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Individual dynamic capabilities and artificial intelligence in health operations: Exploration of innovation diffusion

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ABSTRACT

This research investigates the integration of individual dynamic capabilities (IDC), artificial intelligence (AI), and the Technology Acceptance Model (TAM) within health operations to evaluate their role in fostering innovation diffusion in healthcare. A convergent, multifaceted research approach encompassing quantitative and qualitative methodologies was employed, commencing with a systematic review of the extant literature. This was then complemented by the execution of focus group sessions involving 21 participants. The main objective of this sequential exploratory design was to synthesize existing research present an empirical validation of real-world case studies, and assess AI deployment challenges that influence operational efficiency and service quality in healthcare organizations. The findings underscore the importance of IDC in advancing healthcare practices by driving cross-functional adaptation, facilitating AI implementation, and ensuring smooth operational transformation in line with healthcare standards and best practices. The findings offer valuable insights for operational and executive-level decision-makers aiming to optimize health operations by integrating IDC and AI technologies, enhancing patient care, service quality, and innovative health solutions.

1. Introduction

Healthcare systems worldwide face complex challenges in optimizing operational management, including efficient service delivery, resource allocation, and the adoption of advanced digital technologies (ADT). These demands are intensified by complex regulatory frameworks, rapid technological innovation, and growing expectations for high-quality services. Simultaneously, constrained budgets, demographic shifts, and health disparities further complicate national healthcare systems, underscoring the urgency of effective healthcare management to maintain societal well-being and economic stability [1,2]. A key strategy for addressing these challenges lies in identifying and applying individual dynamic capabilities (IDC)—the capacities to sense opportunities, acquire resources and reconfigure competencies—alongside advanced digital technologies (ADT), particularly artificial intelligence (AI). This integration fosters adaptability, innovation, and continuous improvement in complex healthcare environments. IDC highlights the central role of healthcare professionals (HCPs) in operational transformation, as they drive technological adoption and promote ongoing improvements [3–5].

Although incorporating AI and IDC offers a systematic means of detecting inefficiencies and facilitating targeted interventions, concerns remain about ethical AI use, data protection, and interoperability. These issues are especially pertinent for healthcare organizations (HCOs), which must comply with rigorous regulatory standards that often impede swift innovation and technological diffusion. Nevertheless, robust AI-driven processes can strengthen healthcare operations, reduce service disruptions, and ultimately enhance public health outcomes. Existing research on healthcare operations management has examined AI adoption, quality control, and process improvement but has rarely combined AI, IDC, and innovation models for a holistic view of operational optimization. While frameworks such as the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) have been applied to facilitate technology uptake, they seldom integrate the potential of AI with individual capabilities to amplify benefits across organizational operations. Addressing this gap is essential for building a more resilient and comprehensive operational model that aligns with the healthcare sector's multifaceted demands [2–4].

The objective of this research is to address these gaps by exploring various types of HCOs and their operational components through the perceptions of healthcare decision-makers regarding the implementation of IDC and AI in specific operational domains. The research will

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examine the integration of these concepts into operational management procedures and programs, the perception and assessment of TAM, and the diffusion of innovation. The primary objective of this research is to explore and understand the relevance of IDC and AI to HCOs in the context of operational management. Specifically, the research seeks to: (1) assess healthcare decision-makers and HCPs' perceptions of new operational efficiency through technological advancements in operations management, (2) investigate how HCOs decision-makers implement IDC and AI-driven practices that incorporate TAM and innovation diffusion, and (3) gather insights on industry-related responses to emerging policies and regulatory challenges associated with these innovations.

To achieve these objectives, an integrated mixed-methods research was applied, with a preliminary systematic literature review (SLR) followed by a qualitative focus group methodology, involving 21 healthcare decision-makers and experts. Through structured discussions, participants systematically categorized and evaluated key themes related to healthcare small and medium enterprises innovation, IDC, and AI integration. The data collected from the SLR was analyzed with the resource of geographic, time data analysis, bibliometric mapping, and influential publications analysis, and the qualitative results part of the focus group was analyzed using thematic synthesis and network analysis to uncover critical success factors and potential application domains. The findings offer practical insights into how HCOs can enhance operational efficiency, regulatory compliance, and overall operations management resilience and diffusion of innovative solutions across different spectrums. Collected insights also inform future IDC practices integrated with multivariate frameworks and increase the body of knowledge on AI-related performance discussion, operations impact, and HCOs-focused AI adoption strategies.

2. Background and theoretical framework

2.1. Integration of advanced digital technologies

The integration of AI into healthcare has become a major research focus, with studies highlighting how AI, scaling laws, large language models (LLMs), and the Internet of Things (IoT) can enhance operational efficiency, support clinical decision-making, and promote patient-centered care. These advancements span diagnostics, personalized treatment, administration, patient monitoring, and resource optimization [3–5]. By reshaping traditional healthcare practices, AI-enabled technologies create interconnected systems that support real-time data exchange, advanced analytics, and efficient service delivery. AI algorithms have significantly improved diagnostics, patient management, and treatment personalization by offering predictive analytics for risk assessment and clinical decision-making. In parallel, scaling laws in AI, which analyze performance gains from increasing model parameters, provide a framework for refining these algorithms in highly regulated healthcare settings where accuracy, reliability, and ethical considerations remain paramount [6–8].

Concerns about AI safety and ethics have also gained considerable attention, emphasizing the need for robust and transparent AI systems, particularly in critical clinical environments. Addressing algorithmic bias, patient consent, and trustworthy decision-making fosters confidence in AI-driven solutions. Compliance with data protection regulations, such as the General Data Protection Regulation (GDPR), further underscores the importance of safeguarding patient information and upholding ethical standards, prerequisites for widespread AI adoption. Although LLMs hold promise in patient communication and clinical decision support, their scalability in healthcare remains challenging due to possible inaccuracies, domain-specific adaptation hurdles, and high computational demands [9–11]. These limitations necessitate caution among HCPs seeking to implement LLMs as a complement to—rather than a substitute for—human expertise. Theoretical frameworks such as AI scaling laws, ethical AI principles, and the TAM are instrumental in illuminating AI's role in healthcare. By illustrating how expanded model complexities can boost performance, clarifying fairness and accountability requirements, and identifying factors influencing healthcare professionals' adoption of new technologies, these frameworks inform responsible and effective AI integration [12–14].

The scalability and ethical implications of AI in healthcare remain points of active debate. Advocates emphasize long-term gains in patient outcomes, cost-effectiveness, and operational resilience, while detractors highlight substantial infrastructure requirements, ethical dilemmas, and questions of equitable access for smaller providers [15–17]. Discussions surrounding AI-driven employment shifts further illustrate these complexities, as automation may create opportunities for workforce development but also raises concerns about job displacement and the need for new skills. Meanwhile, data privacy and security remain critical challenges, particularly with the continued integration of AI and IoT into clinical workflows. Meeting regulatory demands such as GDPR compliance requires diligent oversight of data ownership, consent processes, and ethical usage. Thus, balancing innovation with patient safety and data integrity is therefore integral to the future of AI in healthcare [18–20].

2.2. Dynamic capabilities in healthcare operations

The IDC framework focuses on an individual's capacity to adapt, integrate, and reconfigure skills in rapidly evolving environments. In hospital management, IDC is crucial for enabling HCPs to address fluctuations in patient demand, regulatory shifts, and unexpected disruptions. Such capabilities facilitate the swift adoption of novel medical technologies, foster interdisciplinary collaboration, and ensure compliance with patient safety and data privacy regulations—imperatives in a sector prone to abrupt policy changes and high standards of care quality [21–24]. These capabilities align with the dynamic capabilities (DC) framework's emphasis on sensing, seizing, and transforming activities. Sensing involves recognizing both opportunities and challenges in healthcare settings, such as emerging health crises or evolving patient care needs. Seizing directs resources to capitalize on these insights by reallocating staff, integrating new technologies, or updating treatment protocols [25–27]. Transforming centers on the continuous renewal of hospital processes to sustain efficiency and enhance patient outcomes. This model is widely applied in healthcare management literature, illustrating how IDC-enabled hospitals leverage emerging technologies for improved decision-making and operational flexibility. In large HCOs, IDC underscores the importance of acquiring, assimilating, and applying knowledge to strengthen resilience and optimize patient care [28–30]. Critics, however, argue that IDC insufficiently addresses social and relational dimensions of knowledge creation, which are vital for effective collaboration across multidisciplinary teams. Further debates concern the often-blurred line between operational capabilities—daily routines supporting hospital efficiency—and IDC, which facilitates longer-term adaptability. Understanding how these intertwined capabilities can jointly reinforce a robust healthcare strategy remains an essential pursuit [30–32].

Another ongoing discussion addresses whether IDC is transferable across diverse healthcare contexts, given the specialized expertise and regulatory rigor characteristic of hospitals. This question highlights the need to examine contextual factors to determine whether established best practices can be adapted or if new approaches must be devised for settings with unique demands [33,34]. Finally, the role of organizational culture in cultivating IDC persists as a major area of inquiry. While a culture geared toward innovation encourages proactive problem-solving, stringent regulatory environments may constrain the flexibility crucial for dynamic adaptation. Balancing regulatory compliance with an ethos of continuous innovation is thus a complex yet indispensable task for hospitals aiming to expand their IDC [35–37].

2.3. Technology Acceptance Model (TAM), Diffusion of Innovations (DOI)

TAM concentrates on individual-level behavioral intentions, primarily highlighting perceived usefulness and perceived ease of use, as well as clinicians' trust in emerging innovations. This perspective elucidates why HCPs might be more inclined to integrate AI-driven diagnostic tools, telehealth platforms, or electronic health records into their daily workflows if they believe such tools will enhance patient care without adding undue complexity. The DOI framework, meanwhile, focuses on the innovation characteristics themselves—relative advantage, compatibility, complexity, trialability, and observability—and underscores the importance of effective communication, peer influence, and a supportive context in promoting widespread technology adoption [38,39]. Applied across regions such as the United States (U.S.), the European Union (EU), Japan, and China, these models help explain how digital health solutions improve operational efficiency, elevate care quality, and enable more proactive patient services. For instance, hospitals in Japan and China that adopt AI and robotics can mitigate workforce shortages while boosting service efficiency, illustrating the DOI framework's insight that visible benefits and peer support accelerate adoption. In the U.S. and the EU, stringent regulations and reimbursement policies strongly influence how ADT is accepted and used, as TAM highlights the pivotal roles of perceived usefulness and external facilitators [13,39].

Implementing AI-driven analytics in healthcare entails more than procuring the right software and hardware. It requires a skilled workforce of data scientists and HCPs who can interpret AI outputs, along with an organizational culture that values evidence-based decision-making and continuous learning. The result can be significant: AI-enabled clinical decision support systems not only help clinicians make more accurate diagnoses and anticipate patient needs but also reduce hospital readmissions and enhance overall resource utilization [34–37]. Similarly, smart devices for chronic disease management and elder care allow for continuous remote monitoring, contributing to proactive interventions that can improve patient well-being and lessen the strain on hospital infrastructure. Despite these advantages, challenges remain. Cultural resistance can hamper ADT adoption, as some HCPs worry about the reliability of emerging technologies or fear constraints on clinical autonomy. Furthermore, ensuring regulatory compliance, data privacy, and security is paramount. The EU's GDPR and the U.S. Health Insurance Portability and Accountability Act (HIPAA) demands that HCOs establish robust data governance frameworks to safeguard patient information. By drawing on TAM's focus on user acceptance and DOI's emphasis on innovation diffusion, healthcare leaders can navigate these obstacles, secure stakeholder buy-in, and implement ADT solutions that bolster operational resilience, enrich clinical practice, and ultimately improve patient outcomes [34–38].

3. Methodology

3.1. Research Design and methodological approach

This study adopts an integrated mixed-methods approach to investigate the role of IDC and AI in healthcare operational management, with particular emphasis on the TAM and the DOI. The methodology is structured to capture both qualitative and quantitative perspectives: it begins with an SLR to identify key themes, influential studies, and conceptual gaps, followed by qualitative focus groups to validate and extend the insights generated through the SLR. This design aligns with the study's core objectives, which include understanding how IDC and AI are implemented, examining the integration of these concepts into operational management, and exploring decision-makers' perceptions of TAM and DOI within evolving regulatory and sustainability contexts. By combining bibliometric, network, and qualitative analyses, the study ensures a comprehensive investigation that addresses the multifaceted nature of AI adoption, operational efficiency, and innovation diffusion in healthcare [12–14].

Fig. 1 presents the SLR framework divided into three main stages—Research Design and Planning, Data Collection, and Data Analysis—alongside an integrated focus group design. In the Research Design and Planning phase, were defined objectives, specification of research questions, and determination of the necessary exclusion criteria before developing a review protocol and data extraction form. The Data Collection phase involved selecting data sources, executing search queries, and applying snowballing techniques to expand the reference pool, managed with Mendeley. This stage emphasizes consistency in capturing study objectives through structured guidelines and forms. The subsequent Data Analysis phase focuses on bibliometric methods, network analysis, thematic clustering, and qualitative synthesis to create visual representations of findings. Parallel to these review activities, the focus group design included determining participant parameters, sampling strategy, and a recruitment plan, followed by the development of a discussion guide rooted in TAM and DOI principles.

The rationale for this mixed-methods design was grounded in the theoretical framework that underscores TAM's usefulness in assessing technology acceptance, DOI's capacity to capture innovation spread, and IDC's potential to enhance responsiveness and adaptability within healthcare operations. The integration of these frameworks enables a nuanced analysis of how decision-makers perceive and implement AI-driven practices. This approach provides robust empirical validation, as the preliminary SLR illuminates existing research trends and knowledge gaps, while the subsequent focus groups offer in-depth perspectives on practical challenges and successes experienced by HCPs actively engaged in AI and IDC initiatives [12,13].

3.2. Participants and Data Collection

Data collection proceeded in two phases. The first phase comprised the SLR of relevant peer-reviewed articles published between 2006 and 2024 that were gathered from major academic databases, including Web of Science, Scopus, and PubMed. The search terms encompassed "Artificial Intelligence," "Technology Acceptance Model," "Diffusion of Innovation" "Healthcare," "Individual Dynamic Capabilities," "Advanced Digital Technologies," and "Healthcare Organizations Management," combined through Boolean operators to capture a comprehensive range of studies. Bibliographic, co-occurrence, and citation mapping techniques (facilitated by VOSviewer) refined the search results, while inclusion and exclusion criteria ensured that only studies addressing AI, IDC, and operational efficiency in healthcare contexts were retained. Opinion pieces and non-peer-reviewed works were excluded, and the final selection of 119 articles underwent rigorous validation and quality checks. References were managed using Mendeley, which streamlined screening, citation management, and documentation throughout the SLR process.

The second phase involved the focus groups designed to explore how healthcare decision-makers perceive, adopt, and operationalize AI through IDC-driven strategies. A purposeful sampling strategy identified 21 experienced professionals from various HCOs actively engaged in AI initiatives. The recruitment process ensured representation from diverse organizational settings, and privileged participants with leadership roles, hands-on implementation experience, and familiarity with regulatory considerations. Open invitations were extended to experts with demonstrable experience in AI-enabled operational management and IDC implementation to mitigate departmental biases. Each focus group took place in a neutral location to promote open discussion and minimize power imbalances. A semi-structured interview schedule guided conversations on topics such as AI modeling, quality management, IDC, perceived usefulness, perceived ease of use, innovation diffusion, and sustainability imperatives. The sessions took place between 27 February and 10 March 2025 and were audio-recorded and transcribed verbatim. The participants were guaranteed anonymity, to encourage candid

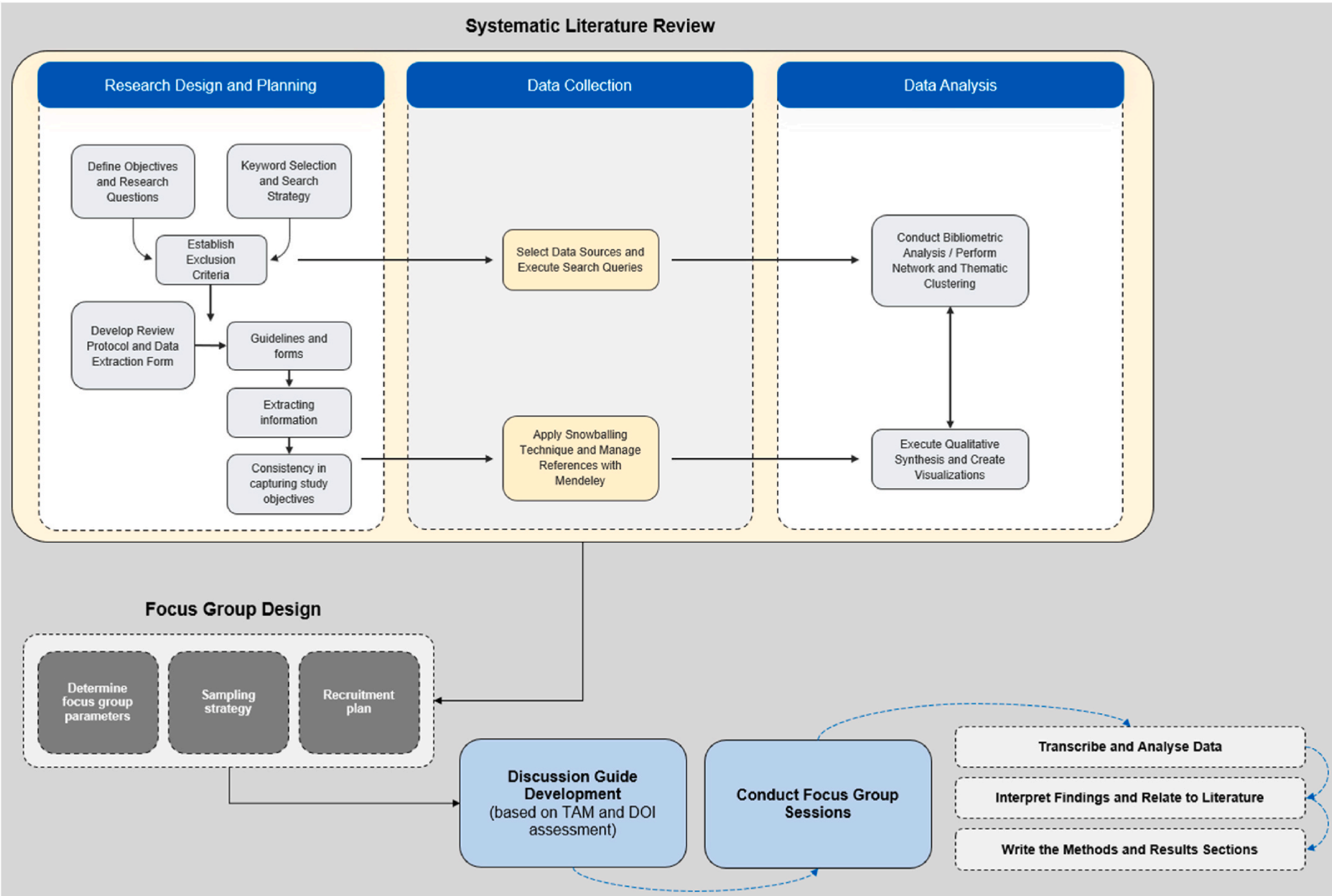

Fig. 1. Methodological approach.

responses. Comprehensive field notes were used to document non-verbal cues and group dynamics, while brief demographic surveys offered contextual information about participants' professional backgrounds [12,17].

3.3. Data analysis

Data analysis for this study integrated quantitative and qualitative techniques to achieve methodological rigor. The first phase (SLR) included bibliometric and network analyses to identify influential authors, emergent themes, and collaboration patterns. VOSviewer facilitated thematic clustering and network mapping, elucidating the interrelationships among studies that focused on AI, IDC, TAM, and DOI within healthcare contexts. Statistical analyses of publication frequency, citation metrics, and thematic evolution offered a quantitative understanding of how AI and IDC converge to influence operational management practices.

The second phase (focus groups) employed thematic and network analyses to interpret participants' perspectives on AI adoption, IDC application, and the relevance of TAM and DOI in enhancing healthcare operations. Audio recordings were transcribed, and a coding framework was developed through iterative readings of the transcripts. Inter-coder reliability was strengthened through collaborative coding sessions in which disagreements were reconciled by consensus, thereby ensuring consistency and accuracy in theme identification. Network analysis then complemented this thematic exploration by mapping the interdependencies among identified concepts, such as leadership vision, resource allocation, and regulatory compliance. Triangulation across transcripts, field notes, and demographic information validated the robustness of emergent findings, while member checking with a subset of participants further verified interpretative accuracy. Following the preliminary phase of the focus group discussions, the participants and the mediator proceeded to separate sessions, each comprising smaller groups of five to six participants. These sessions occurred at various times and days, facilitating more in-depth and detailed discussions. The participants were divided into two groups based on their knowledge areas: technical and non-technical. This division supported the second phase of the most detailed discussions, which involved a deeper extension of the research items. It should be noted that some of the results will also be split accordingly. The integration of bibliometric indicators, network structures, and focus group insights provided a multifaceted understanding of the challenges and opportunities presented by AI adoption and IDC-driven innovation in diverse healthcare environments. This methodological approach ensured that the findings are both empirically grounded and practically relevant, laying a foundation for future research on AI-enabled healthcare strategies and the advancement of IDC in operational management contexts [12,17].

4. Results

4.1. SLR: evidence of importance and preliminary findings

The SLR provided substantial evidence underscoring the critical roles of IDC and AI in optimizing healthcare operations, particularly in managing HCO regulations, standards, and data protocols. IDC, through its stages of sensing, seizing, and transforming, has been instrumental in facilitating the effective implementation of complex regulatory requirements and adherence to standards such as FHIR (Fast Healthcare

Interoperability Resources), ISO/IEC 27001 (Information Security Management), SNOMED CT (Systematized Nomenclature of Medicine – Clinical Terms), HL7 CDA (Clinical Document Architecture), ICD-10 (International Classification of Diseases, 10th Revision), European Health Information Standards (EHI), GDPR (General Data Protection Regulation), CEN/ISO EN 13606 (EHR Communication Standard), and ICCS (International Classification of Health Interventions) [18–20].

The ability to identify, adapt, and integrate relevant technologies within these regulatory frameworks highlights the value of IDC in ensuring compliance and operational efficiency in healthcare systems. The preliminary findings indicate that IDC was associated with various fundamental roles in facilitating the effective implementation of data standards and systems architecture at different organizational levels that necessitate the intricate implementation of data standards, regulations, and policies. During the sensing stage, HCOs identified emerging regulatory requirements, technology gaps, and areas requiring standardization. These included data interoperability and compliance with GDPR, which were connected with IDC in playing a significant role. This involved recognizing opportunities for integrating standards like FHIR and SNOMED CT to enhance data exchange and ensure clinical terminology consistency across systems. The objective was to enable HCOs to effectively navigate complex regulatory landscapes by identifying critical requirements about patient data security, information integrity, and operational compliance (Table 1).

In the seizing stage, HCOs leverage AI-driven solutions to capitalize on these identified opportunities, such as adopting FHIR for interoperability and ISO/IEC 27001 to bolster information security. AI facilitates the implementation of HL7 CDA for structured documentation, thereby supporting seamless information sharing among healthcare providers while ensuring adherence to data protection regulations like GDPR. By integrating AI with IDC, hospitals can mobilize resources to implement these standards effectively, optimizing both administrative and clinical workflows. AI-based decision support tools further assist in alignment with ICD-10 and ICCS, ensuring accurate classification and coding of diseases and health interventions, thus improving the quality of healthcare delivery and compliance with international reporting standards [20–23].

The reviewed studies indicate that IDC is particularly effective in areas requiring strict adherence to quality standards and data protocols, such as information security management (ISO/IEC 27001) and clinical document architecture (HL7 CDA). The synergy between AI and IDC enhances the implementation of these standards, enabling real-time monitoring, automated compliance checks, and predictive maintenance of IT infrastructure, thereby reducing the likelihood of data breaches and ensuring consistent quality in healthcare delivery. Moreover, AI-driven solutions play a vital role in optimizing the integration of these standards throughout different stages of healthcare operations. For instance, the adoption of AI to support FHIR implementation has proven effective in enhancing data interoperability, which is essential for improving patient outcomes through seamless information sharing. This optimization is critical for maintaining continuity of care, particularly in complex hospital environments where timely and accurate data exchange can significantly impact patient safety and treatment efficacy [23,33]. Several studies highlighted the scalability of IDC and its ability to facilitate compliance with standards such as GDPR and ISO/IEC 27001 across various healthcare functions, demonstrating its versatility and applicability in diverse organizational contexts. The integration of AI and IDC introduces predictive and adaptive capabilities that traditional methodologies alone cannot achieve, thereby elevating healthcare quality and operational resilience (Table 2).

The reviewed studies also emphasized the importance of cultivating a culture of continuous improvement and data-driven decision-making, aligning with the principles of regulatory compliance and QM. Hospitals that successfully implement IDC and AI often experience a cultural transformation that supports ongoing optimization and excellence in healthcare delivery. This cultural shift is particularly relevant in highly regulated environments where quality, safety, and compliance are of paramount importance. The research investigations suggest that the synergistic integration of IDC and AI significantly enhances healthcare institutions' ability to implement and manage complex data standards and regulatory requirements effectively [31–35].

4.2. SLR: geographic and time data analysis

Fig. 2 illustrates the growing interest in research topics closely associated with AI and IDC. The consistent increase in publications from 2016 to 2024 reflects the initial adoption of process improvement methodologies, such as IDC, to enhance operational efficiency and regulatory compliance in healthcare systems. This period likely captures the industry's shift towards leveraging AI to complement traditional methodologies and the integration of IDC to respond dynamically to rapidly evolving challenges, such as regulatory compliance and global disruptions. The surge from 2021 to 2024, with publications reaching a peak of 16 in 2023, demonstrates the intensified necessity to address complex healthcare challenges, including the implementation of data standards, optimization of health information systems, and assurance of

Table 1
Key IDC and their roles in healthcare.

IDC Component	Role	Examples of Impact	Relation to Existing Literature
Technological Literacy	Staying current with technological advances and assessing applicability	Improved adoption of AI, IoT, and FHIR for patient care, data management, and interoperability	Aligns with Buzzao, Rizzi [32], Robson, Ojiako, and Maguire [21] emphasizing the role of technological literacy in adopting digital tools for efficiency
Market Insight	Identifying value-creation opportunities through technology	Increased efficiency in resource management and enhanced understanding of market needs	Supported by Pesqueira [36], highlighting how market insight helps in identifying technological value-add opportunities
Analytical Thinking	Evaluating information to derive actionable insights	Enhanced decision-making in clinical operations, effective use of big data analytics	Related to Mazar [22], which discusses how analytical capabilities contribute to effective decision-making
Leadership Commitment	Fostering a culture of continuous learning and improvement	Stronger alignment of clinical, operational, and regulatory functions, streamlined ADT adoption	Supported by Rashid, Ratten [38]; Robson, Ojiako, Maguire [21], which discusses the importance of leadership in cultivating a culture of improvement
Cross-functional Collaboration	Facilitating alignment between teams for innovation management	Effective implementation of ADT initiatives, and improved integration between clinical, administrative, and IT teams	Aligns with Robson, Ojiako, and Maguire [21], emphasizing the role of cross-functional collaboration in fostering adaptability
Continuous Learning and Adaptability	Building and adapting skills to support ongoing technological changes	Better implementation of training programs for doctors, nurses, and support staff	Reflected in Scuotto et al. [24], highlights the significance of continuous learning for technology adoption
Resilience Development	Ensuring robust responses to disruptions and maintaining continuity	Strengthened ability to handle healthcare crises, improved patient outcomes	Supported by Soluk, Decker-Lange, Hack [18], and Mazar [22], emphasizing the role of resilience in healthcare supply chains
Regulatory Knowledge	Understanding and navigating complex regulatory environments	Improved compliance with standards such as GDPR, ISO/IEC 27001, and FHIR	Related to Ball [25], highlighting the role of regulatory knowledge in managing compliance challenges in healthcare

Table 2
Challenges and strategies for ADT implementation in HCOs.

Challenge	Strategy for Overcoming Challenge	Expected Outcome	Relation to Existing Literature
Limited Financial Resources	Phased implementation starting with smaller-scale projects	Gradual internal capability building with minimized risk	Supported by Bhattamisra et al. [26], emphasizing phased approaches to mitigate financial risks.
Lack of Internal Expertise	Leveraging external expertise (consulting, partnerships with universities or specialized firms)	Access to specialized knowledge, reduction in skill gaps	Reflected in Cifuentes-Faura [27], highlighting the importance of partnerships in overcoming expertise gaps
Resistance to Change	Promoting leadership commitment and a culture of continuous learning	Increased adoption and sustainability of ADT initiatives through employee engagement	Javaid et al. [23] discuss how leadership can overcome resistance to change through cultural shifts
Complexity of Regulatory Requirements	Cross-functional regulatory alignment with standards like ISO/IEC 27001, GDPR, and HL7 CDA	Improved compliance, streamlined data exchange and management	Kant & Anjali [28] emphasize the importance of understanding regulatory requirements for successful implementation
Data Security and Privacy Concerns	Adoption of standards such as ISO/IEC 27001 and GDPR compliance	Enhanced data security, reduced risk of breaches, increased trust among patients and stakeholders	Kotcher et al. [29] support the need for data security and compliance to mitigate privacy concerns
Interoperability Issues	Implementation of standards like FHIR, SNOMED CT, and HL7	Seamless integration across different healthcare systems, improved efficiency in data exchange	Pesqueira et al. [2] highlight the role of interoperability standards in ensuring seamless data exchange
Workforce Training Deficiencies	Implement structured training and certification programs	Improved staff competency, effective use of new technologies	Supported by Secinaro et al. [20], emphasizing the role of structured training in addressing skill deficiencies
Scalability Constraints	Adopt modular ADT solutions that can be scaled as needed	Increased flexibility and scalability in technology adoption	Ullah et al. [19], and Wani et al. [30] highlight the importance of modular approaches for scalability in resource-constrained environments

data security. These findings underscore the growing recognition of the collaborative potential of IDC and AI in fostering resilient, efficient, and compliant healthcare systems.

Fig. 3 presents a global overview of research citations, showing a pronounced concentration in a few countries and comparatively limited activity elsewhere. The U.S., representing 65 % of citations (10,137), demonstrates a leading role in advancing methodologies such as IDC and AI, particularly in healthcare operations. Its focus on collaborative care and clinical management underscores its status as an innovation hub. China accounts for 22 % of citations (3,364), reflecting its growing emphasis on scalability, regulatory compliance, and the adoption of digital process improvements to optimize healthcare systems. Meanwhile, European countries, notably Switzerland at 10 %, contribute significantly by integrating rigorous regulatory frameworks (e.g., ISO/IEC 27001, CEN/ISO EN 13606) with data traceability and risk management, ensuring effective service delivery through secure and efficient data governance. This global analysis reveals strong collaboration and regional specialization, with the US and China at the forefront of healthcare innovation, while Europe focuses on digital transformation and regulatory alignment. The increasing participation of Iran, the United Kingdom (U.K.), and Nigeria further underscores a worldwide shift toward methodologies that harness IDC, AI, and robust healthcare systems management to build resilient, efficient, and compliant infrastructures.

A final selection of 7 highly cited papers was examined in detail to enrich and validate the findings, offering deeper insights into the integration of advanced technologies and IDC within healthcare operations. Drawing on these seminal works strengthened the links between theoretical frameworks and practical applications, thus enhancing the overall rigor of the study's conclusions. By systematically assessing each paper's methods, theoretical foundations, and principal outcomes, the analysis expanded the contextual understanding of AI and IDC adoption, covering technical, operational, and strategic considerations. These papers also furnished diverse case examples that illustrated successful implementations in hospitals, clinics, and regional health systems, emphasizing best practices and critical success factors. Moreover, they revealed key barriers and enablers to technology integration, including cultural, organizational, and regulatory dimensions (Table 3).

4.3. SLR: bibliometric mapping and influential publications analysis

From the 174 selected publications for the corresponding analysis, an initial examination was conducted focusing on the bibliographic data and keywords co-occurrence to assess citations and bibliographic coupling. This process led to the identification of 998 keywords, which were subsequently analyzed for their connections, while 102 keywords were deemed valid based on the level of occurrences and their relevance, as determined by the association strength metric. The links between nodes indicate co-occurrence relationships, whereas stronger links signify higher co-occurrence in literature. The color gradient (spanning from 2016 to 2024) highlights the temporal evolution of keyword prominence, and the bibliometric analysis, in turn, identified key themes and clusters within the literature. The occurrence analysis revealed that the most recent publication topics, particularly those closer to 2024, are characterized by frequent occurrences of terms such as "leadership endorsement", "individual dynamic capabilities", "microfoundations", and "dynamic capabilities". These are accompanied by other terms that appear with similar frequency, including "sustainability", "environmental commitment", "competitive advantage", and "resource-based view". These themes reflect the primary focus areas of the publications under analysis.

The concept of IDC emerged as a central theme, with strong connections to terms such as healthcare adaptability, operational performance, and patient-centered care. Its relevance in enhancing flexibility and resilience within healthcare operations is therefore highlighted. Additionally, the keyword "AI-driven healthcare," which is strongly associated with terms such as resilience, performance, and interoperability, reflects its integration with digitalization and advanced technologies in healthcare management. In this context, resilience but also innovation have been positioned as a prominent concept, closely connected to healthcare operations, literature review methodologies, and regulatory compliance, thus underscoring their significance in addressing disruptions and ensuring high-quality patient outcomes. Fig. 4 illustrates the interconnectivity of concepts such as IDC, AI-driven healthcare, and healthcare resilience, along with methodologies like RBV, in fostering innovation and sustainability in healthcare operations.

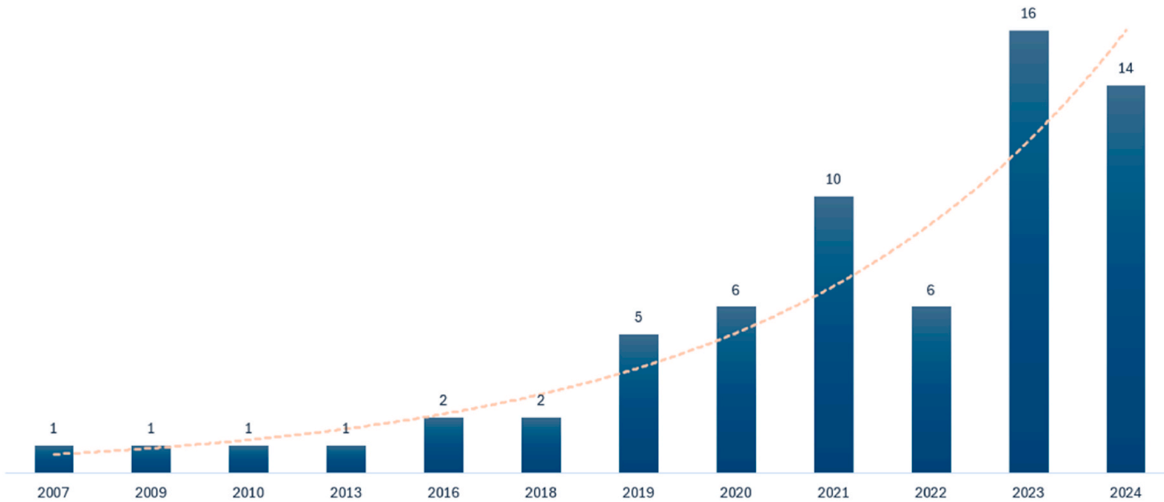

Fig. 2. Publications distribution.

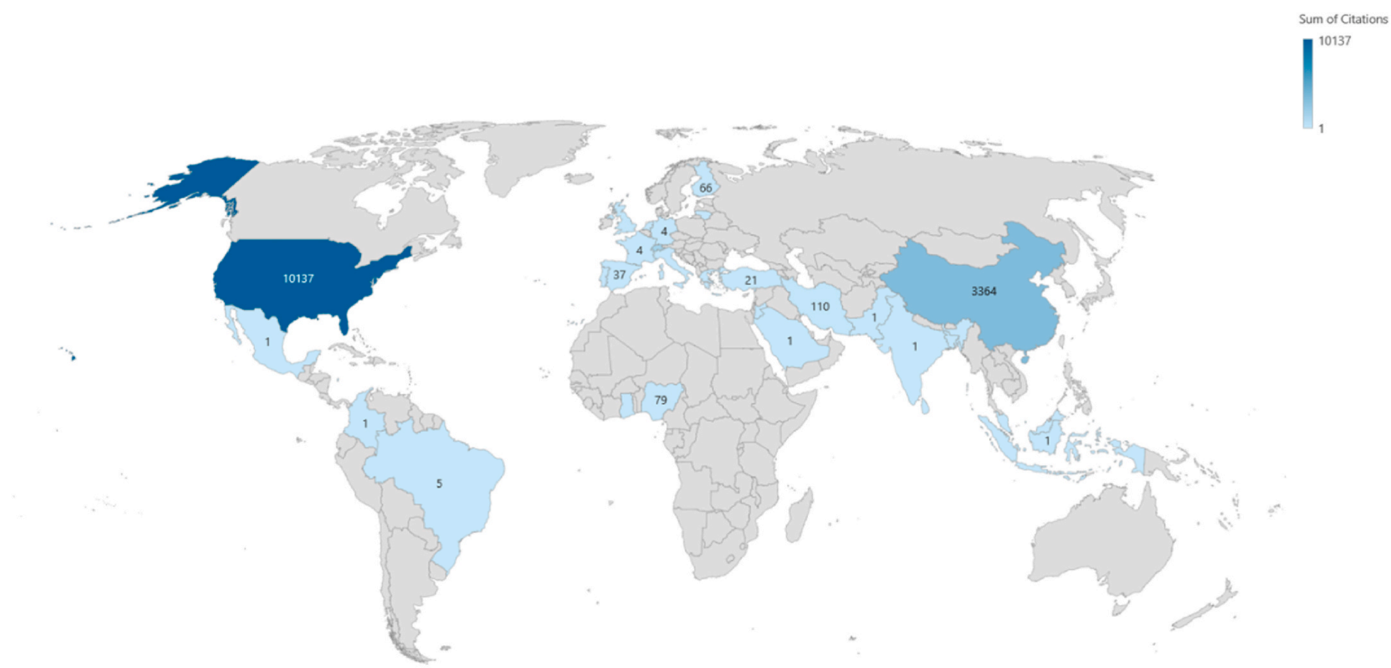

Fig. 3. Citations map distribution per country.

Furthermore, it highlights the increasing significance of leadership endorsement and micro-foundations as integral components of contemporary healthcare management strategies.

Another emerging trend from the analysis is the digital transformation of healthcare, emphasizing the integration of advanced technologies such as AI for enhancing operational efficiency and resilience. The concept of the circular economy, closely connected to sustainability and resilience, also underscores the shift towards environmentally conscious practices within healthcare management. In terms of process improvement approaches, lean methodologies and TAM are being applied to healthcare operations management, QM, and continuous improvement initiatives. This indicates their importance in process optimization and enhancing operational efficiency, particularly within hospitals and other healthcare facilities. Keywords such as agility, resilience, and big data are prominent in recent publications (2022–2024), reflecting the recent research focus on adaptability, digital transformation, and technological innovation in healthcare systems.

According to Fig. 5, at the center of the network, the keyword “capability” emerges as the most prominent keyword, strongly linked to topics such as healthcare operations management, dynamic capabilities, strategy, innovation, research, AI, and collaboration, highlighting their critical role in enabling adaptability and resilience in healthcare settings. Connections to AI perception, career resilience, ISO/EIC, GDPR, and AI-driven healthcare solutions indicate IDC’s application in addressing global healthcare challenges, where the term "strategy" forms a key cluster linked to healthcare agility, sustainability, and flexibility. This reflects the strategic emphasis on resilience and adaptability within healthcare operations management practices.

Keywords like design methodology approach and collaboration indicate a focus on structured frameworks and partnerships, essential for aligning sustainability goals with healthcare performance improvement. Other terms such as patient-centered care, regulatory compliance, ISO/IEC 27001 (Information Security Management), GDPR, and lean management principles emphasize the integration of IDC with specific

Table 3
Most cited papers from collected SLR data.

Publication Year	Author	Title	Citations
2017	Teece, D. J., Pisano, G., & Shuen, A.	Dynamic capabilities and strategic management	56,449
2010	Barreto, I.	Dynamic Capabilities: A review of past research and an agenda for the future	3397
2021	Buzzao, G.; Rizzi, F.	On the conceptualization and measurement of dynamic capabilities for sustainability	147
2017	S Mandal	The Influence of Dynamic Capabilities on hospital-supplier Collaboration and Hospital Supply Chain Performance	110
2019	J Furnival, R Boaden, K Walshe	A dynamic capabilities view of improvement capability	72
2021	O Kokshagina	Managing shifts to value-based healthcare and value digitalization as a multi-level dynamic capability development process	68
2019	Pundziene, A., Heaton, S., & Teece, D. J.	5G, dynamic capabilities and business models innovation in the healthcare industry	23

methodologies, particularly in regulated healthcare environments. This integration is crucial for ensuring compliance with established standards, enhancing data security, and maintaining patient privacy. This network reveals the multifaceted application of IDC in healthcare operations management, highlighting its strategic relevance for agility, collaboration, regulatory adherence, and data-driven innovation. The strong connections to sustainability, digital health transformation, patient care, and adherence to regulations reflect the evolving priorities in healthcare research, addressing both operational efficiency and the challenges posed by global health needs.

Quantitative findings from the bibliometric analysis indicated that 62 % of the reviewed studies reported significant improvements in healthcare operations metrics, such as patient wait time, quality of care, and resource utilization, following the implementation of IDC and leadership endorsement. Furthermore, approximately 30 % of the studies indicated that integrating AI with big data practices and increasing interoperability capabilities through IDC may yield superior outcomes compared to traditional process improvement alone. However, 15 % of the studies reported mixed results, particularly in contexts where resource constraints limited the extent of AI adoption, with its implementation leading to notable improvements in compliance with regulatory standards, as evidenced by approximately 50 % of the reviewed studies. These studies demonstrated that the structured approach to leadership involvement and process standardization inherent to IDC helped hospitals meet regulatory requirements more

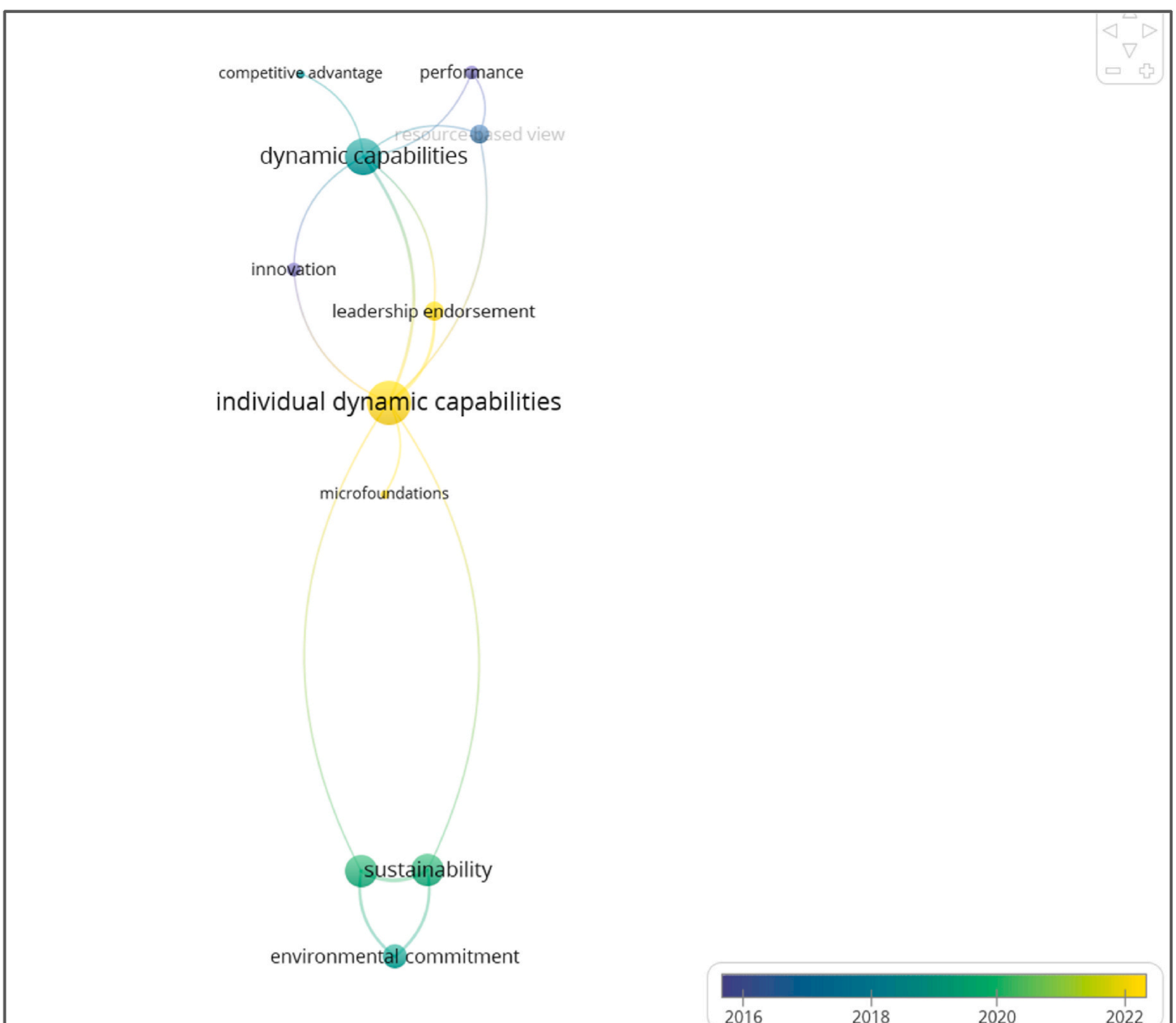

Fig. 4. Bibliographic data with corresponding publication year based on bibliographic coupling.

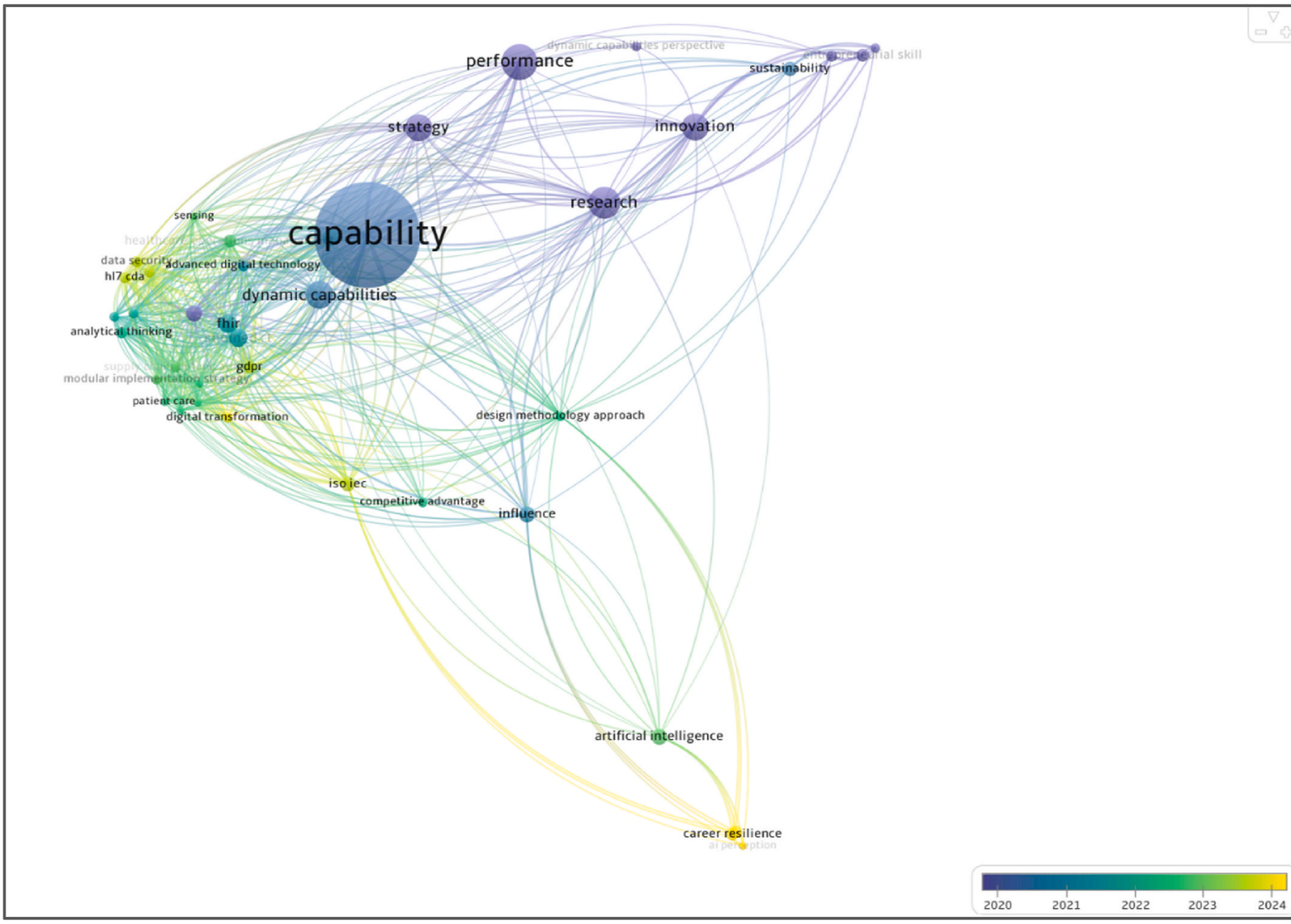

Fig. 5. Text Data analysis based on terms co-occurrence and binary counting.

effectively, thereby reducing the risk of non-compliance and associated penalties.

HCO policies and regulations around AI, big data, and interoperability are critical in shaping healthcare operations. Approximately 30 % of the studies indicated an improvement in staff performance metrics, including care efficiency and adherence to protocols, after the implementation of IDC via leadership endorsement, involvement, and structured learning and training programs for doctors, nurses, and other hospital staff. This highlights the role of IDC in fostering a culture of adaptability, collaboration, and continuous learning within hospitals. Leadership endorsement and training programs are essential to ensuring that hospital staff can effectively utilize AI-driven tools and manage big data analytics to improve patient care, operational efficiency, and compliance with interoperability standards such as FHIR and GDPR. The clustering analysis additionally identified four principal clusters, representing the thematic areas within the literature: regulatory compliance and quality, process efficiency, AI and interoperability integration, and risk mitigation. These clusters underscore the importance of IDC in facilitating healthcare innovations, particularly in ensuring that hospitals can effectively implement AI technologies while adhering to strict regulatory standards and maintaining secure, interoperable data systems.

Fig. 6 presents a visual representation of co-occurrence networks based on density visualization, with the same 31 keywords selected from the fourth figure. These keywords exhibit high total strength and significant occurrence weights, as demonstrated by the density propensity visualization and kernel width.

4.4. *Focus group: participants demographic profile*

The focus group included HCPs and decision-makers from large and medium-sized organizations across North America and Europe, specializing in AI implementation for operational and clinical workflows. Participants represented diverse roles, with 50 % holding senior leadership positions (e.g., C-suite executives, AI strategy directors, or department heads), 35 % in mid-level roles (project managers, AI program leads, or clinical informatics coordinators), and 15 % as emerging leaders (specialists or junior managers in technology integration). Over 60 % had more than a decade of healthcare experience, often leading prior AI initiatives, while 40 % brought 5–10 years of expertise in emerging technologies or operational challenges.

Departmental representation spanned critical areas: 30 % were from IT/health informatics teams (e.g., head of technology, interoperability departmental managers), 25 % from clinical operations (emergency department optimization, resource management, or quality improvement teams), 20 % from data analytics (predictive modeling for patient outcomes or resource forecasting), 15 % from strategic planning (AI roadmap developers or regulatory compliance officers), and 10 % from patient care services (telehealth platforms, AI-driven diagnostics units, or chronic disease management teams). Geographically, participants hailed from 12 North American organizations (7 U.S.-based academic medical centers, 2 Canadian integrated health systems, and 1 Mexican multispecialty clinic) and 9 European institutions (4 German university hospitals, 3 UK NHS trusts, 2 French regional hospitals, and 1 Dutch academic center). Demographically, 55 % were male, with an average age of 48 (ranging from 30 to 65). Organizations included 62 % large-

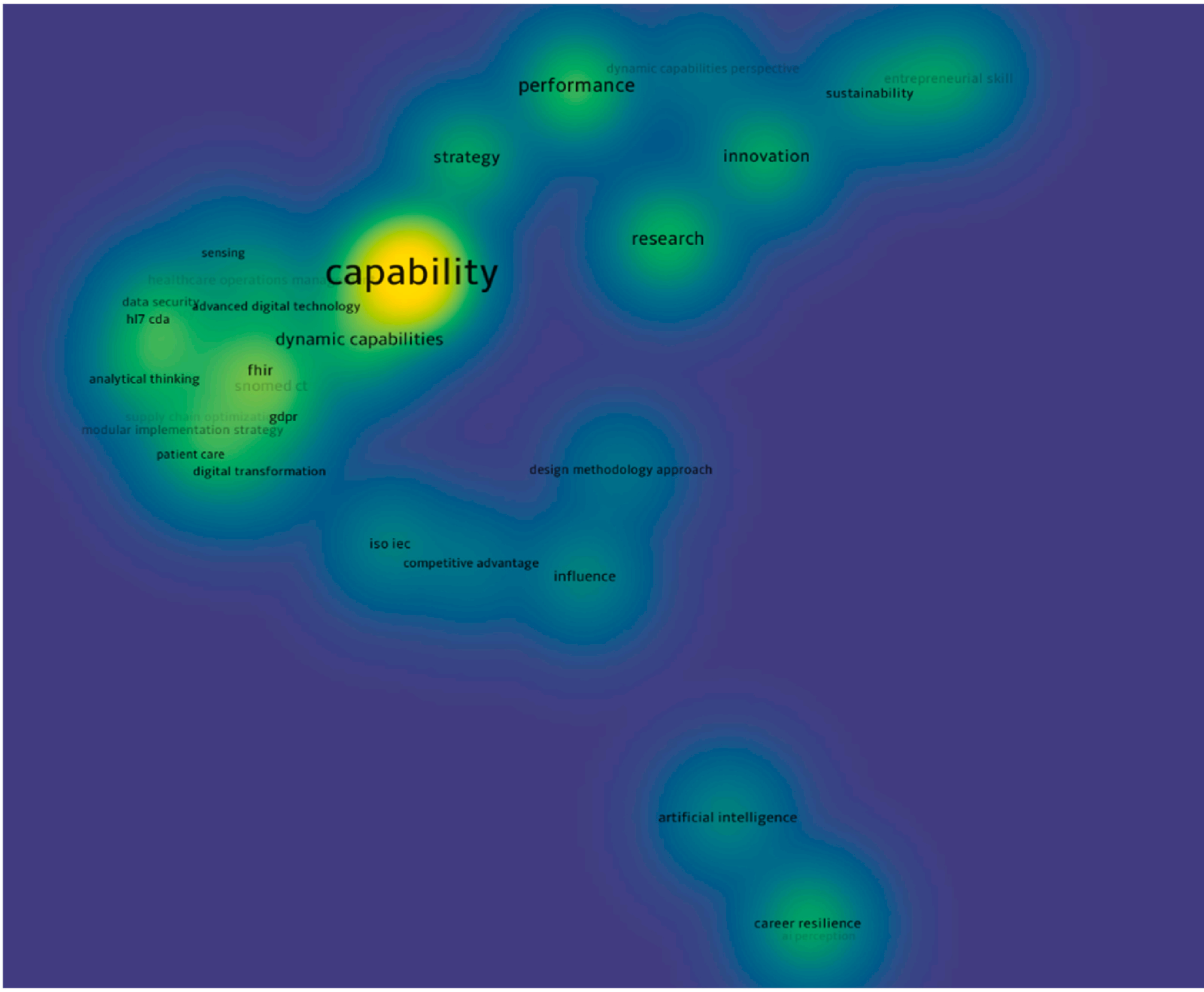

Fig. 6. Keyword co-occurrence network.

scale institutions (academic medical centers, 500+ bed hospitals, or national health systems) and 38 % medium-sized entities (regional clinics, oncology/specialty centers, or community health networks). This mix ensured insights into AI's role in both complex, high-resource systems and agile, specialized care environments.

4.5. Focus group: preliminary results – initial discussion phase

The preliminary results from the initial discussion phase revealed several critical themes, illustrating how HCOs combine DC—encompassing the ability to sense, seize, and reconfigure resources—and micro-managerial skills to integrate AI into their operations. Participants highlighted real-world case studies and survey-based data that demonstrated the tangible benefits of adopting AI tools, such as diagnostic imaging algorithms, within clinical workflows. In these scenarios, DC allowed hospitals to redesign processes and incorporate AI outputs into decision-making. Concurrently, micro managerial skills at the departmental level, exemplified by lean management principles, helped streamline tasks and minimize delays by establishing dedicated AI review stations for radiologists. This seamless integration into Electronic Health Records (EHRs) improved both diagnostic accuracy and operational efficiency.

One participant offered an example from Germany, where a hospital used Hospital Management Information Systems (HMIS) to track inventory, patient flow, and resource allocation, reducing operational costs by 15 % within a year. Effective alignment of technology with organizational objectives, supported by iterative feedback loops, enhanced user engagement, and minimized resistance. Emphasizing the role of perceived usefulness and ease of use, this case underscored the Technology Acceptance Model's relevance, as staff were more receptive once they observed reduced wait times and other immediate benefits. Another participant from the U.S. described how the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey collected patient feedback on care quality, enabling hospitals to identify communication gaps and deploy AI-driven chatbots. This approach improved patient satisfaction and created a feedback loop that aligned patient needs with ongoing operational adjustments. Early adopters in urban clinics served as reference points, fostering peer influence and accelerating broader adoption. Participants also discussed a U.S. hospital's successful application of lean principles to reduce patient discharge delays by 30 %. Micro managerial skills—including cross-departmental collaboration and standardized workflows—subsequently paved the way for AI-driven solutions that predict discharge timelines and refine the lean framework. Another focus group member, representing a global pharmaceutical manufacturer deeply involved in medium and large clinic operations, highlighted real-world evidence for decision-making. Researchers drew on data from electronic health records and insurance claims to inform health technology assessments, forging partnerships with data providers and regulators to ensure compliance and align with the diffusion of innovation criteria.

Throughout the discussions, cultural dimensions and biases emerged as significant concerns. Algorithms trained on non-diverse datasets may overlook regional disease patterns or cultural preferences, creating inequitable outcomes. Divergent regulatory environments also shaped AI adoption rates: while regions with extensive privacy laws, such as parts of Europe, sometimes experienced slower implementation, those with more flexible frameworks might prioritize speed over ethical considerations. Centralized healthcare systems may require government-level coordination for AI deployment, whereas decentralized systems can exhibit varied institution-level adoption rates. Participants noted that AI tools developed for high-prevalence diseases in one region might not meet the needs of another, underscoring the importance of localized adaptation. Further dialogue examined infrastructure challenges, especially in rural areas with limited digital connectivity and human resources, and considered the impact of high clinical autonomy cultures on AI uptake. In places where clinicians are accustomed to independent decision-making, resistance to AI may be stronger unless evidence convincingly supports its added value. Regions with established medical education systems can more seamlessly integrate AI training into curricula, influencing long-term adoption.

Additionally, discussions on ethical and governance considerations revealed that values such as privacy and autonomy shape regulatory oversight. Some regions may favor patient autonomy over data-intensive efficiency, complicating AI deployment. Several participants stressed that a single governance model might not be universally applicable; region-specific frameworks that address cultural nuances—including language barriers or religious practices—could be more effective. Comparisons between Germany and the U.S. illustrated divergent strategies: Germany often prioritizes transparency and ethical governance, while the U.S. may focus on scaling AI solutions rapidly. The group also explored strategies to overcome AI implementation barriers in healthcare. Participants underscored that hospitals can leverage both organizational-level DC and IDC to monitor regulatory changes, adopt emerging technologies, and adjust resource allocation. In one illustration, an EU hospital aligned AI deployment with the GDPR, while a U.S. institution pursued approvals from the Food and Drug Administration (FDA). DC also facilitated the investment in hybrid IT infrastructure, partnerships with technology vendors, and the establishment of AI governance committees to oversee ethical use and align these initiatives with organizational goals. Some participants discussed the importance of adaptive workforce skills. Training programs that build AI literacy, data interpretation expertise, and teamwork can ease resistance and increase clinical professionals' acceptance of AI outputs. Continuous peer-to-peer knowledge sharing further refines AI applications, fostering problem-solving agility and empowering frontline staff to experiment with new tools. Targeted tactics to address specific barriers included partnerships with regulators to co-design AI frameworks, federated learning models to maintain privacy standards and success metrics—such as reduced diagnostic errors—to build trust among clinicians.

Technical experts in the focus group drew attention to data silos and incompatibility, advocating for enhanced data integration, standardized EHRs, and systematic collaboration across departments. These measures can enable AI tools to access diverse datasets and provide more comprehensive insights. By continuously updating AI systems to address emerging diseases and evolving clinical needs, HCOs can maintain effective, sustainable solutions. Furthermore, collaborative networks among hospitals, insurers, and technology firms could reduce implementation costs and share best practices. Across the discussions, participants consistently emphasized that combining organizational DC with individual adaptability can systematically break down barriers, stimulate AI adoption, and cultivate a sustainable competitive edge in healthcare operations.

4.6. Advanced applied data analysis and research questions mapping

The focus group discussions emphasized how standard yet continuously evolving business environments intensify the need for organizational flexibility and deeper stakeholder integration, aligning with the first research question on healthcare decision-makers' perceptions of new methods for managing operational complexity. Participants repeatedly referred to lean management principles, cross-departmental collaboration, and standardized workflows as effective responses to the challenges posed by AI adoption. Thematic analysis underscored the significance of AI-driven tools such as diagnostic imaging algorithms, chatbots, predictive analytics, and federated learning. Although participants could not disclose specific proprietary names or brands, they described pilot initiatives aimed at minimizing misdiagnosis, optimizing patient flow, and predicting discharge timelines.

The conversations further revealed that terms including "Technological Integration," "Bias in AI," "Ethical Values," "Privacy," "Autonomy," and "Transparency" were essential to understanding these innovations in practice. Integrating AI into EHRs for anomaly detection emerged as a dominant theme, as did HMIS for tracking inventory and resource utilization. Participants also addressed cultural and ethical dimensions, highlighting non-diverse datasets that can lead to bias and the need for regional adaptations of AI tools to accommodate varied disease patterns. These findings correlate with the second research question, which examines how decision-makers implement individual and organizational dynamic capabilities to seize collaboration opportunities, adopt decentralized governance models, and reconfigure established processes.

The results indicate a broad spectrum of themes spanning non-technical, healthcare-related issues and strategic decision-making considerations. Among the non-technical themes, Patient Data Protection received the highest average rating (4.82), reflecting a strong consensus on the need to secure patient information. Operational Efficiency & Cost Reduction ranked second (4.79), emphasizing the persistent emphasis on optimizing resource allocation. Within this same category, Ethical Governance (4.61) and compliance-oriented topics, such as GDPR/FDA Alignment (3.51), highlight an unwavering concern for regulatory integrity.

Themes concerning decision-making featured prominently, with Dynamic Capabilities (4.21) demonstrating the perceived importance of organizational agility in adapting to emerging technologies. The themes of AI Impact on Management (4.05) and Evidence-Based ROI (3.12) further emphasize the value attributed to data-driven decision-making and measurable outcomes. The emergence of Cultural & Regional Adaptation (4.06) as an essential consideration is indicative of the recognition of the heterogeneous nature of the healthcare landscape and the necessity to tailor interventions to local contexts. Additionally, Workforce & Training (1.87) received moderate attention, indicating ongoing challenges in equipping clinicians and staff with the necessary skills for AI integration. The frequency of mentions exhibited considerable variation; for instance, Revenue & ROI Drivers (1.08) emerged as a recurrent theme (84 mentions), despite a modest average rating, suggesting ongoing deliberations surrounding financial metrics. Sentiment scores ranged from strongly positive (0.99 for IDC for Technology Acceptance) to more neutral (0.08 for Risk Mitigation), indicating varied attitudes toward each theme. The findings demonstrate a sophisticated interplay between operational, regulatory, and socio-cultural dimensions that shape healthcare innovation and management (Tables 4 and 5).

About the technical findings, emphasis was placed on a diverse range of AI safety, alignment, and scalability topics, highlighting both conceptual and implementation challenges. Catastrophic Risk Mitigation,

Table 4
Rating, frequency of mentions, and sentiment score from panel discussions – Non-Technical.

Areas	Theme	Average Rating	Frequency of Mentions	Rel. Frequency of Mentions	Sentiment Score
Healthcare	Operational Efficiency & Cost Reduction	4.79	78	4.56 %	0.84
Healthcare	Lean Management Principles	3.83	12	0.70 %	0.11
Healthcare	Hospital Management Information Systems (HMIS)	1.29	11	0.64 %	0.69
Healthcare	Predictive Analytics	2.58	32	1.87 %	0.44
Healthcare	Revenue & ROI Drivers	1.08	12	0.70 %	0.12
Healthcare	Patient Data Protection	4.82	94	5.50 %	0.12
Healthcare	Real-World Evidence (RWE)	2.24	89	5.21 %	0.74
Healthcare	Regulatory & Compliance Challenges	4.32	55	3.22 %	0.11
Healthcare	GDPR/FDA Alignment	4.51	66	3.86 %	0.20
Healthcare	Ethical Governance	4.61	61	3.57 %	0.18
Healthcare	Partnerships & Collaboration	4.58	60	3.51 %	0.83
Healthcare	Infrastructure & Resource Gaps	4.03	79	4.62 %	0.10
Healthcare	Interoperability	4.08	70	4.10 %	0.12
Decision-Making	Adoption Strategies	0.42	7	0.41 %	0.84
Decision-Making	IDC for Technology Acceptance	4.16	63	3.69 %	0.99
Decision-Making	Evidence-Based ROI	1.32	11	0.64 %	0.90
Decision-Making	Phased Implementation	4.46	41	2.40 %	0.30
Decision-Making	Cultural & Regional Adaptation	4.06	79	4.62 %	0.11
Decision-Making	Localized and Private AI Models	4.43	78	4.56 %	0.13
Decision-Making	Clinician Autonomy	4.02	55	3.22 %	0.89
Decision-Making	Risk Mitigation	2.46	6	0.35 %	0.08
Decision-Making	Bias & Equity	4.07	6	0.35 %	0.30
Decision-Making	Regulatory Uncertainty	2.83	17	0.99 %	0.67
Decision-Making	Workforce & Training (e.g. AI Literacy)	1.87	9	0.53 %	0.17
Decision-Making	Long-Term Sustainability	2.97	12	0.70 %	0.94
Decision-Making	Dynamic Capabilities	4.21	86	5.03 %	0.89
Decision-Making	Ethical Governance Committees	4.85	83	4.86 %	0.68
Impact	AI Impact on Management	4.05	58	3.39 %	0.82
Impact	Leadership practices	4.24	69	4.04 %	0.44
Impact	Organizational transformation	4.37	64	3.74 %	0.14
Impact	Data protection, consent, ethics	4.36	65	3.80 %	0.15
Impact	Value creation	4.57	65	3.80 %	0.96
Impact	Chronic disease self-management	3.66	12	0.70 %	0.68
Impact	Corporate upskilling in AI	4.73	61	3.57 %	0.39
Impact	Health intervention assessments	2.47	16	0.94 %	0.32
Impact	Preventive care, patient education	3.35	27	1.58 %	0.59

which received an average rating of 4.81, emphasized the necessity of preventing unintended consequences in large-scale AI deployments. Emergent capabilities, such as Chain-of-Thought Reasoning (4.75) and Self-Supervised Learning (4.44), reflect a substantial interest in refining models that can independently generate or interpret information without human annotation. Model architectures, including Auto-Regressive Models (4.83) and Mixture-of-Experts (4.86), are frequently referenced, indicating a broad engagement with methodologies that manage complexity through modular or iterative processing.

The collected results of current frameworks and tools reveal a diversity of average ratings, with prominent platforms such as Hugging Face Transformers (1.51) and PyTorch/TensorFlow (2.73) emerging as essential components for development. Infrastructural innovations, such as Flash Attention (3.10) and Low-Rank Adaptation (2.19), are indicative of ongoing efforts to optimize the efficiency of training. Optimization and scaling strategies, including Distributed Training (4.84) and Scalability Laws (4.52), reflect the community's commitment to meeting the computational demands of increasingly sophisticated AI systems. Training techniques, ranging from Federated Learning (1.07) to Reinforcement Learning from Human Feedback (4.38), demonstrate an evolving focus on balancing data privacy, user collaboration, and performance gains. Concurrently, challenges about generalization, out-of-distribution robustness, and catastrophic forgetting underscore the persistent difficulties in developing reliable and adaptable models. The collective objective of the field is to ensure that AI is safe, interpretable, and scalable, with particular attention paid to emergent behaviors, advanced model architectures, and responsible development.

Sentiment analysis indicated a favorable attitude toward leadership in supporting and sustaining AI-based initiatives, aligning with the third research question. Certain executives reportedly linked AI investments to DC milestones that resulted in measurable progress in responsiveness and stakeholder collaboration. Regulatory and policy considerations figured prominently in the dialogue, with participants noting that pro-innovation strategies are emerging in governmental guidelines, particularly in countries like the UK. Workforce development and strategic partnerships also emerged as essential success factors, reflecting the need for interdisciplinary expertise that spans AI architectures, operational workflows, and regulatory requirements. Collaboration among universities, research institutes, and healthcare organizations was frequently cited as vital for translating AI innovations into scalable and robust implementations.

Overall, the technical discussions highlighted the importance of inference speed, especially in real-time clinical decision-support settings, where delays could compromise patient outcomes. Strategies such as model compression and hardware acceleration may mitigate latency without sacrificing accuracy. However, participants expressed concern about biased AI models that can misdiagnose underrepresented groups. Fairness metrics and data audits are viewed as crucial tools to identify disparities and ensure diverse representation in training datasets. Interoperability likewise proved challenging, given that AI applications must interact seamlessly with existing systems like EHRs. Standardization, improved data governance, and well-defined cleaning pipelines were identified as preconditions for successful AI integration. In examining human-centric barriers, clinical acceptance emerged as a decisive factor, since resistance escalates if AI is perceived as a substitute rather than a complement to professional judgment. Embedding inference results directly into EHR dashboards was proposed as a tactic to maintain clinical workflows and reduce friction. Evaluation criteria for real-time systems included speed, reliability, clinical utility, interpretability, and scalability. Models must produce transparent, actionable outputs while respecting latency constraints, especially in high-stakes scenarios such as critical care.

Table 5
Rating, frequency of mentions, and sentiment score from panel discussions - Technical.

Areas	Theme	Average Rating	Frequency of Mentions	Rel. Frequency of Mentions	Sentiment Score
AI Safety & Alignment	Catastrophic Risk Mitigation	4.81	65	5.88 %	0.32
AI Safety & Alignment	Constitutional AI	0.72	8	0.72 %	0.78
AI Safety & Alignment	Mechanistic Interpretability	2.23	6	0.54 %	0.41
AI Safety & Alignment	Reward Modeling	1.99	7	0.63 %	0.44
Attention Mechanisms	Latent Attention	3.90	8	0.72 %	0.66
Attention Mechanisms	Multi-Head Attention	1.44	13	1.18 %	0.25
Attention Mechanisms	Sparse Attention	3.00	11	0.99 %	0.13
Concepts	AI Compute Trends	1.71	3	0.27 %	0.39
Concepts	Catastrophic Forgetting	1.82	5	0.45 %	0.24
Concepts	Model Distillation	2.34	4	0.36 %	0.70
Concepts	Out-of-Distribution Robustness	0.34	3	0.27 %	0.25
Concepts	Overfitting vs. Generalization	4.11	60	5.42 %	0.50
Concepts	Zero-Shot/Few-Shot Learning	0.37	12	1.08 %	0.65
Emergent Capabilities	Chain-of-Thought Reasoning	4.75	78	7.05 %	0.03
Emergent Capabilities	Few-Shot/Zero-Shot Learning	3.59	18	1.63 %	0.75
Emergent Capabilities	Self-Supervised Learning	4.44	69	6.24 %	0.90
Frameworks & Tools	Hugging Face Transformers	1.51	11	0.99 %	0.59
Frameworks & Tools	PyTorch/TensorFlow	2.73	14	1.27 %	0.12
Infrastructure & Efficiency	Flash Attention (optimized attention computation)	3.10	16	1.45 %	0.32
Infrastructure & Efficiency	Low-Rank Adaptation (LoRA)	2.19	14	1.27 %	0.71
Infrastructure & Efficiency	Neural Architecture Search (NAS)	0.69	8	0.72 %	0.70
Model Architectures	Auto-regressive Models	4.83	66	5.97 %	0.05
Model Architectures	Generative Adversarial Networks (GANs)	4.46	65	5.88 %	0.22
Model Architectures	Latent Variable Models	0.86	4	0.36 %	0.34
Model Architectures	Mixture-of-Experts (MoE)	4.86	88	7.96 %	0.23
Model Architectures	Recurrent Neural Networks (RNNs)	4.09	63	5.70 %	0.50
Model Architectures	Transformer-based Models	1.02	12	1.08 %	0.02
Model Architectures	Sparsity in Large Models	3.41	5	0.45 %	0.29
Optimization & Scaling	Distributed Training (e.g., data parallelism)	4.84	64	5.79 %	0.60
Optimization & Scaling	Gradient Descent Variants (Adam, SGD)	3.59	6	0.54 %	0.99
Optimization & Scaling	Quantization (FP16, FP8, FP4 precision)	3.59	9	0.81 %	0.88
Optimization & Scaling	Scalability Laws (e.g., compute/data scaling)	4.96	89	8.05 %	0.12
Optimization & Scaling	Sparsity in Neural Networks	4.25	72	6.51 %	0.05
Training Techniques	Federated Learning	1.07	6	0.54 %	0.94
Training Techniques	Reinforcement Learning from Human Feedback (RLHF)	4.38	62	5.61 %	0.32
Training Techniques	Sparse Training	3.39	8	0.72 %	0.04
Training Techniques	Supervised/Unsupervised Learning	4.24	54	4.88 %	0.48

4.7. Network analysis

The network analysis, based on participant discussions and a Likert scale ranging from 1 (least important) to 5 (most important), revealed nuanced themes related to AI adoption in healthcare. By mapping and quantifying interactions among participants, topics, and ideas, this analysis provided a heatmap that highlighted both central topics and the significance of patient perspectives in shaping outcomes.

Patient trust in human-AI collaboration consistently emerged as a central element, with discussions underscoring the value of clinicians' expertise in validating AI-generated results. Participants noted that patients are more inclined to accept AI tools when they perceive tangible benefits—faster diagnoses, reduced waiting times, or greater accuracy—and possess confidence in data privacy measures. Conversely, concerns over AI errors in critical conditions (e.g., cancer or sepsis) and fears of commercial data exploitation frequently surfaced. If patients lose confidence in AI recommendations, they may delay or disregard important medical advice, potentially leading to worsened outcomes. Bias in AI systems was another frequently mentioned issue, as limited or unrepresentative training data can exacerbate health disparities, particularly among marginalized populations. Participants stressed that effective AI integration depends on clinicians' judgment in confirming and interpreting system outputs, as well as the availability of explainable AI interfaces that clarify the rationale behind each recommendation.

The comparative analysis further highlighted divergent challenges between small and medium healthcare organizations and large, often urban hospitals. Smaller clinics, especially in rural settings, struggle with insufficient funding, limited IT infrastructure, and minimal data resources. In these contexts, participants suggested modular, low-cost AI solutions and community engagement initiatives to build trust. Larger hospitals face obstacles stemming from bureaucratic inertia, complex legacy systems, and ambiguities in legal liability for AI errors. Resource allocation decisions and staff training also shape the pace of AI adoption. Strategies such as phased implementations, standardized interoperability protocols, and ethics committees were proposed to foster responsible innovation in these environments. Overall, the discussions suggest that addressing heterogeneous needs—low-resource contexts requiring affordable, targeted AI tools, and large institutions requiring systematic governance reforms—remains essential for equitable, effective AI integration across diverse healthcare systems.

As illustrated in Fig. 7, high scores and positive correlations primarily emerge in domains directly influencing operational efficiency, patient well-being, and strategic innovation. Data Protection & Privacy consistently shows elevated values (e.g., an average of 4.4), indicating strong alignment with AI connectivity, DC, and both TAM and DOI frameworks. Similarly, Regulatory, Ethics, and Compliance exhibit robust associations with risk mitigation (4.9) and dynamic capabilities (4.7), highlighting the importance of adaptive governance and ethical oversight in integrating new technologies. Resources Management also stands out, correlating favorably with AI connectivity (4.4), offering evidence that adequate resource allocation underpins successful AI

	Relevance to Patients	Relevance to HCPs	AI Connected	Dynamic Capabilities Connection	Technology Acceptance Relevance (TAM Connected)	Innovation Adoption Rate (DOI connected)	Risk & Challenge Score	Future Investments	Small-Medium HCOs Impact Factor	Large HCOs Impact Factor	Average
Learning, Training and Skills Development	1.4	4.6	4.2	4.6	4.1	4.6	4.7	3.9	4.1	4.8	4.10
Data Governance	4.2	4.5	4.5	4.1	4.7	4.3	4.4	4.3	4.2	4.1	4.33
Management Governance and Decisions	3.5	4.1	4.2	4.7	3.9	3.9	3.4	4.1	4.3	4.5	4.06
Data Protection & Privacy	4.8	4.1	4.8	4.6	3.9	3.5	4.2	4.4	4.6	4.8	4.37
Organizational Transformation and Structure	1.3	3.6	2.8	4.5	3.4	3.8	3.9	3.8	2.6	4.3	3.40
Leadership Practises	3.6	4.1	2.6	4.4	4.6	4.2	2.6	2.9	3.1	3.9	3.60
Interoperability	3.2	3.6	4.1	4.3	4.3	4.5	4.1	3.5	3.6	3.7	3.89
Cybersecurity	4.6	4.1	4.4	4.2	4.5	4.8	4.8	4.1	3.1	4.6	4.32
Financial Availability	3.6	3.2	4.9	2.6	3.5	3.6	1.6	4.1	4.6	4.8	3.65
Regulatory, Ethics, Compliance	4.7	4.8	4.7	3.9	4.2	4.1	4.6	4.8	4.1	4.7	4.46
Resources Management	4.5	4.6	3.4	4.2	4.0	4.1	3.1	3.5	4.3	4.7	4.04
IT Architecture	4.3	3.1	4.3	3.6	4.1	3.9	3.8	3.9	3.1	4.1	3.82
Advanced Analytics	4.1	4.0	4.2	4.6	4.2	4.2	2.1	3.2	3.8	4.1	3.85
Health Intervention	4.8	3.9	3.9	4.5	4.3	4.3	3.6	3.1	2.6	4.5	3.95
Clinical Decision Support	4.6	3.9	3.7	4.4	4.4	4.1	4.1	3.5	2.9	4.3	3.99
Hospital Management Information Systems	4.5	3.5	3.5	4.3	4.5	3.9	4.6	3.9	1.4	4.8	3.89
Cross-departmental collaboration & Data Exchange	1.2	3.3	3.3	3.6	3.5	4.1	1.9	4.6	1.0	5.0	3.15
Human-AI Collaboration	4.2	3.1	3.1	4.5	4.3	4.3	4.2	4.4	4.6	4.8	4.15
Partnerships with Regulators	1.3	4.1	4.3	4.0	4.2	4.6	4.0	4.2	4.4	4.6	3.97
Academic Partnerships	1.1	4.1	2.9	4.3	4.1	4.4	3.8	4.0	4.2	4.4	3.73
Average	3.48	3.92	3.89	4.20	4.14	4.16	3.68	3.91	3.53	4.48	

Fig. 7. Heatmap of key connected themes from network analysis.

adoption. Notably, Health Intervention achieves high averages in relevance to patients (4.8) and dynamic capabilities (4.5), underscoring how clinical advancements benefit from strategic reconfiguration and strong organizational competencies. Equally noteworthy is the role of Hospital Management Information Systems, which shows positive linkages to AI connectivity (4.5) and moderate-to-high impact on small and large healthcare organizations alike.

Across the matrix, improvements in leadership practices, interoperability, and advanced analytics also correlate well with technology acceptance, suggesting that organizational buy-in and shared data standards facilitate smoother innovation diffusion. Finally, the synergy between human-AI collaboration and dynamic capabilities (4.6) reflects how empowered clinicians, coupled with adaptive structures, can accelerate the adoption of emerging technologies. Collectively, these strong scores reinforce the central role of strategic, ethical, and resource-based factors in driving effective AI integration and improved healthcare delivery.

The matrix results shed light on three key areas aligning with our research questions. First, regarding healthcare decision-makers and HCPs' perceptions of operational efficiency through AI (Research Question 1), high scores for Data Protection & Privacy, coupled with strong AI connectivity (4.8 and 4.1, respectively), suggest that safeguarding patient information is foundational to perceived efficiency improvements. This emphasis on privacy aligns with an observed willingness among HCPs to adopt AI-driven solutions when they trust data protection measures. Second, in exploring how decision-makers implement IDC and AI-related practices grounded in TAM and innovation diffusion (Research Question 2), Management Governance & Decisions (3.5 relevance to patients, 4.2 AI connected) and the robust dynamic capabilities link (4.7) indicate that strategic oversight fosters AI acceptance. These findings point to the significance of leadership practices in driving technology adoption, as strong governance and clear decision-making structures appear to bolster both TAM relevance (3.9) and DOI adoption rates (3.9). Such structures may enable more agile resource allocation and cross-departmental collaboration, facilitating smoother AI integration.

Finally, the matrix also provides insights into industry responses to regulatory challenges (Research Question 3). Regulatory, Ethics, and Compliance stands out with high scores in relevance to patients (4.7), HCPs (4.8), and connections to dynamic capabilities (3.9). Combined with high perceived risk and challenge (4.9), this result underscores the centrality of ethical and regulatory considerations in AI deployment. HCOs appear keen to invest in compliance-driven models, as indicated by favorable future investment ratings (4.1), suggesting an adaptive stance toward emerging policies and data protection mandates.

5. Discussion

5.1. Interpretation of results

Overall, participants provided concrete examples illustrating how DC—encompassing the ability to sense market and technological opportunities, seize resources, and reconfigure workflows—drives the adoption of AI-based tools. In hospital diagnostics, for instance, AI algorithms were integrated into radiology workflows to reduce misdiagnosis rates. Managers reported using lean management principles and standardized protocols (i.e., micro managerial skills) to ensure that these AI outputs seamlessly complemented clinical decision-making. Such operational streamlining reflects a broader perception among clinicians and executives that AI improves care quality and organizational responsiveness, thereby speaking to RQ1 on operational efficiency.

The results also show that successful AI implementation hinges on IDC at both organizational and individual levels: managers must align technology with strategic goals while clinicians acquire the skills to interpret AI outputs. One German hospital's adoption of an HMIS exemplified how real-time data analytics can improve resource allocation by 15 %, illustrating RQ2's emphasis on how TAM constructs—particularly perceived usefulness and ease of use—facilitate acceptance. Additionally, the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey data enabled U.S. hospitals to deploy AI chatbots, increasing patient satisfaction by identifying and resolving communication gaps. These use cases highlight how decision-makers leverage DC to sense emerging technologies, seize relevant resources, and reconfigure processes in a manner consistent with both TAM (user buy-in) and the DOI framework (peer influence, visible benefits).

In line with RQ3's focus on policy and regulatory considerations, divergent approaches emerged based on varying national regulations and cultural norms. Participants from Germany reported that strict data privacy laws sometimes slow down AI deployment, while U.S.-based participants highlighted a faster pace of implementation constrained primarily by FDA approvals and cost-benefit analyses. Many HCOs reported adopting region-specific strategies, such as federated learning to protect patient data in jurisdictions that prioritize privacy and rigorous oversight. Across all examples, leadership involvement—and particularly the ability to provide clear directives and training—proved crucial to overcoming barriers such as clinician resistance, infrastructural constraints, or concerns over ethical governance. This leadership-driven alignment of AI initiatives with institutional objectives underscores DC as essential for navigating external policy shifts and internal stakeholder priorities.

Finally, participants consistently underscored how cultural and contextual factors influence AI's potential to improve operational efficiency. Some hospitals in rural or low-resource settings face connectivity challenges, limiting their capacity to adopt AI at scale. Others must address high levels of clinical autonomy or patient skepticism, shaped by fears of misdiagnosis or privacy breaches. Focus group members noted that where trust in AI is low—often due to data exploitation concerns—adoption stalls, reinforcing the need for robust patient engagement, clinician oversight, and transparent governance structures. Collectively, these findings confirm that operational benefits are maximized when HCOs balance advanced analytics with tailored strategies addressing regulatory, infrastructural, and cultural realities.

The findings align with established literature that positions DC as integral to successful innovation adoption in healthcare. Previous research has underscored leadership support, staff training, and organizational readiness as key enablers of quality improvement initiatives. The focus group results extend this understanding by illustrating how AI-driven tools can flourish within IDC frameworks, particularly when micro managerial tactics (e.g., lean implementation, standardized workflows) align with high-level strategic objectives. They also challenge assumptions that only large, well-funded institutions can leverage AI effectively. Although small and medium-sized entities often struggle with resource constraints—supporting well-documented concerns about cost, infrastructure, and regulatory complexities—they can still reap the benefits of AI by starting with smaller-scale pilot projects, forming strategic partnerships, and gradually expanding their scope. This approach reinforces existing calls for phased implementation to manage risks and ensure staff buy-in.

From a theoretical perspective, the findings corroborate the applicability of TAM to healthcare contexts. Positive staff perceptions of AI's usefulness (e.g., improved diagnostic accuracy, reduced waiting times) and ease of use (e.g., user-friendly chatbots, integrated EHR dashboards) were repeatedly cited as decisive factors in adoption. The data also reinforce the DOI model, showcasing how early adopters at certain hospitals influence peers and accelerate broader uptake. Moreover, by pairing IDC (focusing on employees' adaptive abilities, leadership engagement, and continuous learning) with these models, the study provides a more holistic viewpoint: AI systems are most effective when they are not only technologically sound but also strategically embedded within a flexible organizational culture.

Practically, the results underscore the importance of tailoring AI solutions to specific regional and institutional contexts. Rural clinics and small hospitals may prioritize cost-effective, cloud-based tools that do not require extensive IT infrastructure, whereas large urban hospitals need advanced interoperability standards and governance committees to handle complex data-sharing ecosystems. Across all settings, the focus group highlights the need to address data bias and ethical considerations—particularly when algorithms are trained on non-representative samples. Hospitals can employ data auditing, fairness metrics, and inclusive governance strategies to mitigate the risk of exacerbating health disparities. These practices, alongside transparent communication and clinician involvement, build trust and reduce resistance. In addition, training programs aimed at improving AI literacy and data interpretation skills can position clinicians as informed decision-makers, preserving professional autonomy and enhancing patient confidence in AI-enabled care.

Policy frameworks also feature prominently in this study. By illustrating how GDPR constraints in Europe can decelerate AI adoption, while less restrictive environments focus on rapid deployment, the findings highlight the broader trade-offs between patient privacy and innovation speed. Policymakers seeking balanced approaches may consider region-specific guidelines—such as federated learning or anonymized data-sharing protocols—that safeguard patients while still promoting technological progress. Expanding government incentives, subsidies, or partnerships with academic institutions could further alleviate the resource barriers smaller HCOs face. Ultimately, policy interventions that encourage robust data governance, ethical oversight, and cross-sector collaboration stand to accelerate AI adoption without compromising patient welfare or privacy. In light of these implications, the study's results point to several real-world applications. Healthcare leaders can systematically integrate AI into current workflows, using performance metrics (e.g., reduced diagnostic errors, and shorter hospital stays) to justify further investment and encourage staff buy-in. Collaborative initiatives between large and small providers—perhaps brokered by regulatory bodies—could yield the sharing of best practices and cost-effective technology transfer, reducing the digital divide in healthcare. Extending professional training programs to emphasize AI literacy, data quality management, and inclusive governance would ensure that clinicians and administrative teams alike can adapt to emerging tools. These interventions collectively strengthen the readiness of HCOs to capitalize on AI's transformative potential while safeguarding quality and equity in patient care.

6. Conclusion

Three principal findings emerged, each corresponding to the original research questions. First, practitioners widely view technological advancements—particularly AI tools integrated into diagnostics, workflow optimization, and patient engagement—as essential to achieving operational efficiency. Second, successful AI implementation hinges on structured IDC deployment, where leadership commitment and employee skill development enable organizations to sense emerging technologies, seize resources, and reconfigure processes. Third, emerging regulatory and policy contexts significantly influence adoption rates and strategies, pointing to the necessity of balancing data privacy, ethical safeguards, and the drive for innovation. These outcomes have several important implications. The observed alignment between IDC and AI underscores the need to broaden theoretical perspectives in healthcare technology management by incorporating organizational learning, leadership, and continuous adaptation as core elements. In practice, the emphasis on region-specific regulatory environments, limited infrastructure in certain settings, and cultural differences indicates that uniform policies may be less effective than tailored approaches. Small and medium-sized healthcare providers, for instance, require accessible, cost-efficient solutions and targeted support to navigate resource constraints. Larger institutions must address interoperability challenges, clinician resistance, and legal uncertainties related to algorithmic accountability.

Despite providing robust evidence of IDC's efficacy in diverse contexts, the research suggests several avenues for future study. Comparative analyses of small versus large HCOs, particularly across multiple countries or healthcare systems, could yield more nuanced insights into localized and adaptive strategies. Further investigations might also explore the longitudinal impact of newly introduced AI tools, assessing whether short-term efficiency gains translate into sustained improvements in patient care quality and regulatory compliance. Studies employing mixed-method approaches—combining longitudinal data analysis with qualitative focus groups—could offer deeper insights into user acceptance patterns, ethical dilemmas, and governance challenges. The findings contribute to both theory and practice. From a theoretical standpoint, this work bridges IDC, TAM, and DOI by illustrating how each framework explains distinct yet interrelated facets of technology adoption: individual skills development, perceived usability, and the gradual spread of novel practices. Practitioners gain evidence-based strategies for integrating AI responsibly, ranging from phased implementations tailored to small clinics to advanced governance committees in large urban hospitals. Policymakers also benefit: these results underline the value of flexible, context-aware regulations and the central importance of ethical oversight in legitimizing AI solutions.

The research underscores IDC's pivotal role in optimizing healthcare operations through AI applications, demonstrating clear pathways for enhancing efficiency, compliance, and patient outcomes. By situating these findings within recognized frameworks, the study offers a comprehensive roadmap for future investigations and policy deliberations, reinforcing the argument that systematic, adaptive, and ethically grounded strategies are key to realizing AI's transformative potential in healthcare.

CRediT authorship contribution statement

Antonio Pesqueira: Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Maria José Sousa:** Visualization, Validation, Supervision. **Rúben Pereira:** Validation, Supervision, Resources, Investigation.

Ethics statement

This study adheres to the highest ethical standards in academic research. All data utilized in this research were obtained from publicly available sources or secondary datasets, ensuring no direct involvement of human participants, and no ethical approval was required. The research methodology strictly followed recognized best practices for systematic literature reviews, ensuring rigor, transparency, and reproducibility. Furthermore, all referenced works have been appropriately cited to uphold academic integrity and to recognize the contributions of original authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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