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Enhancing Healthcare with Artificial Intelligence: A Configurational Integration of Complementary Technologies and Stakeholder Needs

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Enhancing Healthcare with Artificial Intelligence: A Configurational Integration of Complementary Technologies and Stakeholder Needs

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Abstract:

Knowledge of complementary technologies is crucial for realizing optimal value from artificial intelligence (AI) in healthcare. However, they still remain under-researched. Resultantly, we identify technologies complementing AI applications and investigate their configurational impact on healthcare services from a multi-stakeholder perspective. Through topic modeling analysis of 11,814 research articles, we unveil that healthcare digitalization (DIG), healthcare information management (HIM), and medical artificial intelligence (MAI) are the key complementary technologies bolstering AI implementations in the healthcare ecosystem. Furthermore, building on the foundations of configurational theory, we develop propositions delineating the interplay of technological synergies. We propose a conceptual framework comprising technological drivers for successful AI applications in healthcare. Our fuzzy-set qualitative comparative analysis (fsQCA) offers important revelations: first, DIG is instrumental for AI-driven HIM, second, DIG and HIM are crucial for enhancing MAI. Third, but most importantly, we also establish that accommodating multi-stakeholder interests (MSI) is quintessential for the success of AI applications in healthcare. Our findings present a roadmap for healthcare administrators, emphasizing the role of synergies and stakeholder interests in enabling AI as a strategic initiative in healthcare service delivery.

Keywords: AI, Healthcare, STM, Configurational Theory, fsQCA, Digitalization, Information Management, Stakeholder Interests.

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1 Introduction

The landscape of artificial intelligence (AI) technologies has catalyzed a paradigmatic shift in the healthcare service ecosystem (McKinsey & Company, 2020; Rajpurkar et al., 2022; WHO, 2021). Cognizant of these technological progressions, information systems (IS) scholarship has persistently emphasized the role of AI in healthcare research and practice (Ågerfalk et al., 2022; Dennehy et al., 2023; Raddatz et al., 2023). In this realm, studies have shown the profound potential of AI algorithms in healthcare, e.g., applications related to disease detection, treatment planning, insurance customization, emergency vehicle logistics, and customer service innovation (P. Kumar et al., 2023; Su et al., 2023; Yu et al., 2024). Literature shows that AI implementations streamline decision-making and information management practices. This, in turn, fosters quick medical interventions and optimal operational processes (Chen et al., 2021; B. Wang et al., 2023; Y. Wang, Zhang, et al., 2023). Overall, the discussions are concentrated on the refinement of AI models for niche medical applications or AI-augmented decision-making for physicians and healthcare administrators (Bertsimas et al., 2022; Jussupow et al., 2021). However, today, healthcare executives need a roadmap to leverage AI as a strategic toolkit and realize its optimal value in conjunction with multiple stakeholders.

The literature suggests that driving key constituents of a successful AI strategy include compatibility, effective data use, and understanding relative benefits (Alsheiabni et al., 2020). Additionally, a mindful orchestration of complementary technologies is stressed for a successful AI strategy in organizations (Eastwood, 2023). It is further noted that novel technologies such as mobile health applications, smart wearables, cloud computing, internet-of-medical-things (IoMT), and big data analytics extend the outreach of AI-enabled healthcare services (D. Kumar et al., 2022; J. Li et al., 2022; Xiang et al., 2024). Echoing this perspective, scholars have underlined AI as a synergistic system materialized from the integration and implementation of bundled technologies (Abadie et al., 2023; Vannuccini & Prytkova, 2024). Recent industry reports have also acknowledged the existence of complementarity of technologies in healthcare practices (Kiron & Schrage, 2019; Mate et al., 2024). The challenge rests upon the identification of such synergies and their causal configurations for a successful AI strategy in healthcare.

Therefore, it is imperative for the practice to uncover the complementary technologies and their interaction schema for realizing high-value propositions. This clearly remains a gap in the extant literature, mainly due to the following challenges: first, the stakeholder base for healthcare is diverse, and second, the mechanism to improve value for diverse stakeholder needs is complex. The literature underscores the significance of end-user attitudes and their perspectives toward the value-generation mechanisms of technological tools in healthcare (Abraham et al., 2021; Martínez-Caro et al., 2018). On these lines, Sujan et al. (2022) delineated stakeholder perspectives on safety concerns associated with AI augmentation in healthcare. Vo et al. (2023) assessed the preferences of patients, practitioners, and the public regarding AI utilization in healthcare services. Moreover, configurational knowledge of AI technologies is crucial for addressing the needs of multiple healthcare stakeholders (Kim et al., 2024; Sujan et al., 2022). Hence, we underscore the importance of fulfilling stakeholder requirements while investing in AI and complementary assets for healthcare organizations. At this juncture, a theoretical distinction of AI and related taxonomy is warranted to delineate the conceptual boundaries of the terminologies used in this study, as mentioned in Table 1.

Table 1. Working Definitions of Various Terms

Term	Operational Definition	Adapted From
Medical	We refer to the practice of medicine, encompassing diagnostics, treatment, research, direct-patient examination, and clinical care.	Merriam-Webster[1], X. Huang et al. (2023), and Stöger et al. (2021)
Healthcare	We refer to the broader healthcare delivery system comprising hospitals, clinics, pharmaceuticals, insurance, regulators, suppliers, government, and the infrastructure, operational activities, and the personnel involved in providing medical services.	Cambridge Dictionary[2], Dai & Tayur (2022), and Lämmermann et al. (2024)

[1] https://www.merriam-webster.com/dictionary/medical
[2] https://dictionary.cambridge.org/dictionary/english/healthcare

Artificial Intelligence	We refer to agents, systems, or machines that mimic intelligent human behavior using machine learning, deep learning, neural networks, natural language processing, or rule-based expert systems in order to interpret, learn, adapt, and execute.	Akter et al. (2021) and Davenport et al. (2020)

Without an understanding of complementary forces, healthcare organizations cannot capitalize on the technological landscape of AI for an overarching stakeholder base. Such a novel investigation would guide healthcare administrators to strategically navigate the ocean of AI-enabled sophistications while addressing problems of siloed interests (Pagani & Champion, 2020). It will enable researchers to understand the characteristics of AI-driven healthcare processes and their causal mechanisms. Therefore, an in-depth understanding of the technological configurations complementing AI applications is warranted for a strategic and successful AI provision in healthcare organizations. To date, the works have fallen short of delineating the complementary technological drivers of AI in healthcare. The extant works are also silent on the configurational interactions of AI technologies and their effect on healthcare stakeholders. We, thus, aim to plug this gap by addressing the following research questions:

RQ1: What are the complementary technologies scaling the AI strategy in healthcare?

RQ2: What configurations of these technologies are vital for stakeholders' interests?

To identify the technological drivers and their orchestration, we seek inputs from the configurational theory. The theory states that, in general, multiple causal conditions affect an outcome of interest. We can observe the impact of these atomic causal conditions as several configurations for the phenomena under investigation (Ragin, 2009; Rihoux & Ragin, 2009). As argued, AI acts as the anchor of complementary technologies, which, together with a configurational bouquet, foster strategic healthcare service delivery. Simultaneously, configurational theory offers the appropriate foundations for investigating the conjunctural synergies within complementary technologies in the context of AI-driven healthcare interventions and associated stakeholders. Thus, we conduct an empirical study grounded in configurational theory to identify the complementary technologies and configurations fulfilling stakeholder needs. We operationalize this examination via a multi-phased research methodology.

In the first phase, we systematically identified 11,814 relevant research studies from 2014 to 2024. We then perform structural topic modeling (STM) analysis to uncover pertinent dimensions of technologies complementing AI applications in healthcare (Kuhn, 2018; Sharma et al., 2021). STM enables our study to take an all-embracing viewpoint of AI-related technological progressions in healthcare. In the second phase, we identify individual characteristics of the explored complementary technological dimensions. Drawing upon the configurational theory, we propose a conceptual framework and posit inter-relationships among these technological drivers. Through an intensive examination of literature, we adapt scale items to operationalize the dimensional constructs. Further, we design an online survey instrument to collect responses from healthcare AI experts. In the third phase, we conduct fuzzy-set qualitative comparative analysis (fsQCA) to empirically validate our propositions. fsQCA is deemed superior to conventional methods while dealing with intertwined and complex causal relationships (Mandal et al., 2023). It also emphasizes the configurational combinations of independent variables for explaining the outcome rather than promoting competition for the best predictor (Duşa, 2018).

We address the above-mentioned research questions and identify gaps in AI in healthcare literature through the results of this study. Notably, we observe that healthcare digitalization (DIG), healthcare information management (HIM), and medical artificial intelligence (MAI) are the key technological drivers reinforcing AI-enabled healthcare services. This implies that healthcare organizations must invest in digitalization, information management, and algorithmic technologies to extract maximum benefits from AI implementations. We further found that multi-stakeholder interests (MSI) must be factored in while planning for specific AI interventions in healthcare. Most importantly, through fsQCA, we confirm that the configurational synergy of DIG, HIM, and MAI is vital for attending MSI. Accordingly, we inform the AI in healthcare literature about the prerequisite technological drivers and essential configurations for MAI and fulfillment of MSI.

Similarly, our findings have multi-faceted implications for the healthcare practice. The findings imply that the digitalization of organizational assets and the establishment of information management practices are essential for MAI's success. Together, these technologies accentuate standardization and accessibility of healthcare data. They further foster better decision-making, and consequently, organizations observe improved patient care and healthcare research. In their absence, MAI may lack reliability, resulting in inefficiencies, biases, and a diminished impact on healthcare outcomes (Lehne et al., 2019). In addition, the findings suggest that AI can be successfully embedded as a strategic initiative in healthcare organizations by addressing MSI. To fulfill MSI, organizations need effective digital governance, robust information management practices, and customized MAI infrastructure. Without adequate technology governance and stakeholder expectation mapping mechanisms, AI-driven strategies can cause fatigue among healthcare stakeholders instead of facilitating their workflows (Rozenblit et al., 2025). This work, therefore, provides a strategic AI roadmap for healthcare administrators by emphasizing the interaction of technological facets surrounding AI applications and stakeholder needs.

We organize the rest of the article as follows. Section 2 delineates the detailed literature review. In section 3, we describe theoretical and methodological approaches. Section 4 presents the identification of configurational dimensions and the proposed conceptual framework. Section 5 describes the research design, data collection, measurement procedures, and fsQCA analysis. Section 6 provides the results and robustness analysis. In section 7, we provide a discussion of configurational analysis, contributions, limitations of our study, and a few future research directions. Lastly, section 8 concludes the analysis and results of this research.

2 Literature Review

In recent IS literature, several works have focused on developing niche AI and machine learning (ML) models for improving individual medical applications. For example, in organ transplantation operations, it is important that the recipient's body does not reject the transplanted organ. Related works depict how ML approaches can determine the chances of graft acceptance (Topuz et al., 2018). This can allow hospitals to decrease the risk associated with such high-stakes medical complications. In similar lines, a few works aim to predict patient treatment pathways. Johnson et al. (2022) proposed a multi-stage AI model to predict prognosis for lung cancer patients. Such approaches can aid physicians in developing treatment plans for patients and predicting the chances of their survival over the years. Consequently, various patient-directed applications have made the literature and practice cognizant of the potential of AI models for medical applications.

At the same time, healthcare organizations also deal with scarce medical resources, and as a result, optimal utilization is warranted. For instance, the accurate prediction of the length of stay for a patient can help hospitals manage their resources better. Alnsour et al. (2023) developed an AI system to enhance capacity planning processes and the efficient utilization of limited resources. Concurrently, in medical practice, drug prescription is an information-intensive process for physicians. Adverse drug reactions can take place because of medical ignorance or the unavailability of data for all possible factors associated with a patient. Fan et al. (2020) proposed a deep learning (DL) model for accurately detecting adverse drug reactions. Amid expansions of AI in healthcare, some studies propose AI applications in medical insurance (Yu et al., 2024), supply chain (Gu et al., 2024), and human resource management (Li et al., 2023). In sum, the literature contains multiple such studies that drill down on the development of AI models for applications in healthcare processes.

Through such point-level AI applications pertaining to both medical and non-medical scenarios, the literature has demonstrated enhancement in medical services and the healthcare ecosystem. For instance, Pham et al. (2024) showcased that integration of AI technologies can improve healthcare operations, productivity, occupancy rates, and total revenue. In parallel, another set of literature that deals with the augmentation of practitioners, adoption of AI, and promotion of responsible AI. For example, Agarwal et al. (2024) talked about redesigning medical workflows that can facilitate a synergistic augmentation of AI to healthcare practitioners' cognitive abilities. Hou et al. (2024) highlighted the impact of awareness about AI smartness and AI transparency in AI assistants on physicians' adoption rate in real-world healthcare settings. Similarly, Gupta and Srivastava (2024) discussed the factors that contribute to the barriers to AI adoption in hospitals and provided an AI adoption framework. Therefore, the literature has showcased AI benefits and ways through which institutions can promote AI implementation in the healthcare ecosystem.

However, the literature remains silent on the technological drivers that are quintessential for running successful AI services in healthcare (Abadie et al., 2023; Vannuccini & Prytkova, 2024). AI is inherently a landscape of a multitude of technologies. For example, effective operations of AI systems depend on the quantity and quality of data that is fed into the model. In healthcare, much of this data is being collected through IoMT devices. In light of this technological complementarity, Alqaralleh et al. (2024) proposed a blockchain-assisted medical data transmission system to facilitate an IoMT-enabled real-time diagnosis environment. In this context, although the AI model met the primary diagnostic objective, its realization was fundamentally enabled by the parallel synchronization of multiple technologies. Similarly, Bag et al. (2023) discussed the implementation of big data analytics (BDA) in conjunction with AI to enable increased absorptive capacity of healthcare supply chains. The literature also advocates the cognizance of multiple technologies as well as digital health interventions for an effective AI-driven healthcare service delivery (Arslantaş, 2024). Thus, AI-enabled healthcare operations will require an adequate presence of complementary technological infrastructure and processes. However, so far, the literature has only tangentially acknowledged the technological complementarities associated with AI in healthcare.

It is also important to note that to develop an organization-wide AI strategy, we must determine the cause-and-effect relationships between these technological sophistications. The literature is silent on how these complementarities affect AI development and implementations. The determination of these interrelationships is crucial for enabling successful AI integrations in healthcare organizations. But so far, the literature falls short of studies discussing such dependencies among AI-supporting technological drivers in healthcare. At the same time, most of the studies have analyzed AI-led transformations from either a practitioner's or a patient's perspective (Dai & Tayur, 2022; Latif et al., 2024; Pan et al., 2019). However, the literature has begun to take cognizance of multi-stakeholder views while making such technological interventions. For example, Lämmermann et al. (2024) state that adequate informational exchange mechanisms are needed between diverse stakeholders for managing AI applications in healthcare. Literature now recognizes that healthcare stakeholders have differing needs and expectations from AI (Kim et al., 2024). It calls for the inclusion of diverse healthcare stakeholder viewpoints on critical issues such as AI safety and assurance (Sujan et al., 2022). Hence, in the context of this study, we must determine promising configurational settings of these drivers from a holistic multi-stakeholder perspective.

Based on the analysis of the literature, this study provides a theoretical bridge to replace the above-mentioned missing links between AI and healthcare. This study aligns itself with the scholarship that emphasizes the interconnected nature of the technological landscape of AI. We identify the key technological drivers that are necessary for fruitful AI implementations in healthcare. We also determine the nature of the interplay between these dimensions and AI. The study also adheres to the emerging multi-stakeholder perspective in the literature, wherein the requirements and difficulties of all are given due importance. We delineate the overall configurational impact of AI and complementary technologies on healthcare stakeholders. Consequently, our study provides a coherent amalgamation of various technologies, AI, and healthcare. The next section sheds light on the theoretical lens and methodological details.

3 Theory and Methodological Approach

3.1 Configurational Theory

Determination of cause-effect relationships that explain the complexity of organizational structures lies at the core of organizational science (Fiss, 2011). The main argument of the configurational theory is that the outcome of interest or the observed effect is almost always linked to multiple causal conditions intertwined in a complex configurational interdependence (Rihoux & Ragin, 2009). Thus, we need typologies that acknowledge and complement the complex web of cause-effect relationships through causal configurations for organizational theory building. Essentially, it advocates a shift from studying the net linear effects of independent variables to a contextual understanding of configurations. Such configurations comprise a combination of variables that explain variance in the outcome of interest (Fiss, 2011). The theory also states that a single causal condition may have a different effect depending on the configuration with other causal conditions (Schneider & Wagemann, 2012). Fundamentally, configurational theorizing deals with three key aspects (Ragin, 2009). First is conjunctural causation, which underlines that a single condition's effect unravels in the presence of other causal conditions. The second is equifinality, which states that multiple configurations can lead to the same outcome. Third is causal asymmetry, which argues that conditions leading to the presence of an outcome might be different from the causes that explain its absence (Papagiannidis, 2022). In summary, the configurational theory provides the mechanism to formulate statements that delineate recipes of causal conditions that explain the phenomena under observation (Ordanini et al., 2014).

This theoretical lens allows one to move beyond linear causal effects and explore the complex interdependencies among technological capabilities, organizational processes, human requirements, and contextual conditions. As a result, we tend to identify the multiple combinations of atomic drivers for AI-based interventions in healthcare. Further, we must understand their configurational interplay and identify the causal conditions that lead to the fulfillment of stakeholder needs and facilitate successful AI strategy in healthcare. Rather than treating digitalization of medical processes, information management practices, and AI interventions in isolation, configuration theory emphasizes that it is the synergistic alignment of these elements that determines stakeholder-focused outcomes. For instance, the efficacy of AI applications is contingent upon information management systems, the maturity of digital infrastructure, and the alignment of expectations across physicians, administrators, patients, and regulators. By identifying distinct and coherent combinations of pertinent factors, this study adopts a configurational approach to uncover integrated causal conditions under which AI can be integrated effectively into healthcare service delivery. This perspective recognizes that there is no single best model for success; instead, it emerges from a fit among interdependent factors tailored to the specific context. In the next sub-section, we describe the research selection process and topic modeling analysis conducted to obtain configurational typologies, present in the context of AI interventions in healthcare.

3.2 Research Selection

To retrieve a comprehensive set of research publications, we created two different sets of keywords. For technologies associated with AI, we used "*artificial intelligence", "ai", "machine learning", "deep learning", "neural network", "big data", "analytics", "data mining", "text mining", "decision support system", "internet of things", "IoT", "industry 4.0", "cloud computing", "blockchain", "classification",* and *"prediction"* as our keywords. At the same time, we used "*health", "healthcare", "hospital", "care", "nurse", "pharmaceutical", "medical", "medicine", "drug", "patient",* and *"physician"* for filtering healthcare literature. To create a near-exhaustive set of keywords, we systematically derived them from the author keywords of previous research articles. These previous studies were first identified using keywords mentioned in Ali et al. (2018), Chen and Srinivasan (2023), Galetsi et al. (2020), M. Kumar et al. (2020), Rajabion et al. (2019), and Zhao et al. (2018). These selected seminal studies were either published in relation to AI or healthcare or both.

We selected the Scopus database to run the Boolean search query because of its higher title coverage (Mongeon & Paul-Hus, 2016). We limited publications to subject areas: decision sciences, business, management, and accounting, as well as economics, econometrics, and finance. These subject areas were selected to restrict the focus to the management science domain and filter out tangentially related or technology-centered studies. Next, we included only journal articles published in the English language. It is also vital to note that AI is a constantly developing field. The AI practices that were deemed essential in the past decades may no longer hold relevance in the current landscape. The annual report by the Stanford Institute for Human-Centered AI indicates that the acceleration in computational power, especially after 2014, has pushed the industry to produce AI models (Perrault & Clark, 2024). Therefore, we limited the research corpus to the last ten years to identify the latest practices around AI in healthcare research. Thus, we systematically gathered a corpus of 11,814 research articles relevant to our scope.

3.3 Structural Topic Modeling Analysis

Structural topic modeling (STM) has emerged as a sophisticated method for analyzing large-scale textual data and uncovering hidden thematic structures (V. Kumar & Srivastava, 2022; Tonidandel et al., 2022). STM has also been utilized for its advanced natural language processing (NLP) capabilities to analyze the experiences of healthcare workers during COVID-19 (Lamb et al., 2022) and their opinions about the adoption of AI (Nitiéma, 2023). STM is a probabilistic topic model that generates data for each document, which is then used to define values for different computational model parameters. It assigns two fundamental values: the document-topic and the topic-word distributions. Fundamentally, each document (D) is defined as the mixture of a few latent topics (K), and each topic is defined as a concoction of key terms (N). The discussion of the statistical models used to compute these parameters is beyond the scope of this study. However, a plate diagram of the core model adapted from Roberts et al. (2013) and Sharma et al. (2021), which extends the correlated-topic model, Dirichlet-Multinomial Regression topic model, and Sparse Additive Generative topic model, is shown in Figure 1.

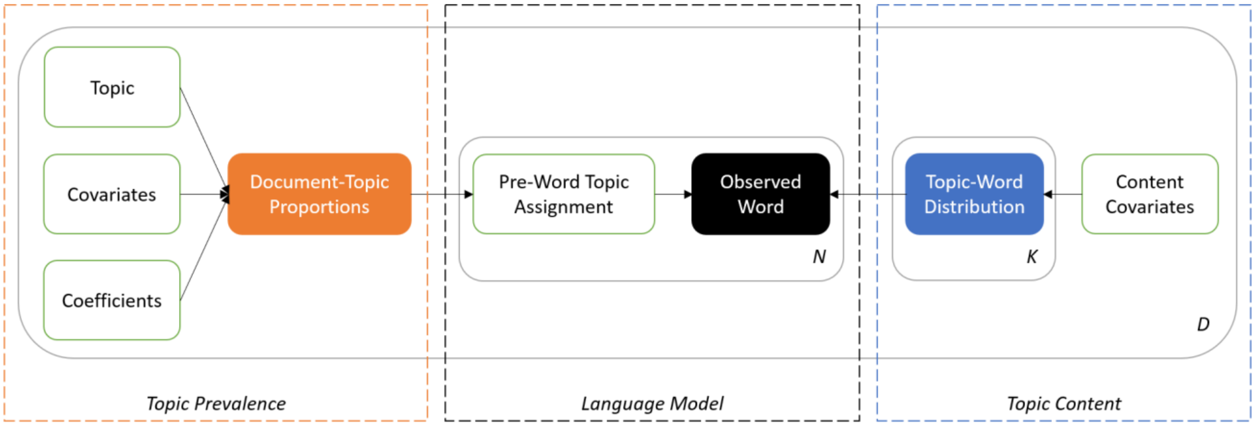

Figure 1. Representative Diagram of the STM Model

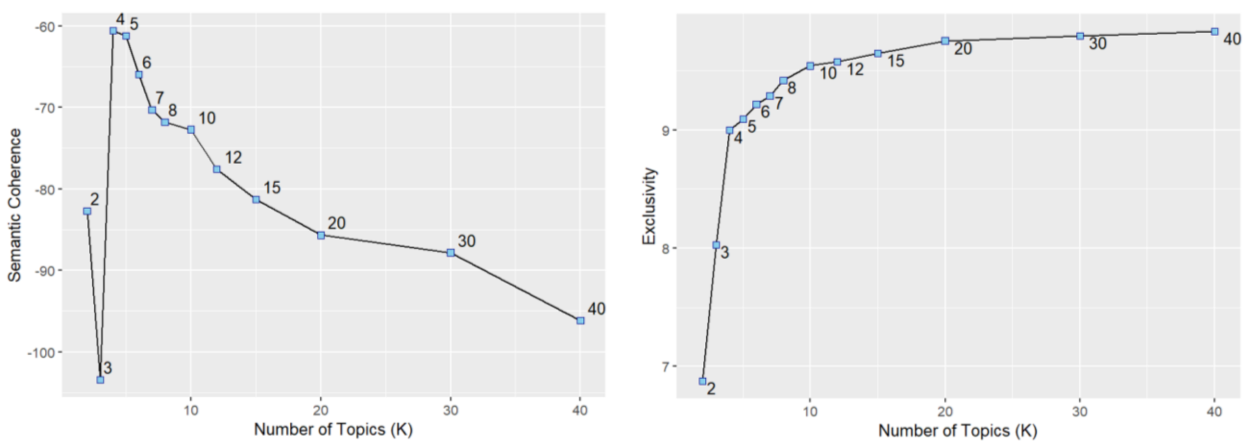

Figure 2. Semantic Coherence (left side) and Exclusivity (right side) Plots for Determining K

We used the R programming interface to execute STM analysis on the abstracts of 11,814 research articles through a multi-stage protocol (Tonidandel et al., 2022). In stage 1, we cleaned the text corpus by converting the text into lowercase and removing numbers, symbols, and punctuation. We removed default stop words and words with a word length of less than two characters. We also reduced words to their root form by performing stemming and lemmatization procedures. In stage 2, we generated the document-term matrix, which provides the frequency of each term in every document. This process leads to a highly sparse matrix where most cells have a zero value. Therefore, we decreased sparsity by removing 99.97% of the empty cells. In stage 3, we used the *"stm"* package from the R library to conduct topic modeling (Roberts et al., 2019). We analyzed semantic coherence and exclusivity for up to 40 topics (refer to Figure 2). This visual inspection is similar to the scree plot examination in exploratory factor analysis. The highest semantic coherence score of -60.582 was obtained, corresponding to four topics, and topic exclusivity also started to saturate at 8.999 after the same number of topics. As a result, we decided to proceed with four themes present in our corpus.

Lastly, in stage 4, we generated an STM solution corresponding to four topics. We then identified the characteristics of four themes through commonly used criteria presented in Table 2. First, the top 20 highest probability words were obtained corresponding to each topic (Figure A1). These words are the most frequently found in a topic. Second, we obtained FREX words, which are the most frequently occurring and exclusive terms for a given topic. Third, the Lift parameter penalizes words that present more frequently in other topics. Fourth, Score is also a similar parameter in which words are rated based on the ratio of log frequency in a topic to other topics. The top seven terms (refer to Table 2) across these four parameters were independently studied by the authors, two IS professors, and four healthcare practitioners. Followed by an in-depth discussion, the experts agreed on the labeling of the four themes as healthcare digitalization (DIG), healthcare information management (HIM), medical artificial intelligence (MAI), and multi-stakeholder interests (MSI). The same was validated by the analysis of top research articles corresponding to the four topics and top parametric terms. A detailed synthesis of the top terms and relevant literature is delineated in the following section.

Table 2. Top 7 terms obtained through STM

Topic	Topic Label	Criteria	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
1	Healthcare Digitalization	Prob	system	technolog	manag	develop	servic	health	can
		FREX	monitor	iot	secur	devic	smart	cloud	sensor
		Lift	air	cloud	devic	emiss	energi	iot	monitor
		Score	iot	abstract	sensor	smart	pollut	cloud	devic
2	Healthcare Information Management	Prob	data	use	inform	health	healthcar	medic	decis
		FREX	big	avail	data	mine	healthcar	drug	analyt
		Lift	avail	languag	prescript	summar	text	queri	unstructur
		Score	avail	data	big	mine	topic	drug	medic
3	Medical Artificial Intelligence	Prob	model	use	method	predict	propos	algorithm	result
		FREX	predict	algorithm	accuraci	classif	neural	classifi	deep
		Lift	algorithm	cnn	coeffici	discret	gene	heurist	interv
		Score	breast	algorithm	classif	accuraci	predict	neural	diagnosi
4	Multi-stakeholder Interests	Prob	social	use	media	hospit	effect	manag	market
		FREX	social	media	market	custom	consum	valu	interact
		Lift	feel	crisi	employe	food	market	mediat	organis
		Score	social	brand	media	valu	market	interact	custom

4 Configurational Dimensions and Framework

One of the objectives of this study was to understand the configurational dimensions supporting AI in healthcare settings. Thus, to answer RQ1, we performed STM analysis in conjunction with a scholarly synthesis of AI-focused research articles in the intersection of healthcare and intelligent systems space. This investigation revealed three crucial technological complementors, namely, DIG, HIM, and MAI, which are consistently linked to diverse AI-enabled healthcare applications. Along with these dimensions, we also uncovered that MSI is a major thrust across various works in this part of the literature. Hence, taking cognizance of the healthcare IS scholarship, we transcribed these dimensions into four pertinent constructs. The following subsections discuss the thematic characteristics and IS literature encompassing these research areas.

4.1 Healthcare Digitalization

Healthcare digitalization (DIG) advocates the implementation of innovative technologies to digitalize human and infrastructural resources in healthcare (Majcherek et al., 2024). According to the IS literature, successful DIG strategies enable data creation and capturing systems across the organization (Zhao & Canales, 2021). To achieve DIG, Bag et al. (2023) recommend a multi-pronged approach towards technological implementation in the healthcare ecosystem. A large cohort of AI-powered technologies has facilitated the digitalization of healthcare processes and services (Fosso Wamba & Queiroz, 2023; Gunasekeran et al., 2021). For instance, mobile health technologies have seen a dramatic rise in wellness management (Lau et al., 2020). Sensors embedded in smart devices such as phones and watches can gather patient activity data (Chui et al., 2019; Zhu et al., 2021). AI models can analyze this data for assistance provision in a multitude of activities, such as medication adherence, sleep regulation, and exercise (Liu & Varshney, 2020; Tarafdar & Bose, 2021). IoMT covers the entire gamut of these digital healthcare devices. Srinivasa K G et al. (2018) showcased that coupled with AI models, these devices can transform infant monitoring and patient rehabilitation services and can also provide support to blind people. Digital sensors, digital twin technology, and AI models can together create smart healthcare environments (Manocha et al., 2024). Such cyber-physical systems can aid healthcare service providers in monitoring individual health and predicting diseases.

Cloud and fog computing architectures have also emerged as critical facilitators for remote patient health monitoring. These technologies have enabled the processing of remote sensor data at the end devices, AI-based disease detection in the cloud, and the transfer of results to healthcare professionals (D. Kumar et al., 2022). At the same time, IoMT devices are connected in near real-time with healthcare facilities, transferring crucial medical information from patients to back-end AI systems. Blockchain-assisted information exchange models have the capability to alleviate personal data security concerns, enforce trust, and improve data accessibility (Xiang et al., 2024). Federated learning techniques have also enabled secure IoMT services in smart healthcare systems (Banabilah et al., 2022). Literature suggests that DIG combined with AI can lead to substantial enhancement of the healthcare ecosystem (Piccialli et al., 2021). However, organizations still face challenges in leveraging AI algorithms due to the lack of complementary phenomena like the digitalization of healthcare processes (Dicuonzo et al., 2023). In summary, we define DIG as digital technologies dealing with the design, deployment, and integration of AI-supported digital infrastructure and healthcare services.

4.2 Healthcare Information Management

Traditionally, healthcare information management (HIM) is associated with data standardization and storage, integration of dissimilar computer platforms, and enterprise-wide information access (Lorence & Spink, 2004). The IS literature showcases HIM systems being responsible for prescription tracking, telemedicine, insurance claims management, and building patient health records (Sadeghi R. et al., 2022). However, the explosion of digital healthcare has led to the genesis of big biomedical data. Legacy information management systems can no longer handle this amplified availability of health data in terms of both volume and variety. Consequently, AI-enabled BDA approaches have become vital for effectively utilizing data, uncovering patterns, and making timely interventions (J. Li et al., 2022). A significant amount of healthcare data still needs to be extracted from an unstructured format, such as hand-written healthcare practitioner notes and informal patient communication over internet channels. Text mining technologies such as NLP are crucial for structuring this data and understanding colloquial terminology (Babaian & Xu, 2024). Similarly, AI can also process electronic health records (EHRs) to provide disease information and facilitate capabilities for drug discovery (Liu et al., 2024; Lou & Wu, 2021). EHR systems utilizing AI-enabled BDA models have also been considered a breakthrough in HIM (Chen et al., 2020).

HIM practices also involve management of data accuracy, integrity, maintenance, and information processing to operationalize data assets (Moore, 2004). AI can be used to summarize healthcare data collected through the HIM systems. AI insights can provide crucial knowledge to practitioners and inform stakeholders in crucial decision-making scenarios. Kellner et al. (2023) showcased that AI can be used to retrieve information from online platforms and inform healthcare institutions about potential disease cases and demand for medical facilities. The healthcare organizations can utilize AI tools to support medical experts in making more accurate data-driven diagnostic decisions. Fang et al. (2021) proposed a prescriptive analytics method to reduce the cost associated with medical decision-making and to recommend optimal solutions in complex decision processes. AI can also support insurance companies to efficiently decide premiums for patients via simultaneous analysis of comorbidity risk information (Yu et al., 2024). Therefore, we define HIM as the collection, processing, and analysis of healthcare data to facilitate information provision and decision support through AI systems.

4.3 Medical Artificial Intelligence

Medical artificial intelligence (MAI) comprises computational models that support healthcare stakeholders in decision-making tasks ranging from diagnosis, treatment pathway recommendations, to predicting operational outcomes (X. Huang et al., 2023). A bouquet of AI algorithms vis-à-vis ML, DL, and neural networks has been proactively deployed to analyze data managed through healthcare IS. In the literature, MAI models have been found useful in independent disease detection, smart hospital management, providing support in surgical procedures, online query answering, radiology report analysis, and epidemic information dissemination (Huo et al., 2022; Y. Wang, Song, et al., 2023). However, these AI models need to be adapted to improve medical results. For example, DL and convolutional neural networks have been tuned for classifying CT scan images to delineate benign versus malignant lung tumors (X. Huang et al., 2020). Similarly, H. Wang et al. (2018) modeled support vector machines and ensemble learning algorithms to increase the diagnostic accuracy of AI models in breast cancer. We also found studies based on heuristic techniques and ML models for creating screening schedules and predicting outcomes for cancer patients (Karimi et al., 2023; F. Wang et al., 2018). To this end, a fruit fly optimization algorithm has been proposed for optimizing the coefficients of support vector machines in medical data classification problems (Shen et al., 2016).

Given the large heterogeneity of health data, it becomes imperative to first perform considerable training and optimization to develop accurate MAI models (Li et al., 2021). We observed that scholars have combined genetic algorithms with support vector machines to select optimal features from large, feature-rich medical datasets. Such developments aid in the accurate prediction of quality of life after organ transplantation procedures (Oztekin et al., 2018). Similarly, Jiang et al. (2018) proposed an integrated framework that combines particle swarm optimization and ML models to predict re-hospitalization rates and, therefore, healthcare service quality based on hospital IS data. Ahady Dolatsara et al. (2020) also devised a two-stage modeling framework based on ML to predict monotonic probabilities of organ transplantation survival. Hence, healthcare scholars have established multi-stage AI frameworks enabling the development of models that can unravel insights from medical information. AI models also require extensive medical databases and complex, multi-structured algorithmic training for them to be scalable, cost-efficient, and customizable for developing reliable MAI models for the healthcare ecosystem (Stöger et al., 2021).

Based on this extant understanding, we conceptualize MAI as a focused subset of AI applications that are directly involved in medical decision-making, diagnostic support, and patient care. We advocate this terminology, in contrast to terms such as "Clinical AI" or "Healthcare AI," as they can get restrictive to only direct-patient interactions or can become conceptually overloaded with administrative tools, public health analytics, or general-purpose operational activities. Our use of MAI is intentionally restricted to AI models and systems designed for medical use cases in the healthcare ecosystem. From a thorough survey across trade articles[3], research works (Rajpurkar et al., 2022; X. Huang et al., 2023), and practitioner blogs[4], we define MAI as the development of computationally intelligent AI systems to enhance decision-making processes through self-learning mechanisms, promote effective human-AI collaboration, and the organizational sharing of insights to support continuous improvement in healthcare service delivery. Thus, MAI refers to the refinement of AI models and the creation of AI applications specific to the healthcare industry.

4.4 Multi-stakeholder Interests

Extant works in IS literature emphasize that incorporating a multi-stakeholder perspective is crucial for effective technological intervention in healthcare (Breeman et al., 2021; Nudurupati et al., 2015; Palas & Bunduchi, 2020). A multi-stakeholder approach towards AI in healthcare should encompass relevant stakeholders, including patients, physicians, nurses, medical staff, administrators, suppliers, technicians, regulators, financiers, and society (Vo et al., 2023). In the context of AI applications, such a perspective can help uncover stakeholder needs and preferences to strengthen the value chain of healthcare organizations (Breeman et al., 2021; Leone et al., 2021; Schiavone et al., 2021). Thus, it is important to address the diversity of needs and opinions of heterogeneous stakeholders in the rapidly emerging AI in healthcare ecosystem.

Social media platforms have become a popular channel for healthcare stakeholders to share opinions and disseminate information. Patients proactively interact in consumer-to-consumer informational exchange and avail emotional support from online health communities (K. Y. Huang et al., 2019). Healthcare organizations can use ML systems on social media platforms to detect people in emotional distress and, as a result, prevent suicides by providing mental health assistance (Chau et al., 2020). AI models can assess the quality of answers to medical queries and promote the best medical information in such forums (Mousavi et al., 2020). User-generated content can be classified using NLP techniques to identify health emergency situations quickly. Accordingly, governments and healthcare institutions can manage

[3] https://www.ibm.com/think/topics/artificial-intelligence-medicine
[4] https://research.google/blog/advancing-medical-ai-with-med-gemini/

healthcare crises by providing timely information to generate public awareness and engagement (K. Li et al., 2022; Rao et al., 2020).

Together, AI and social media can provide insights to match the needs of healthcare stakeholders effectively. For example, Nguyen et al. (2023) proposed that DL-based sentiment analysis of online news outlets can help predict pharmaceutical demand during disease outbreaks. Studies have also highlighted the facilitators and deterrents for AI adoption uptake among physicians and healthcare stakeholders (Dalvi-Esfahani et al., 2023; Prakash & Das, 2021). Thompson et al. (2022) used ML models to predict employee attrition rates based on EHR usage. P. Kumar et al. (2023) argued that hospitals can improve management of customer relations through AI capabilities, as it leads to service innovation and flexibility. Consequently, we define multi-stakeholder interests (MSI) as comprising stakeholder-aware AI adoption, gauging stakeholders' preferences, incorporating varied views, and facilitating healthcare institutions' online engagement on social media platforms through AI systems. In the next section, we provide details of the conceptual model that binds these four atomic dimensions under one conceptual framework.

4.5 Conceptual Framework

In our analysis of the literature, we observed that apart from the differentiating features of each dimension of AI research in healthcare, some studies accentuate their interrelationships. AI-enabled Industry 4.0 technologies have revolutionized the digitalization of healthcare products and services. IoMT and online medical platforms have established numerous digital touchpoints for the healthcare ecosystem (Rani et al., 2023). DIG has created an abundance of big bio-medical data that needs to be gathered, processed, and updated from time to time (J. Li et al., 2022). Healthcare organizations will need HIM processes to capitalize on DIG transformations. Thus, DIG calls for the creation of AI-powered HIM. Health data will deliver business value if it is readily accessible to the relevant practitioners and society through EHRs (Liu et al., 2024). Organizations need AI algorithms to process unstructured, high-dimensional, voluminous, and a variety of data formats to utilize digital health effectively. In healthcare, the technological processes of data generation and information management will require the capabilities of sophisticated AI models. Thus, efficient HIM and effective DIG further call for the deployment of MAI. Further, ML and DL models need to be tuned to generate medical insights in applications such as demand prediction, disease classification, knowledge discovery, and optimal resource utilization (Ahady Dolatsara et al., 2020; X. Huang et al., 2020).

More importantly, the core of the transformation of healthcare services lies in the fulfillment of the needs of its stakeholders. DIG achieved through wearable devices and telemedicine consultations has provided patients and practitioners with new avenues for health monitoring and remote delivery of healthcare services (Srinivasa K G et al., 2018). Similarly, an effective healthcare ecosystem warrants the provision of the best possible medical data and information to its stakeholders (K. Li et al., 2022). It also requires AI-powered information management systems capable of providing decision support to healthcare practitioners and administrators (Yu et al., 2024). However, developing integrated AI frameworks is crucial for stakeholders to manage digital health data and IS. Healthcare institutions and governments can deploy AI models to understand healthcare stakeholders' needs and expectations through social media and online platforms (Kellner et al., 2023). Therefore, we argue that simultaneous DIG, HIM, and MAI enhancements should cater to MSI in healthcare services. Hence, grounded on the configurational approach, cognizant of the literature and the identified causal conditions, we make the following propositions (refer to Figure 3):

Proposition 1: **DIG should emerge as a necessary or sufficient configuration for HIM.**

Proposition 2: **(a) DIG should be a causal condition for MAI, and (b) HIM should be a causal condition for MAI. There should also be a configuration of DIG and HIM that enables MAI.**

Proposition 3: **A causal configuration of DIG, HIM, and MAI should facilitate MSI in healthcare.**

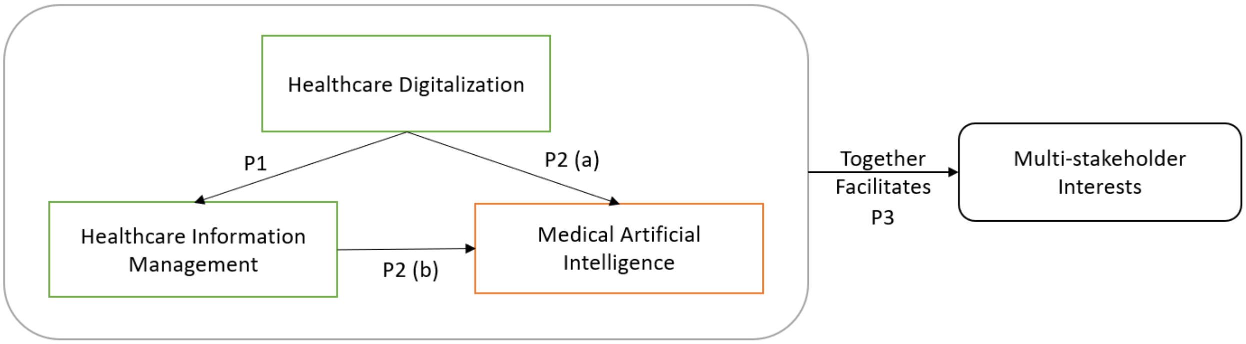

Figure 3. Nomological Network of Configurations Building MSI

5 Data Collection and Measurements

We empirically delineate the intricacies of the methodologies used to establish the configurational interplay in the following sub-sections.

5.1 Scale adaptation

We adapted previously established scales for the measurement of four latent constructs that were identified through STM. The scale adaptation procedure was executed in two stages: item generation and refinement, and item purification (Mishra et al., 2023). First, we performed an extensive literature search to detect scales related to DIG, HIM, MAI, and MSI. We borrowed only relevant items for this study, and overlapping items were dropped. Then, certain modifications were made to the existing items, such as fitting the context, changing the wording, and the response scale. We followed the recommendations provided by Heggestad et al. (2019) while making such adaptations to any scale items. Second, two IS professors evaluated an initial set of 27 statements corresponding to four constructs. Statements were scrutinized for appropriate wording and redundant statements to provide a true reflection of the underlying constructs. Four healthcare practitioners further evaluated these statements and their application to respective constructs. In this process, five items were eliminated, and the remaining items with suitable face validity were retained.

5.2 Data collection

We developed a 22-item questionnaire for measuring four latent constructs. All statements were rated on a Likert scale ranging from 1 = strongly disagree to 5 = strongly agree (refer to Table A1). We employed a 5-point response scale as it is the preferred choice for capturing absolute perspectives instead of abstract judgments (Lietz, 2010). We administered the finalized survey questionnaire to prospective respondents through an online Google form. The questionnaire was preceded by a preamble providing instructions and assurance of privacy (refer to Figure A2). We collected data from healthcare professionals practicing across cities of the Indian sub-continent (refer to Table A2). We followed the snowball sampling method to ensure respondents' know-how about AI applications in healthcare practice. Our target population was hard to reach as it required knowledge of medical AI applications. Therefore, the respondent-driven sampling method was deemed appropriate (Goodman, 2011). We first identified seven medical practitioners; newer respondents were identified through their referrals. In total, we collected 76 responses through this method. To ensure data quality, we kept an attention check question asking respondents to fill out a specific answer. Consequently, ten responses had to be removed.

5.3 Measurement and Validation

Next, we assessed the reliability and validity measures of the indicators and their respective reflective constructs. For setting parametric thresholds, we relied on the guidelines outlined by (Hair et al., 2013). First, we ensured indicator reliability through a minimum standardized loading estimate of 0.50. This parameter informs the amount of the indicator's variance explained by the respective construct. Second, internal consistency reliability provides information about the closeness of the association of indicators measuring the same construct. It was confirmed through appropriate levels of three measures: Cronbach's alpha, composite reliability, and reliability coefficient, all above 0.70. Third, the threshold of 0.50 for the average variance extracted (AVE) measure ensured the convergent validity of each construct. Lastly, discriminant validity reflects how distinct each construct is from the rest. We used the heterotrait–monotrait ratio (HTMT) to confirm discriminant validity with an upper ceiling of 0.90 (Hair Jr et al., 2021). Values for reliability and convergent validity are present in Table 3, whereas the discriminant validity measure can be found in Table A3.

Table 3. Details of Reliability and Validity Parameters for Constructs and Their Items

Construct	Item	μ	σ	λ	α	ρ_C	ρ_A	AVE
Healthcare Digitalization	D1	4.379	0.924	0.601	0.869	0.870	0.875	0.529
	D2	4.712	0.651	0.725				
	D3	4.379	0.890	0.723				
	D4	3.833	1.145	0.734				
	D5	4.515	0.769	0.732				
	D6	4.455	0.807	0.832				
Healthcare Information Management	I1	3.712	1.120	0.647	0.861	0.863	0.869	0.559
	I2	4.091	0.956	0.777				
	I3	4.318	0.807	0.842				
	I4	4.182	0.991	0.682				
	I5	4.621	0.718	0.773				
Medical Artificial Intelligence	C1	4.212	0.832	0.874	0.842	0.842	0.849	0.573
	C2	3.712	1.212	0.703				
	C3	3.939	1.036	0.718				
	C4	3.788	1.170	0.719				
Multi-stakeholder Interests	S1	3.758	1.110	0.917	0.866	0.864	0.879	0.519
	S2	4.030	0.877	0.668				
	S3	3.727	1.131	0.774				
	S4	4.076	1.042	0.596				
	S5	3.955	0.968	0.624				
	S6	3.606	1.162	0.695				

Note: μ = mean; σ = standard deviation; λ = loading; α = Cronbach's alpha; ρ_C = rohC; ρ_A = rhoA; AVE = average variance extracted

5.4 Fuzzy-set Qualitative Comparative Analysis

Qualitative comparative analysis is the formalized method for the configurational approach that relies on sets, Boolean logic, conjunctural causation, and implications. It deviates from the traditional assessment of variables, linear algebra, interaction terms, and covariation (Thiem et al., 2016). Specifically, fuzzy-set qualitative comparative analysis (fsQCA) is a mixed qualitative-quantitative set-theoretic method where membership scores ranging from 0 to 1 are assigned to sets concerning the outcome effect. fsQCA comprises two main tests for each causal condition and configuration. The test of necessity determines conditions that exist when the outcome occurs, and the test of sufficiency determines conditions whose presence will always lead to the occurrence of the outcome variable (Mattke et al., 2021). The implementation of the fsQCA approach was done in the R programming language within the integrated development environment of RStudio software. Specifically, the *"qca"* package was utilized to perform the computational analysis. This library works on the Quine-McCluskey minimization algorithms, which return reproducible prime implicants for the truth table. Stating the complete implementation details of the methodology is out of the scope of this study; interested readers can refer to Duşa (2018).

fsQCA essentially helps in connecting the qualitative paradigm to the quantitative algorithmic methodologies. Additionally, compared to the traditional regression-based research methods, fsQCA provides certain benefits. First, it enables the discovery of multiple and conjunctural causal conditions that affect the dependent variable. Second, the implications of the independent variables are not established in controlled silos. Instead, every variable is incorporated to explain the phenomenon under investigation.

Lastly, we can obtain reliable results from very small sample sizes (where N < 50) to very large sample sizes (Pappas & Woodside, 2021). Consequently, there is a substantial body of research following the fsQCA technique (Mandal et al., 2023; Park et al., 2017; Y. Wang et al., 2019). fsQCA has been utilized in the literature to explain the configurational impact of social determinants of health over health outcomes (Kokkinen, 2022) and the impact of various motivations and emotions that explain user satisfaction in social networks (Pappas et al., 2020). The following subsection describes the data treatment procedure required for Likert scale data to perform fsQCA.

5.4.1 Data Calibration

To perform fsQCA, survey data needs to be processed to generate corresponding fuzzy scores. In this study, we followed the calibration procedures recommended by Pappas and Woodside (2021). First, single value scores are required for each construct for each observation. Therefore, we allocated scores for each latent construct by calculating the mean of all indicator responses (DiStefano et al., 2019). Second, we classified these values into different membership categories. We used the direct method to assign scores into three sets: full-set membership, intermediate-set membership, and full-set non-membership. We used the recommended 0.95, 0.50, and 0.05 percentiles as the thresholds for the respective memberships (Pappas & Woodside, 2021). Third, construct scores were then converted to fuzzy scores calibrated into log-odds metrics ranging from 0 to 1. Lastly, fuzzy values equal to 0.5 get dropped in our analysis as they correspond to the point of maximum ambiguity. Thus, to resolve this issue, we added a constant of 0.001 to all fuzzy scores except for values equaling 1 (Fiss, 2011).

6 Results and Analysis

We performed a test of the necessity of the causal condition DIG for the outcome HIM (i.e., DIG <= HIM). Analysis revealed a higher occurrence of HIM within the set of DIG. The necessity inclusion score, which determines the proportion of HIM within the intersection of the two fuzzy sets, was 0.867, above the minimum recommended threshold of 0.750 (Pappas & Woodside, 2021). Analysis of fuzzy scores of DIG and HIM on a scatter plot revealed a higher instance of cases below or just above the main diagonal (see Figure 4). Additionally, very few cases were observed in the plot's top left quadrant, which established the necessity of DIG. Nevertheless, we also checked for the presence of a simultaneous subset relation involving the negation set of DIG (i.e., ~DIG <= HIM). The necessity inclusion score of 0.406 alleviated such apprehensions.

We further checked for the relevance of the fuzzy set DIG for the outcome HIM. Coverage of DIG by HIM was found to be 0.850. Meanwhile, the relevance of the necessity score of 0.847 confirmed the non-trivialness of the causal condition DIG (Ragin, 2009). The presence of a higher number of cases in the top right quadrant compared to the bottom right quadrant of the plot confirms the relevance of the necessity condition DIG for HIM (see Figure 4). Thus, a minimum level of DIG is both relevant and necessary for healthcare organizations to proceed with HIM.

In this regard, it is imperative to check whether the causal condition of DIG is sufficient to obtain the outcome HIM (i.e., DIG => HIM). We performed the test of sufficiency and obtained a high consistency score of 0.850. A lower sufficiency inclusion score of 0.418 for the negation of HIM within the DIG set removed the possibility of simultaneous subset relation (i.e., DIG => ~HIM). Simultaneously, a high proportional reduction in the inconsistency score of 0.778 with HIM and a lower score of 0.138 with the negation of the outcome further ensured the sufficiency of DIG. Next, a raw coverage score of 0.867 exhibited that 86.70% of HIM is explained by the causal condition of DIG (Duşa, 2018). Therefore, after the series of above validations, we conclude that the presence of DIG is crucial for facilitating HIM in healthcare. Hence, DIG is a fundamental building block for planning transformational endeavors in the intersection of technology and healthcare.

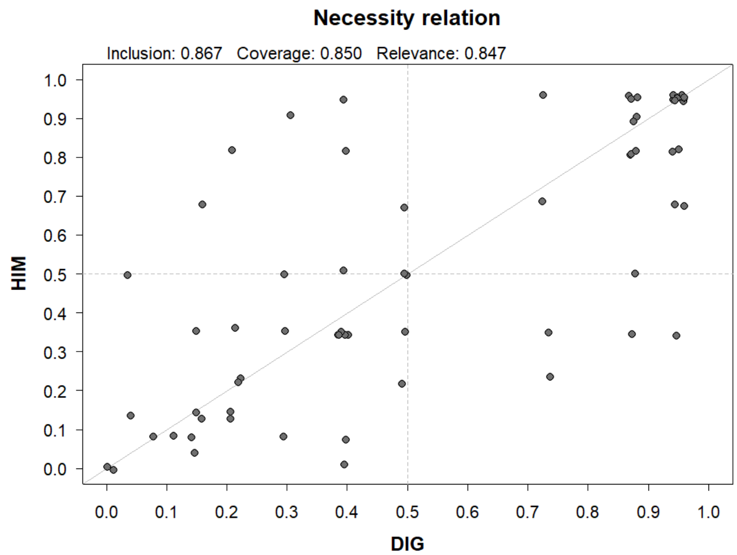

Figure 4. XY Plot for Investigating the Test of the Necessity of Healthcare Digitalization

Similarly, we conducted tests of necessity for all possible causal conditions for the outcome MAI. We observed high necessity consistency scores of 0.859, 0.818, and 0.777 for MAI within the atomic configurations of DIG and HIM and a conjunctional configuration of DIG and HIM (i.e., DIG*HIM), respectively. Whereas lower necessity inclusion scores were obtained for the negation of the same configurations corresponding to MAI (refer to Table 4). This observation rendered causal atomic configurations redundant, as the conjunction itself implies the necessity of both DIG and HIM. The coverage scores of 0.844, too, implied a higher proportion of cases within the intersection of the conjunction and the outcome. Additionally, we observed a very high relevance score of 0.881 for the conjunction of atomic configurations. The presence of simultaneous sub-set relations was not found (refer to Table 4). These findings provided evidence for the non-trivialness of the necessary causal conjunction of DIG and HIM for MAI.

Table 4. Results of Configurational Tests for Medical AI

Test of Necessity	inclN	RoN	covN	Test of Sufficiency	inclS	PRI	covS
DIG <= MAI	0.859	0.801	0.794	DIG => MAI	0.794	0.702	0.859
~DIG <= MAI	0.417	0.691	0.463	DIG => ~MAI	0.462	0.223	0.508
HIM <= MAI	0.818	0.791	0.771	HIM => MAI	0.771	0.664	0.818
~HIM <= MAI	0.445	0.690	0.483	HIM => ~MAI	0.477	0.234	0.515
DIG*HIM <= MAI	0.777	0.881	0.844	DIG*HIM => MAI	0.844	0.765	0.777
~DIG*~HIM <= MAI	0.365	0.756	0.480	DIG*HIM => ~MAI	0.454	0.176	0.425

Note: incl = inclusion/consistency score; RoN = relevance of necessity; cov = coverage; PRI = proportional reduction in inconsistency

Subsequently, we proceeded with tests to determine the sufficiency of the same configurations for MAI. The highest sufficiency inclusion scores of 0.794, 0.771, and 0.844 were observed across DIG, HIM, and the conjunctional configuration. Furthermore, lower inclusion, PRI, and coverage scores are reported corresponding to the three configurations for the negation outcome set, respectively (refer to Table 4). Consequently, we ascertain the absence of simultaneous subset relations. Moreover, high sufficiency scores across three parameters of atomic configurations reflected the redundancy of the analysis of conjunctional configuration expression (refer to Table 4). Through raw coverage score, we found that conjunctional configuration explains 77.70% of MAI. Accordingly, we now deduce that the causal conjunction of DIG and HIM is both necessary and sufficient for MAI. Resultantly, we conclude that for a robust MAI, the interactions of both DIG and HIM are essential. In this pursuit, the practice be informed that to reap the benefits of medical AI and to develop similar capabilities, data and information architecture simultaneously will play an instrumental role.

Table 5. Truth Table with Three Causal Conditions and One Outcome

DIG	HIM	MAI	OUT	n	%	Raw Consistency	PRI Consistency	SYM Consistency
1	1	0	0	3	4.55	0.88255	0.61480	0.61480
0	1	1	0	3	4.55	0.87078	0.35316	0.35316
1	1	1	1	24	36.36	0.84317	0.74445	0.80659
1	0	1	0	4	6.06	0.80994	0.37967	0.42160
1	0	0	0	3	4.55	0.80645	0.14140	0.16380
0	0	1	0	5	7.58	0.80247	0.25580	0.29236
0	1	0	0	7	10.61	0.79084	0.18325	0.19633
0	0	0	0	17	25.76	0.49301	0.03820	0.04057
Note: OUT = outcome set; n = number of cases; % = percentage of cases; SYM = symmetric								

To investigate MSI, we resorted to truth table analysis of all possible causal configurations. We adhered to the threshold recommendations of Pappas and Woodside (2021) for all parameters. Given the sample size of 66 cases, we adhered to the guidelines for the threshold for the number of cases as 2. Raw consistency and PRI consistency thresholds were maintained at 0.75 and 0.70, respectively. Hence, despite high raw consistency scores for the first and second configurations (refer to Table 5), they were dropped as an outcome, as low PRI scores entail the presence of simultaneous subset relations (Duşa, 2018). A careful observation of the truth table revealed that only one configuration crossed the recommended cut-offs. The third causal configuration comprised the presence of all atomic configurations (i.e., DIG, HIM, and MAI) and had 36.36% of the total number of cases. A high PRI consistency score of 0.744, which was also closer to the raw consistency score of 0.843 compared to other configurations, justified this configuration's positive occurrence (Greckhamer et al., 2018). Parallelly, a symmetric consistency score of 0.806 ensured the robustness of the third configuration for both the presence and negation of the outcome (i.e., for MSI and ~MSI).

Thereafter, we proceeded with the Boolean minimization process. We obtained a singular configurational solution across conservative, parsimonious, and intermediate solutions. As conjunction was found to be sufficient, the rest of the configurations were automatically deemed redundant. The conjunction of DIG, HIM, and MAI was the simplest expression of possible configurations that explained the outcome set (i.e., DIG*HIM*MAI = > MSI). According to Fiss (2011), a causal condition is deemed to be core only if it occurs consistently across the three types of solutions. Consequently, this observation also indicated that the conjunctional occurrence of DIG, HIM, and MAI is a core causal condition for MSI. No peripheral causal condition was obtained across conservative, parsimonious, or intermediate solutions. This configurational solution obtained both high sufficiency inclusion and sufficiency coverage scores of 0.843 and 0.673, respectively. The conjunctional configuration was highly consistent and accounted for 67.30% of the studied outcome. Therefore, we conclude that the conjunction of all three causal conditions, i.e., DIG*HIM*MAI, is closely associated with MSI. Based on our findings, we inform the practice that building robust data and information architectures is instrumental while following the AI pathway to substantiate healthcare service delivery.

6.1 Robustness Analysis

An important step in confirming the validity of results is performing robustness checks (Cangialosi, 2023). In fsQCA, we relied on benchmark cut-offs for different parameters. Nevertheless, to demonstrate the consistency of our analysis and findings, we performed a sensitivity analysis for consistency, frequency, or number of cases, and PRI scores. We conclude that the causal configuration of DIG*HIM*MAI remains unchanged for the same outcome, MSI in our case (refer to Table 6). Similar results were also obtained for the first and second propositions. Hence, the results of this study have multiple implications for both the theoretical and practical worlds. Subsequently, we discuss key contributions, their implications, and some of the limitations of this work.

Table 6. Robustness Checks

Parameters	Thresholds	Change in Causal Configuration	Solution Consistency	Solution Coverage
Consistency	0.85	No configuration obtained	NA	NA
	0.80	DIG*HIM*MAI	0.843	0.673
	0.75			
Frequency	2	DIG*HIM*MAI	0.843	0.673
	3			
	4			
	5			
PRI	0.80	No configuration obtained	NA	NA
	0.70	DIG*HIM*MAI	0.843	0.673

7 Discussion, Limitations, and Future Agenda

The findings of this study provide avenues for extending the discourse on successful AI applications in healthcare. Foremost, with respect to RQ1, we found that there are technological complementarities associated with AI in healthcare (refer to Figure 5). The results of the STM analysis showcased the presence of three technological complementors: DIG, HIM, and MAI, which were structurally embedded within AI applications in healthcare. For instance, digitalization of healthcare services was found to be associated with the deployment of IoMT, cloud computing architecture, wearable health devices, patient monitoring systems, and smart healthcare environments. In organizational setups, the deployment of digital infrastructure generates data sources that drive AI systems. Similarly, the literature underscores the foundational role of DIG in leveraging AI for healthcare (Fosso Wamba & Queiroz, 2023). In addition, we observed that information management becomes increasingly critical as the volume of health data generated through digitalization expands. This data should be stored in the EHRs of individual patients and institutional medical databases for easy access and retrieval. Healthcare organizations further require big data processing mechanisms in conjunction with AI models to standardize and analyze high-volume, heterogeneous data and thereby facilitate knowledge discovery. The literature has emphasized HIM practices for maintaining the quality of data and insights obtained from healthcare AI systems (Lämmermann et al., 2024). Hence, DIG and HIM technologies act as complementary strategic assets to AI initiatives in healthcare services.

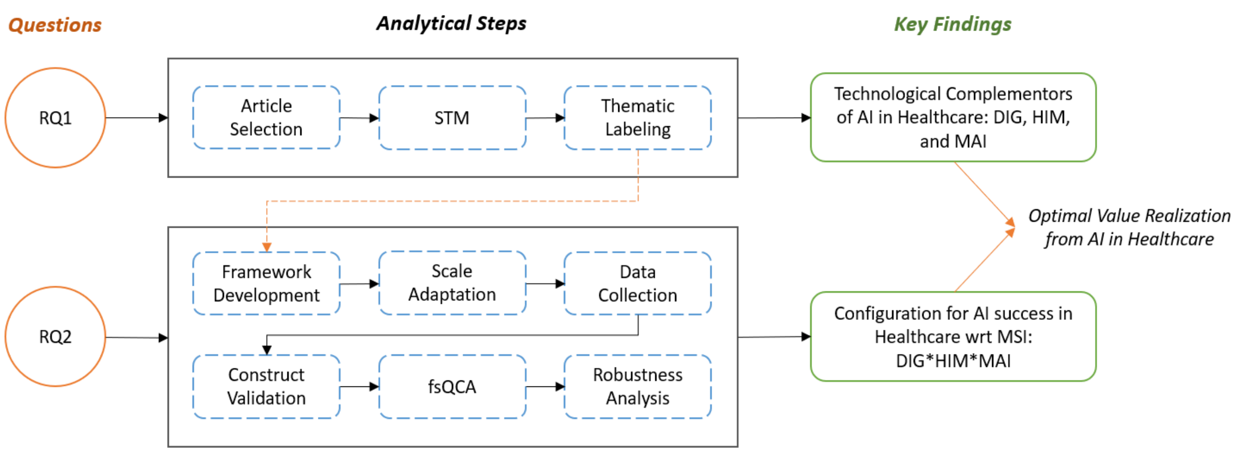

Figure 5. Mapping of RQs, Key Analytical Steps, and Findings

Furthermore, STM findings suggest that the refinement and adaptation of AI models are essential for applications in healthcare settings. AI algorithms must be configured to solve medical and administrative challenges via prediction and classification models. Depending upon the complexity of the problem at hand, developers have a wide variety of sophisticated computational techniques to choose from. The key idea behind model development remains to achieve higher accuracy and make AI models suitable for production. The same can be observed in the literature, wherein scholars consistently propose improved MAI models (Gu et al., 2024; Rehman et al., 2024). Consequently, fostering of MAI technologies in healthcare settings will strategically enable scaled AI applications for service providers. In addition, the findings of STM analysis highlight the importance of MSI in healthcare. We found that it is imperative for healthcare organizations to acknowledge the importance of stakeholder viewpoints that include a large network of internal and external actors, who are directly affected, as well as the local communities. Therefore, the emphasis should be on gauging stakeholder needs, expectations, and their interactions with AI-enabled workflows and services. The literature has increasingly emphasized the significance of MSI for AI interventions in healthcare (Kim et al., 2024).

Thereafter, with respect to RQ2, results obtained from fsQCA analysis shed light on the configurational nature of causal relationships within complementary technologies and their alignment with stakeholder interests (refer to Figure 5). First, we found that DIG acts as a core causal condition for HIM. Digitalization efforts aimed at enabling AI would inherently lead to the generation of large volumes of digital health data. As digitalization gains momentum in the healthcare practice, it would also facilitate the generation of new sources across multiple functions in the organization. Thus, further strengthening the foundation for effective HIM. Our findings suggest that DIG would be imperative for healthcare organizations to utilize AI-powered information management practices. HIM would further enable the efficient and effective utilization of digital data resources for solving informational challenges in the healthcare ecosystem. IS scholars have also suggested the complementarity between the two technological drivers of AI (Riedl et al., 2017).

Second, findings from the fsQCA analysis also confirm that atomic configurations of DIG and HIM independently affect MAI implementations in healthcare. This result implies that effective governance of deployed digitalized assets is quintessential for AI interventions in healthcare. The availability of integrated healthcare devices, digital health networks, and cloud computing infrastructure would fulfill the data requirements of MAI models (Tariq et al., 2023). At the same time, the robust HIM practices would maintain the quality and effectiveness of AI-generated results. Information management would standardize different data formats, data accessibility, data storage, and data analysis in healthcare (Gangavarapu et al., 2020). Hence, if the information flow is reliable, accurate, and fast, the organizations would be better equipped to exploit MAI investments. More importantly, we also found that the conjunctural configuration of DIG and HIM explains more of MAI than the atomic counterparts. This finding advocates the synergistic nature of technological drivers. It further implies that successful MAI developments would warrant the presence of effective digital governance and streamlined information management practices.

Lastly, in fsQCA analysis, a configuration involving DIG, HIM, and MAI emerged as the core causal configuration for MSI. On the other hand, the atomic configurations were found to be insufficient for the achievement of the same. This result suggests that the interests of multiple stakeholders are protected only when AI in healthcare is complemented by DIG, HIM, and MAI practices. Together, in this configuration, these complementary technologies would ensure that AI advancements align with the varied demands of healthcare stakeholders. All digital data sources, when integrated through information management architectures, would offer continuous and rich insights. At the same time, these architectures must ensure that spurious, false, or incorrect information and data anomalies are completely avoided from front-end healthcare applications. This digital integration must be guided by end-user feedback to accurately ascertain the nature, scale, and specific prototypes required, as well as to assess how systems are responding to their needs. Therefore, for a successful AI strategy, rather than looking in a progressive manner, backward propagation would be instrumental in building AI systems aligned with MSI. These findings corroborate the extant literature recognizing AI applications catering to patients (Kumar et al., 2023), employees (Agarwal et al., 2024), and external stakeholders (Cadden et al., 2022) in the healthcare ecosystem. We contribute to this literature by highlighting the unique configuration of DIG, HIM, and MAI, which is essential for alignment with MSI in healthcare. In the following subsections, we present the implications for research and practice.

7.1 Research Implications

Foremost, our study found that DIG, HIM, and MAI are complementary driving forces that together foster MSI in healthcare. We also highlight individual nuances and the scope of the explored elements through an extensive synthesis of the IS literature. The findings imply that DIG involves deploying AI-complementing digital infrastructure, while HIM deals with collecting, processing, and providing data using technology artifacts. MAI incorporates the enhancement of algorithmic models and the development of AI frameworks specific to healthcare. This study provides a theoretical framework encapsulating research topics as causal conditions for building a positive stakeholder outlook in healthcare. The configurational theory helps the IS literature to conceptualize the building blocks for AI in healthcare and the overall stakeholder needs, resting on such complementarities. However, the most important implication of this study is the discovery of a unique configuration that satisfies MSI. Previously, the formula to enable the creation of business value from AI systems was largely unknown (Enholm et al., 2022). This study highlights that only when DIG, HIM, and MAI practices are implemented sequentially, and thereafter, ensuring their simultaneous usage, they significantly fulfill the needs of various healthcare stakeholders. As a result, this study contributes to the business value realization aspects of AI in healthcare literature.

The study also delineates the procedures to measure the impact of causal conditions, i.e., technological complementors of AI implementations, on the outcome of interest, i.e., MSI, within the healthcare ecosystem. We utilize the existing scales in the IS literature to mold the research themes into measurable constructs. The development of reliable and valid instruments to capture the essence of the observed facets can further help in advancing successful applications of AI technologies. These instruments can be used for other theoretical inquiries about AI implementations in healthcare. It can also be borrowed or adapted for reference in other disciplines that are going through similar technological interventions. Lastly, our study provides empirical evidence to support the existence of relationships between the four dimensions. We utilize the theoretical foundations of configurational theory to develop three propositions stressing the internal dynamics of the technological synergies associated with AI in healthcare. These findings imply that certain technological complementors are necessary prerequisites for successfully addressing MSI and for realizing optimum value from the implementation of AI strategies in healthcare.

7.2 Practical Implications

This study also offers multiple takeaways for the healthcare practice. The findings of our study confirm that healthcare organizations must envisage a cascade mechanism when planning AI-driven transformational endeavors. Findings suggest the digitalization of medical processes is the beginning point for an AI-led strategic initiative. Healthcare facilities must invest in digital infrastructure to create AI-powered smart healthcare facilities to generate digital data points. After such implementations, the healthcare facilities would be able to collect, store, analyze, and provide information to the relevant stakeholders as and when required. Suitable for the scale of digitalization, healthcare organizations would warrant the need for more sophisticated computational capabilities, e.g., big data processing channels. Such information should be extended to stakeholders to enable AI-driven decision support. However, a robust information management landscape will benefit only if digitalization has reached maturity.

Thereafter, computational algorithms would leverage the developed data and information architectures to create unique AI capacities. In this pursuit, we offer a roadmap for healthcare provision through a sequential set of technological transformations. Most importantly, it is quintessential for healthcare organizations to prioritize and address stakeholders' interests. Our findings highlight that healthcare institutions should tap into social media platforms and online communication channels to understand their customers, employees, and society. Such a data-capturing mechanism would pave the way for creating external data sources, further augmenting the digitalization phase. Configurational analysis showcases that when DIG, HIM, and MAI are in tandem, they will result in intended benefits, i.e., fulfillment of MSI in healthcare. At the same time, healthcare managers have to ensure the smooth adoption of AI tools among their employees via familiarization and incorporation of their viewpoints. Healthcare institutions must also increase consumer interaction and engagement through online AI systems. This will enable practitioners to observe positive stakeholder-oriented outcomes in healthcare organizations. Hence, we suggest that healthcare professionals and organizational executives be wary of technological complementarities in AI-supported interventions.

7.3 Limitations

We also acknowledge certain inevitable limitations of this study. First, the labeling convention of the discovered thematic dimensions is subjective. However, we have tried to objectify the identification process through the parametric outputs of the STM methodology. We ensured independent analysis of the STM findings among the authors and corroborated with external healthcare AI experts. Second, the findings of this study are based on a small sample size and the snowball sampling method. This technique can lead to selection bias wherein participants exhibit similar characteristics. However, healthcare practitioners with comprehensive AI knowledge are a hard-to-reach population. Consequently, we had to tap into the exclusive knowledge networks of established AI experts in Indian healthcare settings. At the same time, we used the fsQCA methodology to analyze data collected from this elusive and small population. This methodology has been deemed suitable for diminishing such concerns in even smaller sample sizes. Third, the study did not control for demographic variations among its respondents, given the small sample size. In addition, the respondents were from the Indian sub-continent, and therefore, the generalizability of the study remains limited. Lastly, the findings rely on experts' perceptions of AI-enabled transformations and healthcare improvements. Nonetheless, given that this is an emerging area of research, the analysis stands strong for supporting preliminary findings. Future studies can address these limitations as technology artifacts mature in healthcare practices.

7.4 Future Research Directions

Building on the results, we propose certain research agendas. We have found DIG to be an important precursor to AI in healthcare. In future studies, one can investigate how digitalization coupled with AI affects the accessibility of healthcare services to the underserved masses. DIG can be further studied to leverage AI models to create digital twins and simulate outcomes of medical interventions in advance. The findings also confirmed the crucial role of HIM in AI-based healthcare applications. In this regard, our results highlighted the importance of integrated digital information management architectures in AI-enabled healthcare services. Such research would help address the issues of multimodality of healthcare data and the lack of interoperability of healthcare data management systems. Moreover, future studies can specifically explore the integration of blockchain technology as an enabler for AI systems in facilitating decentralized management and secure sharing of health data. Our study emphasizes fulfillment of MSI, and we also found that the customized development of computational models, i.e., MAI, is a core driver of AI applications in healthcare. Thus, in the future, interested scholars can examine the scope of AI models for building practitioner, admin, and patient-centric healthcare solutions such as precision medicine and drug discovery systems.

8 Conclusion

In sum, we state that IS research pertaining to the AI landscape in healthcare has risen exponentially within the last decade. The study has established the presence of technological complementarities with AI implementations in the healthcare ecosystem. Our STM analysis showcased the occurrence of technology enablers of AI and initial evidence of interdependence among DIG, HIM, MAI, and MSI. Therefore, configurational theory was employed to make three core propositions that amalgamated the identified technological drivers, AI, and healthcare stakeholders under one conceptual umbrella. Further, our fsQCA analysis empirically validated the intertwined nature of these technologies. It also showcased that their interactions with AI have the potential to successfully address MSI in healthcare. Our findings offered complementary technological dimensions associated with AI applications and the knowledge of their configurational interplay, which can aid healthcare organizations in realizing optimal value from AI. In this pursuit, we also offered an actionable roadmap of sequential technological implementations for the healthcare ecosystem to effectively spearhead AI-driven strategic endeavors.

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Appendix A

Topic 1:
system, technolog, manag, develop, servic, health, can, propos, design, oper, implement, monitor, iot, applic, comput, secur, process, devic, base, integr

Topic 2:
data, use, inform, health, healthcar, medic, decis, patient, provid, process, care, can, analysi, support, approach, big, knowledg, applic, analyt, mine

Topic 3:
model, use, method, predict, propos, algorithm, result, learn, perform, patient, diseas, featur, problem, machin, network, imag, base, optim, accuraci, classif

Topic 4:
social, use, media, hospit, effect, manag, market, purpos, result, servic, custom, industri, health, onlin, model, consum, impact, practic, inform, limit

Figure A1. Top 20 Highest Probability Words for Each Topic

This is an ongoing research project at the *Indian Institute of Management (IIM) Sambalpur*.

We require your medical expertise to answer a few statements related to the possible impact of augmenting AI-led technologies in the healthcare sector.

The questionnaire contains 7 sections in total.

For section 2 - 6, we need your opinion on a scale of 1 - 5, where:

- 5 = Strongly Agree
- 4 = Agree
- 3 = Neutral
- 2 = Disagree
- 1 = Strongly Disagree

In section 7, kindly provide details regarding your professional occupation.

Note: *This form is exclusively intended for academic purposes only. The anonymity of the respondents will be preserved.*

Figure A2. Preamble to the Online Questionnaire Form

Table A1. Measurement Items and Respective Constructs

Construct	Item	Item Description	Original Reference(s)
Healthcare Digitalization	D1	Digital technologies (such as analytics, cloud computing, social media, mobile, and embedded devices) can create a broad set of data sources in healthcare.	(Abou-foul et al., 2021; Mishra et al., 2023; Westerman et al., 2014)
	D2	Digitalization enables capturing of detailed patient medical records.	
	D3	Digital integration of operational processes can enable timely data-driven decisions.	
	D4	Smart digital devices such as Internet-of-Medical-Things (IoMTs) can facilitate real-time monitoring of patient's vitals.	
	D5	Data storage and analysis over digital cloud servers can ensure effective data repositories.	
	D6	Investing in cutting-edge digital technologies can streamline healthcare service delivery.	
Healthcare Information Management	I1	Data sensing mechanisms over social media platforms and internal organizational sources are crucial to gauge comprehensive healthcare information.	(Kettinger & Marchand, 2011)
	I2	Collection and filtration of relevant medical big data can aid in achieving better results from intelligent algorithms.	
	I3	Accuracy and completeness of structured and unstructured health data sources can enable discovery of essential insights.	
	I4	Data mining techniques can lead to successful transformation of medical information into valuable knowledge.	
	I5	Frequently updating of healthcare information databases can ensure availability of latest medical records availability.	
Medical Artificial Intelligence	C1	Hiring of skilled practitioners can enable complete utilization of computationally intelligent information processing systems.	(Belhadi et al., 2021)
	C2	AI techniques should be utilized for outcome prediction at all levels of the healthcare service delivery.	
	C3	Development of self-learning AI mechanisms can enable accurate decisions over time.	
	C4	Sharing of AI outcomes across the organization can support decision-making.	
Multi-stakeholder Interests	S1	Medical AI can aid in understanding patient needs resulting in better competitive strategies.	(Yau et al., 2007)
	S2	AI can enable systematic and frequent assessment of patient satisfaction.	
	S3	AI systems can aid in fulfilling the commitment of correctly diagnosing patient conditions.	
	S4	AI can help in attending after-discharge services for patients.	
	S5	Utilization of AI can make medical practitioners better at their jobs.	
	S6	Senior management can rely on AI systems to comprehensively address stakeholder needs.	

Table A2. Sample Demographics

Particulars	Sub-category	Number of Respondents	Percentage
Gender	Male	48	72.73%
	Female	18	27.27%
Experience	< 1yr.	2	3.03%
	2 – 5 yrs.	13	19.70%
	6 – 10 yrs.	15	22.73%
	11 – 15 yrs.	15	22.73%
	16 – 20 yrs.	10	15.15%
	> 20 yrs.	11	16.67%
Organization	Public	6	9.09%
	Private	60	90.91%
City	Tier 1	36	54.55%
	Tier 2	16	24.24%
	Tier 3	14	21.21%
Role	Administrator	4	6.06%
	AI Consultant	2	3.03%
	C-Suite Professional	2	3.03%
	Dentist	5	7.58%
	Physician	53	80.30%
Specialty	Cardiology	3	4.55%
	Dermatology	7	10.61%
	Diabetology	2	3.03%
	Gastroenterology	1	1.52%
	General Physician	5	7.58%
	General Surgery	5	7.58%
	Internal Medicine	6	9.09%
	Oncology	5	7.58%
	Ophthalmology	2	3.03%
	Orthopaedics	2	3.03%
	Pathology	1	1.52%
	Pulmonology	1	1.52%
	Radiology	4	6.06%
	Sexologist	2	3.03%
	Surgery	7	10.61%
AI Usage	Yes	10	15.15%
	No	56	84.85%

Table A3. HTMT ratio for the Assessment of Discriminant Validity

Construct	HIM	MAI	MSI
DIG	0.863	0.798	0.676
HIM	.	0.838	0.697
MAI	.	.	0.723

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