive management levels of the organization.

5.1 Theoretical contributions and implications

The theoretical contribution of our research is that we describe a theoretical approach (i.e., the AIAMA model) that depicts management factors and practices that can promote information processing capabilities of healthcare organizations to reduce task uncertainty when managing AI applications. Therefore, we expand theoretical knowledge about AI management from an information processing perspective while considering the specific constraints of the healthcare domain. By relying on the information processing theory as a core concept, the AIAMA model contributes to research as a theoretical framework in terms of an integrated AI management approach for overcoming information processing issues among heterogeneous stakeholder groups in healthcare. In doing so, the AIAMA model proposes four management functions (i.e., contextual restrictions, medical process, patient requirements, and AI application) that describe what factors the AI management must consider when managing AI applications in healthcare. The AIAMA model further describes four factor management cycles (i.e., patient requirements management, medical process management, contextual management, technical AI management) and one integrating management cycle (i.e., integration management). All factor management cycles are interconnected via the integration management cycle. The purpose of the interrelated factor management cycles is to facilitate information processing among the stakeholders and reduce task uncertainty. To promote effective information processing, the AIAMA model proposes three managerial phases (i.e., perceiving, aligning, and replying) that enable the capabilities required to cope with the ever-evolving information needs. Through the perceiving phase, organizations take measures to actively sense the AI's environment. Through the aligning phase, the AI management becomes capable of defining the respective stakeholders that are required to satisfy the information needs of a particular management task executor. Through the response phase, the management tasks are ultimately executed. The management factors, as well as the cycles, consisting of the three management phases, aim to describe theoretical concepts to increase AI management's ability to process information more efficiently and make better management decisions.

Furthermore, we contribute to the organizational information processing theory. The AIAMA model represents a specific instantiation of management approaches to foster information processing by incorporating the concepts of the OIPT. Accordingly, the results provide practices to promote information processing and reduce task uncertainty that can be assigned to existing concepts of the OIPT framework from Haußmann et al. (2012). Interestingly, our results show that the organizational design problem is not only determined by the *nature of the task,* as originally proposed by Galbraith (1973) but also by *inter-departmental / inter-organizational relations* and *interpersonal relations* as Haußmann et al. (2012) propose. In doing so, our research contributes to the recent theoretical view within the OIPT, arguing that sociological factors within organizations play a pivotal role in developing organizational approaches to successfully promote information processing (Haußmann et al., 2012).

Operating AI applications in healthcare requires many different stakeholders from various organizations to work together and exchange information for solving complex tasks. However, the different stakeholder types mostly have highly siloed areas of expertise, impeding mutual understanding. Accordingly, management practices are providing measures to support interpersonal development (e.g., multi-skilling) to increase information processing among the stakeholders, which can have a significant impact on reducing task uncertainty and equivocality. Moreover, as incorrect behavior of AI applications often remains opaque to the user and the patient, we also recognize that the OIPT strategy of *investing in information systems* concerning transparency-ensuring features may be particularly beneficial in AI management. In doing so, AI developers can better track technical challenges without requiring notice from users. Furthermore, the OIPT concept of *creating slack resources* also finds significant representation in our findings. Many interview experts refer to dedicated expert roles (i.e., AI product owners and chief AI officers) aside from the typical disciplinary structure to improve information processing among the stakeholders.

5.2 Practical implications

We contribute to practice by providing management practices that promote information processing and decrease task uncertainty when managing AI applications in healthcare. Therefore, we describe management factors illustrating the scope of AI management. Furthermore, the AIAMA model enables AI managers to derive and establish efficient AI management practices that improve the information processing among the AI stakeholders. In doing so, the AIAMA model helps practitioners in estimating the affected stakeholders and required information for an AI management task. Moreover, the management practices support practitioners in developing effective information paths to mitigate them. One exemplary information path could be achieved by deploying AI monitoring measures at process stages far from technical operation processes. The monitoring can enable a direct information path to qualified AI engineers, avoiding the risk of failed perception by the medical staff, for instance. Accordingly, AI managers can ensure functioning information flow on process performance, even when users of the AI would not recognize deviations from intended AI behavior. Concerning the generalizability of the AIAMA model, our results indicate that the model is applicable to different types of healthcare organizations beyond hospitals. It is not limited to specific organizational structures in the healthcare sector. While developing the AIAMA model, we deliberately considered the various types of healthcare organizations. Accordingly, the AIAMA model does not explicitly illustrate roles or organizational entities. Concerning the generalizability in terms of concrete AI use cases in healthcare, we would like to emphasize the AIAMA model's particular consideration of medical processes and patient requirements as management factors. Accordingly, the AIAMA model primarily addresses use cases in which the AI applications directly affect or interact with the patient. In our view, suitable use cases of the AIAMA model are organizations using AI applications in medical processes such as medical diagnostics, medical treatment, patient monitoring, appointment scheduling, and similar processes. In contrast, healthcare organizations operating AI applications only for advancing administrative tasks (i.e., not requiring the consideration of medical or patient requirements), such as for inventory management, financial management, or marketing, may not benefit from the AIAMA model's proposed management mechanisms.

Furthermore, our managerial practices allow practitioners to derive concrete measures to achieve robust AI management across all organizational levels. At the role level, the strategies foster essential skills and capabilities and how roles should optimally collaborate and interact. With regard to the role-level practices, we further describe explicit AI management roles that practitioners can adopt for their AI management. Task-level management recommendations specify how to accomplish efficient and reliable work routines and tasks around AI operations. The results indicate that successfully managing AI applications at the task-level can be facilitated by stakeholders' active awareness for tasks, for instance, by establishing monitoring and vigilance procedures. Concerning the information processing gaps among stakeholders leading to potential loss or misinterpretation of the frequent information exchange, we recognize promoting the multi-skilling of stakeholders as a key success factor for AI operations in practice. Furthermore, the derived management cycles contribute to the common view that AI application management should be understood as a continuous endeavor. The unexpected future deviation between underlying data and reality and the call for implementing vigilance structures advocate for continuous control and management of AI applications.

Moreover, our results pose various implications for practitioners concerned with policymaking and regulation of AI applications in healthcare. The definition of AI management as a multi-party process underscores the paramount importance of delineating clear operational responsibilities, ensuring that legal liability and accountability are not left ambiguous. Furthermore, our AIAMA model elucidates various managerial factors that entail continuous management activities. These are essential for maintaining the AI application's performance and quality, prompting us to argue for the meticulous establishment of careful application surveillance standards by policymakers to ensure ongoing application conformity. Moreover, our results imply that it becomes vital that AI managers cultivate a dedicated awareness of regulatory shifts and legal adaptations after application release. The policymaking and regulation of AI applications is still in a nascent stage, with comprehensive changes anticipated in the future. Policymakers and AI managers alike must heed these facets to ensure the effective and responsible deployment of AI in healthcare settings.

The paper's results contribute to improving the operation of AI applications in healthcare by providing a scaffolding for dedicated AI management, shedding light on organizational governance structures and information flows among stakeholders. Therefore, our paper acknowledges AI management in healthcare as a system of inter- and intra-organizational interactions with specialized and siloed competencies inducing information barriers and task uncertainty. AI applications are not managed by a single actor but arise from the orchestration of different actors in a network that is specialized in certain services (e.g., model adaptions, technical monitoring, testing, retraining, legal evaluation, ethical conformity checks, etc.). Among others, we demonstrate how such orchestration can be achieved through dedicated integration management and how individual actors in the network should contribute to solving management challenges resulting from the used AI applications. Thereby, the AIAMA model can disclose the management-related consequences of the identified challenges for individual actors in the AI application's scope.

5.3 Limitations and future research directions

However, our research has limitations. Concerning methodological limitations, our literature review may not have covered all existing literature since some relevant papers could have been missed through our search string. However, we are confident that we captured the most relevant papers as we reached a certain degree of saturation toward the end of the literature analysis concerning our synthesized constructs. Moreover, our interview study faces the limitation that we only interviewed experts from Germany. Nonetheless, we are confident that the global perspective of our literature analysis mitigates any potential region bias from the interview study. Furthermore, we are aware that the coding process of the interviews may lack objectivity, as interview coding is a subjective process. However, we followed reliable guidelines from Krippendorff (2013) and Gioia et al. (2013) to ensure the highest standards of objectivity. Also, managerial practices have not yet been investigated in productive real-world environments. Thus, we have studied the effects of the AIAMA model primarily from a qualitative and not a quantitative perspective. Furthermore, we had to make certain conceptual choices that limited our research results. First, the guiding concepts of the AIAMA model put the management of information processing into the foreground. In doing so, the model constructs do not capture individual stakeholders or roles. Accordingly, the model does not provide distinct recommendations on specific AI management roles. Furthermore, we have approached AI management from an information processing perspective, focusing on information-related constructs critical for successful AI management. While solving information processing is a primary contributor to successful AI management, there are still other requirements for AI management to be considered.

Complementing the study's limitations with suggestions for future research, we see great potential for future research to draw on our scientific work and to further expand existing research on AI management. Current research has mainly focused on conceptualizing AI management, laying the groundwork for the young research field. Embedding our research in the current research stream, we push the scientific frontier forward and shed light on AI application management from an information processing perspective. We encourage fellow researchers to take up our research to further investigate the managerial workings of AI operations through specialized perspectives. For instance, research could focus on more prescriptive research proposing concrete management procedures building on our management practices. Furthermore, future research could focus on developing specific AI management roles specifying their required skill sets and task profiles. Thus, researchers can investigate the interdependencies and interactions between the roles and departments, potentially revealing inefficiencies and conflicts. Also, research could ask what other factors beyond improving information processing contribute to the management of AI applications. Fellow researchers could further draw on the AIAMA model as a guiding framework depicting what management functions have to interact to execute certain AI management tasks. Further, the AIAMA can also be used to expand the organizational perspective, supporting the assignment of the developed roles to organizational structures (i.e., departments or teams). Besides advocating for future research to push the scientific frontier forward, we also see great opportunities to widen the research body by re-constructing our research in a completely new context. In this thesis, we developed an AI management model with a close consideration of the medical domain. Possibly, the conceptual workings of the AIAMA model may also be suitable to describe AI management in other domains and industries.

6 Conclusion

In summary, the integration of AI applications in healthcare has the potential to bring about significant improvement. However, successfully operating AI applications in healthcare require novel forms of management due to the specialties of both AI technology and the healthcare domain. AI management complexity mainly arises from stakeholders' heterogeneous competencies, understandings, and information needs, leading to information gaps and task uncertainty. To overcome these issues, AI management must have relevant information at hand, promote information flow, and establish adequate organizational structures. In our paper, we answer what the factors are for managing AI applications in healthcare and how they are related. Additionally, we respond to the question of what management practices improve information processing among stakeholders in AI management. Based on our multi-perspective literature review and interview study, we developed the comprehensive AI application management (AIAMA) model, which theorizes the theoretical constructs of AI management in healthcare concerning information processing among stakeholders when addressing AI challenges. This study increases theoretical understanding and promotes the development of strategies for managing AI applications from an information processing perspective. Summarizing the outlook for future research, we see promising opportunities for fellow researchers to conduct scientific work in the field of AI management. Successfully managing AI applications is a challenging yet extremely promising endeavor with great potential for healthcare and improving care delivery. We trust that we have provided a foundation for further research that will foster meaningful AI applications in healthcare.

7 References

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Appendix

Appendix A: Concept matrix of the literature review

Table 3. Concept matrix of the literature revies (adapted from Webster and Watson (2002))

Concepts / Articles	Management factors									Management best practices		
	Data management factors	AI technology management factors	Economic management factors	Organizational management factors	Regulatory management factors	Infrastructure challenges	Socio-ethical management factors	Process Management factors	Medical process management factors	Organizational-level best practices	Role-level best practices	Task-level best pracitces
Ahangama and Poo (2015)	x			x			x			x	x	x
Ala-Kitula et al. (2017)			x	x			x		x	x	x	x
Alsheibani et al. (2018)				x	x	x				x		
Alsheibani et al. (2019a)			x	x	x	x	x			x		
Alsheibani et al. (2019b)	x			x		x						
Amodei et al. (2016)		x							x			x
Baier et al. (2019)	x	x	x	x	x	x	x	x			x	x
Bygstad et al. (2019)	x			x	x	x			x	x	x	x
He et al. (2019)	x	x	x		x		x		x	x	x	x
Ben-Israel et al. (2020)	x	x										
Carter et al. (2020)				x	x		x					
Cetindamar et al. (2009)		x		x				x		x		
Challen et al. (2019)	x	x					x	x	x			x
Char et al. (2018)	x				x		x		x		x	x
Chen and Decary (2020)	x	x		x			x		x	x		
Cresswell and Sheikh (2013)				x					x	x		
Cresswell and Sheikh (2015)			x	x					x	x		
Ellahham et al. (2019)	x	x			x		x					x
Esteva et al. (2019)	x	x										
Guan (2019)							x					
Hashimoto et al. (2018)	x	x					x				x	x
Holzinger et al. (2019)		x					x					
Hummer et al. (2019)	x	x			x	x		x				x
Iveroth et al. (2013)				x					x	x		
Kelly et al. (2019)	x	x			x	x	x	x			x	x
Litwin et al. (2012)		x		x								x
Menachemi et al. (2011)				x						x		
Miao et al. (2017)	x	x										x
Pumplun et al. (2019)		x		x	x							
Racine et al. (2019)							x			x		
Rippen et al. (2013)	x	x	x	x	x	x	x	x	x	x		
Sendak et al. (2019)	x	x	x	x						x	x	
Shaw et al. (2019)	x	x	x	x	x	x	x				x	
Sligo et al. (2017)		x	x	x	x	x	x	x	x			
Stanfill and Marc (2019)	x				x		x			x		
Sun and Medaglia (2019)	x	x	x	x	x	x	x			x	x	x
Vartak et al. (2016)		x										
Wiens et al. (2019)	x	x					x		x			x
Yu et al. (2018)	x				x		x	x		x		x
Yu and Kohane (2019)	x		x				x	x	x		x	x

Appendix B: Coding scheme based on literature analysis

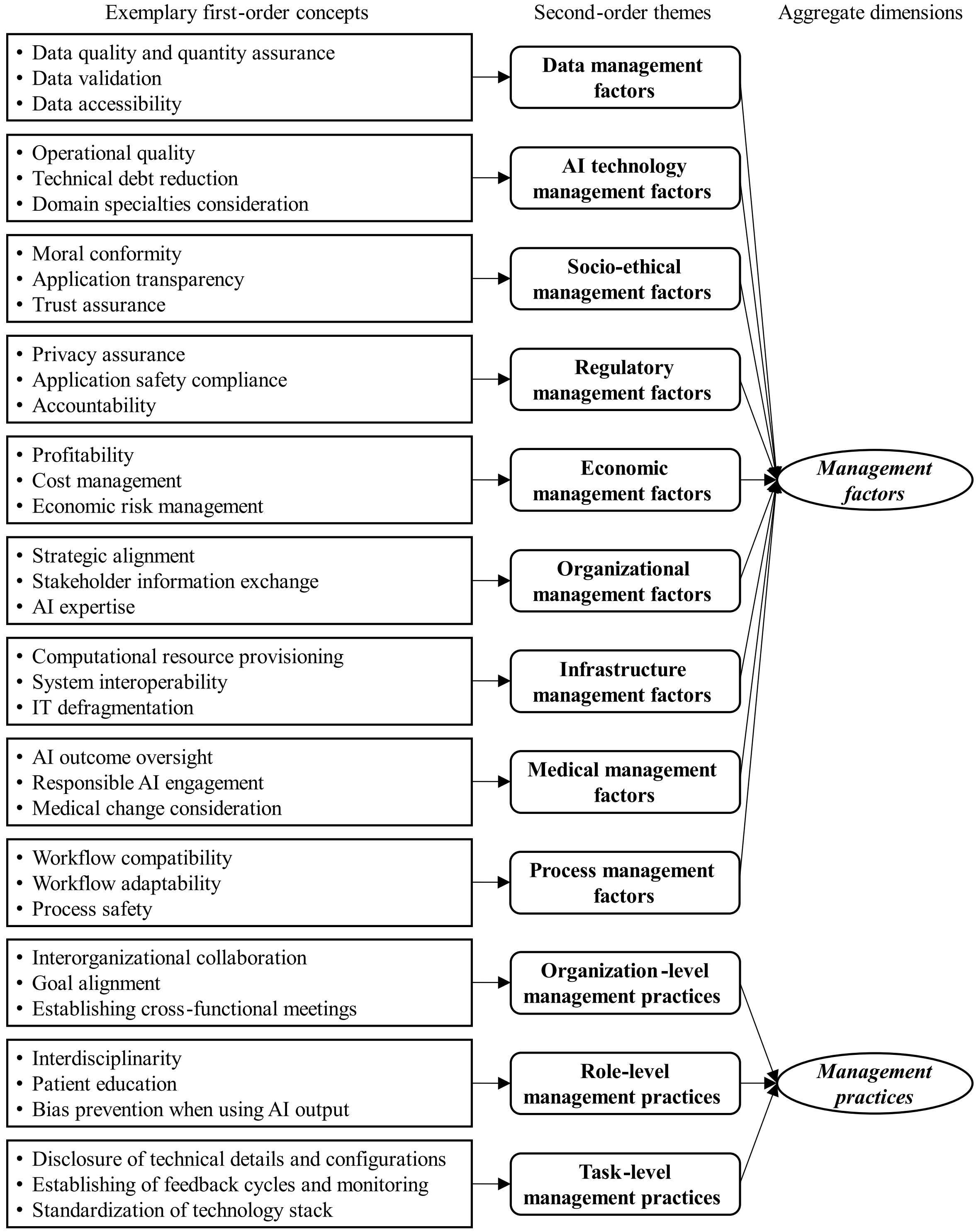

Figure 5. Coding scheme based on literature analysis (adapted from Gioia et al. (2013))

Appendix C: Interview guideline

Chapter 1: Introduction

Activity: Overview of research project

Activity: Establishment of a shared understanding of the research concepts: management, artificial intelligence, healthcare

1.1 What is your personal, educational and professional background?
1.2 What is your current professional activity?
1.3 What are your touchpoints to AI there?

Chapter 2: General statements on operating and managing AI applications

2.1 What major issues of AI applications do you currently identify regarding the operation of AI applications in healthcare? How can they be addressed?
2.2 From your point of view, how could holistic AI management improve the application of AI? What should such an AI management achieve?
2.3 Do you know best practices for AI applications in healthcare?
2.4 How do you expect operating AI applications to affect processes and responsibilities? If change is expected, should it occur and in what way?
2.5 Where do you expect the strongest resistance from stakeholders to the operation and management of AI?

Chapter 3: Model presentation and theoretical validation

Activity: Presentation of preliminary theoretical understanding and discussion

3.1 Do you understand the model's core concepts?
3.2 Are there elements you would like to add to or remove from the model?
3.3 Does it describe and simplify reality in a reasonable way?
3.4 Can you identify objects and relations that may play predominant roles?
3.5 Who should be responsible for which management activity?
3.6 How do you see the need for organizational interaction regarding the management tasks?
3.7 How do you see the need for coordination within the AI application management?
3.8 Where would you see yourself within the model?

Chapter 4: Construct-specific questions

Contextual restrictions

4.1 What organizations may participate in operating AI application?
4.2 How do economic considerations affect the management of AI applications?
4.3 How do you assess the interaction with other platforms and IT-infrastructure?
4.4 How does current regulation and compliance affect AI application management?

AI application

4.1 How do you assess the need for continuous changes and adaptions of AI applications?
4.2 How do you generally deal with the model-specific risks like data drift, concept drift, etc.?

4.3 What major retrospective changes to you consider? How are later changes distributed regarding frequency, complexity, responsibility?
4.4 From your point of view, how do existing AI management approaches satisfy the quality assurance and evaluation requirements in the healthcare sector? Are medical considerations present, too?

Patient requirements
4.1 How would you consider patient requirements regarding the AI management?
4.2 How are patients supposed to benefit from AI application management in what way?
4.3 Are there feedback mechanisms and evaluation metrics checking on individual requirements and their change? How are patients to be involved within the feedback cycle?

Medical process
4.1 How does the connection of AI and Non-AI personnel and procedures work? Are there obstacles arising? Are there medical conflicts of interest?
4.2 From a medical perspective, how do you assess the integration of AI applications into existing medical processes?
4.3 How do you manage retrospective medical changes or future medical adaptions? (e.g., medical procedures change)

Chapter 5: Closure

5.1 Synthesizing and summarizing of discussed statements
5.2 Statements and insights you want to share not fully covered by the interview
5.3 Information to next steps of the research project
5.4 Recommendation of potential interviewees
5.5 Feedback on the interview

Appendix D: Coding scheme based on interview analysis

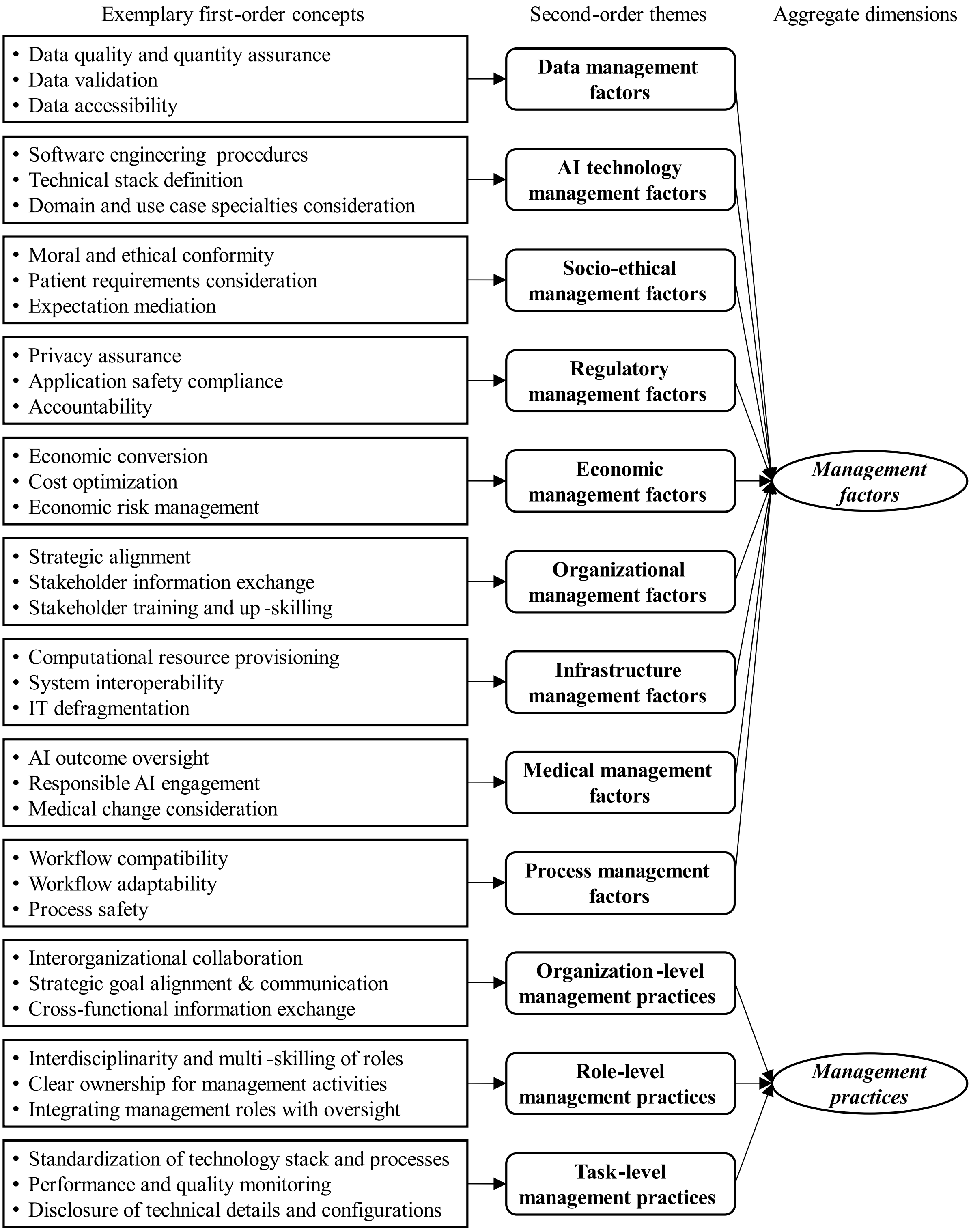

Figure 6. Adapted coding scheme based on the interview analysis (adapted from Gioia et al. (2013))

Appendix E: Application of the management challenges to the AIAMA model

We illustrate the AIAMA model application by the management of outdated medical practices. Outdated medical practices may result from updated medical guidelines by healthcare authorities. We exemplify the model application by the case of a hospital having to react to changing medical guidelines as it affects their AI application.

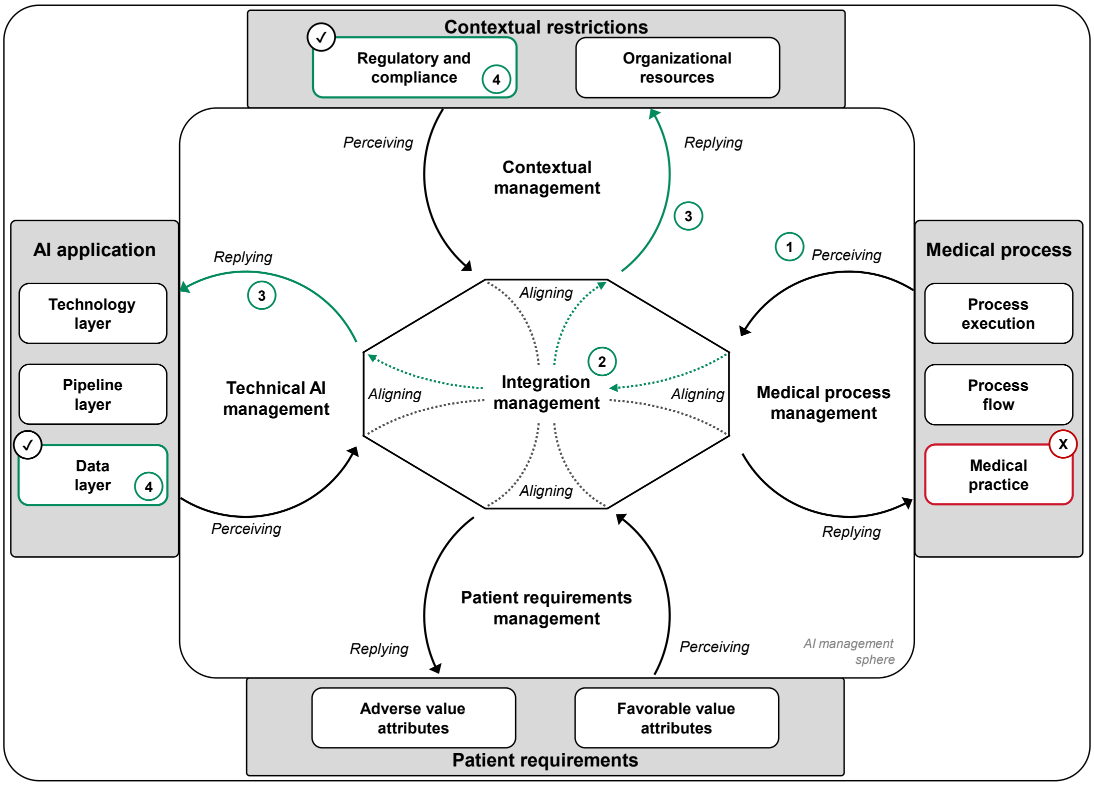

Figure 7. Model application exemplified by the management of outdated medical practices

In the AIAMA model, the adapted medical guidelines induce a change of the medical process (X). The stakeholders of medical process management recognizes potential impact on the AI application and the requirement to consider the novel guidelines within the AI. Considering the potential complexity of incorporating the medical practices with respect to the AI application, the medical process management reports the issue to the integration management (1). The integration management seizes the information from the medical process management and assesses the implications on the AI application operations. After discussing the implications in a team of selected experts, the AI management agrees on adopting the medical guidelines (2). In line with technical, medical, and regulatory concerns, the integration management develops a holistic approach for the adoption procedure and triggers necessary responses to the relevant fields (i.e., regulatory and compliance, data layer) (3). The technical AI management starts acquiring and preparing the required data for the AI application and merging it with the existing database. After that, the AI application is retrained. Once the output reaches promising results, stakeholders from regulatory and compliance (i.e., regulatory experts) conduct a legal review ensuring that the novel model version complies with the legal requirements (4). Finally, the updated AI application is deployed and complies with updated medical guidelines (✓).

Table 4. Application of the AIAMA model

		Problem side				**Solution side**				
	Exemplary task of the management factor	**AI application**	**Contextual restrictions**	**Patient requirements**	**Medical processes**	**Technical AI management**	**Contextual management**	**Patient requirements management**	**Medical process management**	**Integration management**
Data management factors	Managing data quality issues	root cause, occurrence				solution				
	Managing data quantity issues	root cause, occurrence				solution				
	Managing lacking data accessibility	occurrence	root cause			solution	information provider			information provider
	Managing data validation	occurrence	root cause			solution				information provider
AI technology management factors	Managing lacking software engineering procedures	root cause, occurrence				solution				
	Managing the technical stack	root cause, occurrence				solution				
	Managing lacking domain and use case specialties consideration	root cause, occurrence			occurrence	solution		information provider	information provider	information provider
Economic management factors	Managing profitability		root cause, occurrence			information provider	solution			information provider
	Managing scalability	root cause			root cause, occurrence	solution			information provider	information provider
	Managing th lack of real-world value	root cause			root cause, occurrence	solution		information provider	information provider	information provider
Organizational management factors	Managing strategic conflicts	root cause, occurrence	root cause, occurrence	root cause, occurrence	root cause, occurrence		solution			information provider
	Managing lacking stakeholder information sharing	root cause, occurrence	root cause, occurrence	root cause, occurrence	root cause, occurrence		solution			information provider
	Managing lacking stakeholder training	root cause, occurrence	root cause, occurrence	root cause, occurrence	root cause, occurrence		solution			information provider
	Managing lack of information	occurrence	root cause		occurrence		solution			information provider
Regulatory management factors	Managing privacy requirements	occurrence		root cause		solution	information provider			information provider
	Managing application inconformities	root cause			occurrence	solution	information provider			information provider
	Managing unclear accountability		root cause, occurence		root cause		information provider		solution	information provider
Infrastructure management	Managing the shortage of computational ressources	occurrence, root cause				solution	information provider			information provider

factors	Managing interoperability	root cause, occurrence				information provider	solution			information provider
	Managing IT fragmentation	occurrence	root cause			information provider	solution			information provider
Socio-ethical management factors	Managing moral conformity			root cause	occurrence	information provider	information provider		solution	information provider
	Managing application opaqueness	root cause		root cause	occurrence	information provider	information provider		solution	information provider
	Managing lack of patient trust	root cause		root cause	occurrence	information provider	information provider		solution	information provider
	Managing lack of patient understanding	root cause		root cause	occurrence	information provider	information provider		solution	information provider
	Managing results interpretability			root cause	occurrence					
	Managing exaggerating patient expectations			root cause	occurrence	information provider	information provider		solution	information provider
Process management factors	Managing workflow incompatibility				root cause, occurrence	information provider			solution	information provider
	Managing workflow disruption				root cause, occurrence	information provider			solution	information provider
	Managing process deviation				root cause, occurrence	information provider			solution	information provider
Medical management factors	Managing negligent AI interaction	root cause			occurrence	information provider			solution	information provider
	Managing lacking AI outcome engagement	root cause			occurrence	solution			information provider	information provider
	Managing missing sense of caution	root cause			occurrence				solution	
	Managing outdated medical practices				**root cause, occurrence**	**solution**			**information provider**	
	Manage lacking practices oversight	root cause			occurrence	information provider			solution	information provider

Legend: Root cause (i.e., describes where the root cause of the task is)
Occurrence (i.e., describes where the task becomes visible)
Solution (i.e., describes where the task is solved)
Information provider (i.e., describes whose information is needed)