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We're implementing AI now, so why not ask us what to do? – How AI providers perceive and navigate the spread of diagnostic AI in complex healthcare systems

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ABSTRACT

Despite high expectations of artificial intelligence (AI) in medical diagnostics, predictions of its extensive and rapid adoption have so far not been matched by reality. AI providers seeking to promote and perpetuate the use of this technology are faced with the complex reality of embedding AI-enabled diagnostics across variable implementation contexts. In this study, we draw upon a complexity science approach and qualitative methodology to understand how AI providers perceive and navigate the spread of AI in complex healthcare systems. Using semi-structured, one-to-one interviews, we collected qualitative data from 14 providers of AI-enabled diagnostics. We triangulated the data by complementing the interviews with multiple sources, including a focus group of physicians with experience using these technologies. The notion of embedding allowed us to connect local implementation efforts with systemic diffusion. Our study reveals that AI providers self-organise to increase their adaptability when navigating the variable conditions and unpredictability of complex healthcare contexts. In addition to the tensions perceived by AI providers within the sociocultural, technological, and institutional subsystems of healthcare, we illustrate the practices emerging among them to mitigate these tensions: stealth science, agility, and digital ambidexterity. Our study contributes to the growing body of literature on the spread of AI in healthcare by capturing the view of technology providers and adding a new theoretical perspective through the lens of complexity science.

1. Introduction

The widespread deployment of information technology in healthcare systems has generated a vast amount of health data. This data abundance, along with increased computational power, has sparked a growing interest in harnessing the clinical and financial value of pooled patient information through artificial intelligence (Shaw et al., 2019; Chen et al., 2012). Artificial intelligence (AI) can be defined as the emulation of cognitive human behaviour by machines to automate the tasks of identifying and solving complex problems (Åström et al., 2022; Lee et al., 2019). Many AI applications are being used to improve and extend the performance of existing electronic clinical decision-support tools, which have long aimed to standardise and improve decision-making in medicine (Sutton et al., 2020). One expanding use case of AI in healthcare is the (pre-)diagnosis of diseases, particularly those that are rare and difficult to diagnose. AI-enabled clinical diagnostic tools are widely seen as the most promising applications of AI in healthcare due to their potential to increase the accuracy and timeliness of medical diagnoses (Berente et al., 2021). It is therefore unsurprising that a wave of new stakeholders has recently entered healthcare systems seeking to commercialise the technology (Zahlan et al., 2023).

AI providers have been keen to exploit the optimism around AI technologies and promote the spread of AI across healthcare systems (Garbuio and Lin, 2019). However, while local initiatives to implement AI-enabled diagnostic tools have proliferated in recent years, predictions of the extent and rapidity of their spread have so far not been matched by reality. Indeed, there are numerous reports of organisations abandoning or failing to implement such tools (Raji et al., 2022; Sun and Medaglia, 2019). AI providers are thus confronted with the paradox of 'pilotitis', where an abundance of AI pilot projects are initiated but fail to be replicated elsewhere (Scarbrough and Kyratsis, 2022; Horton et al., 2018).

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Numerous studies have examined the difficulties of translating the success of clinical decision support tools from one site to another. In particular, the strong interdependence between technical, social, and organisational dimensions suggests that there is no single prescriptive approach to promoting the spread of such tools (Greenhalgh et al., 2004; Berg, 2001). Moreover, AI providers seeking to commercialise their products are confronted with varied implementation contexts that render the spread of technology across organisations highly complex (Pumplun et al., 2021; Shaw et al., 2019). Complexity science (Kauffman, 1995; Mainzer, 1997) offers a conceptual framework to understand these contexts as "an intrinsic part of a complex system; a dynamic environment that must be factored in for any intervention to be successfully taken up" (Braithwaite et al., 2018 p. 7).

In the present study, we draw on complexity science and qualitative research methods with the aim of understanding how providers of AI-enabled diagnostics perceive and navigate the spread of AI in complex healthcare systems. Much of the previous literature has focused on the perspective of adopting organisations (Lebcir et al., 2021; Watson et al., 2020; Weinert et al., 2022). In contrast, we explore the perspective of AI providers and their emerging practices as a form of self-organisation, echoing the conviction of Lanham et al. (2013, p.195) that "understanding self-organisation could lead to implementation designs that recognize the importance of local contexts, increasing the likelihood of achieving scaleup". Our results therefore contribute to a better understanding of this new group of stakeholders and how their practices may shape healthcare systems and the spread of AI-enabled diagnostics.

Our results highlight the challenges perceived by AI providers as they seek to promote the spread of AI-enabled diagnostics in the sociocultural, technological, and institutional subsystems of complex healthcare systems. We illustrate the perspectives of AI providers as they address these challenges through emergent practices of stealth science, agility, and digital ambidexterity. Our results suggest that rather than seeking to exercise direct control over technology spread, AI providers are developing practices that allow them to navigate healthcare systems in a flexible and adaptive way. By outlining the implications of these practices for the AI adoption pathway, we contribute to current theories of AI spread in healthcare, adding an overdue narrative of provider-driven, purposeful technology spread.

2. Theoretical background

2.1. The slow spread of clinical decision-support tools in healthcare

Characterising the adoption journey of clinical decision-support tools is a known challenge. Previous research has long established that even well-performing decision-support tools often fail to be replicated across organisational boundaries (De Dombal et al., 1972). Numerous models have attempted to identify factors that foster or hinder successful adoption (Ammenwerth et al., 2006; Tornatzky et al., 1990; Yusof et al., 2008). Although these models highlight different factors, they share a focus on the fit between technology and the implementation environment, revealing a range of interdependencies among different dimensions of technology adoption. Taking this notion one step further, Berg (2001) illustrates that this fit is the result of a socio-technical process that requires mutual adjustments of the implementation environment, its inhabitants, and the decision-support system. Similarly, in developing their holistic framework for the organisational adoption of AI-enabled diagnostics, Pumplun et al. (2021) illustrate how the adoption of these tools spans multiple dimensions, entailing a process of "continuous embedding". Processes of sensemaking, knowledge production, and changing belief systems defy boxes-and-arrows models because they involve redistributions of power and emotions, often played out via recursive practices and nonlinear change of technology use over time and scale (Greenhalgh and Stones, 2010). Together, these factors make it difficult to replicate examples of successful technology implementation. This difficulty is compounded in the case of AI due to its unprecedented autonomy, ability to learn, and inscrutability, which are seen as pushing the boundaries of healthcare and medical ethics (Berente et al., 2021). In particular, medical technology incorporating AI poses unique challenges in terms of clinical responsibility, black-box decision-making, and data consent (Shaw et al., 2019). These uncertainties constitute also risks and sources of mistrust that may deter prospective users.

Controlling the *spread* of AI technologies across organisational boundaries is particularly difficult because it requires de-localising locally embedded and highly context-dependent tools. The established research divide between implementation science and theories of technology diffusion challenges our understanding of the interconnected processes between the organisational and system levels. Conjunctive thinking can thus help us explore the sociotechnical processes behind user–technology interactions distributed across multiple system levels (Essén and Värlander, 2019; Cruz, 2022; Lupton and Jutel, 2015). Recent approaches to marry both perspectives via an 'embedding' logic (Scarbrough and Kyratsis, 2022) allow us to examine mechanisms of system-wide spread that can scale local implementation knowledge and efforts.

2.2. A complexity science approach to understanding AI spread in healthcare

By regarding technology spread as complex patterns and processes situated in local interactions (Greenhalgh et al., 2004), complexity science (Kauffman, 1995; Mainzer, 1997) provides a conceptual framework for understanding the challenges of AI spread. Complexity is defined as "the dynamic and constantly emerging set of processes and objects interacting with each other and being defined by these interactions" (Cohn et al., 2013, p. 42). From this perspective, healthcare systems are complex because the actions of each agent redefine the context across multiple levels and subsystems (Plsek and Greenhalgh, 2001; Greenhalgh and Papoutsi, 2019). Beyond enabling conjunctive thinking, a complexity approach highlights the unpredictability that arises from agency and tensions in healthcare, both of which are underdeveloped in current models of AI spread.

Agency is defined as the cognitive, motivational, and emotionally driven intentional behaviours that actors employ to achieve their end goal (Byrne and Callaghan, 2013; Long et al., 2018). Drawing on notions of material agency, it is also assumed that technology itself accommodates or resists certain practices of human agents (Pickering, 1993). Providers of AI-enabled diagnostics are actors within complex healthcare systems who have an agenda to deploy their technology across the largest possible number of organisations. Whether their behaviours are motivated by profit-maximising goals or by conviction in their technology's purpose, we assume that these behaviours are intentional and directed at increasing and perpetuating the spread of their technology. AI providers thus use their agency to deliberately intervene in the technology translation and adoption pathway (Sendak et al., 2020).

At the same time, commercialisation of AI in healthcare requires considerable flexibility and reinvention of AI providers, as changes in the implementation environment impact the performance of algorithms (Åström et al., 2022). AI providers can thus be seen as intermediaries whose experiences capture learnings across organisational implementation contexts (Scarbrough and Kyratsis, 2022). However, despite their inter-organisational experiences, technology providers remain a "surprisingly underused resource" in research on technology spread (Cresswell et al., 2015). This is particularly true with regard to providers of diagnostic AI considering the relatively recent emergence of commercial ventures in this field (Zahlan et al., 2023). By focusing our inquiry on the perspectives and actions of these technology providers, we may gain insights into providers' impact on AI spread in healthcare.

Taking a complexity science approach to this research question also entails exploring the *tensions* that arise from the introduction of new technologies (Greenhalgh and Papoutsi, 2018). Bahar (2018, p. 361) describes what she calls ‘essential tensions’ arising in complex systems: “a balance between cooperation and competition, a balance between interactions at the local level […] and external pressures originating beyond these local interactions. [… The] balance of these apparently opposing drives plays a crucial role in the emergence of an ensemble of elements into a new individual in its own right”. Emergent properties and behaviour describe the ability of small independent system parts to self-organise and thereby transcend the “sum of [their] parts” (Paina and Peters, 2012). From such emergent behaviour, new practices and patterns evolve at a system level which often elude top-down regulation or control (Braithwaite et al., 2018).

In essence, complexity science highlights the unpredictability of introducing a new technology into healthcare systems. This notion makes the agency of AI providers a focus of our inquiry into the spread of diagnostic AI.

3. Methods

3.1. Research design

Qualitative research of complex systems requires focusing on nonlinearity, identifying patterns across multiple levels, shifting foreground and background, and understanding that patterns change under different circumstances (Anderson et al., 2005). In practical terms, we achieve this by drawing on various sources of data that capture the practices of AI providers from multiple angles.

To fulfil our aim of examining the impact of AI providers’ perceptions and practices on the spread of AI-enabled diagnostics, we defined stakeholders who were directly involved in developing and selling the technology as the appropriate informants for our interviews. As we were interested in the *spread* of AI and were seeking to capture AI providers’ perceptions of real-life provider–user interactions, we included only companies that had already commercialised their technology. After a horizon scan of diagnostic AI providers based in Europe, we contacted all 19 companies that met this criterion and invited them to participate in our study. Of these companies, 14 accepted our invitation, covering different medical specialties and operating across various European countries.

3.2. Data collection

Data triangulation was crucial to our analysis because we used diverse data sources and multiple methods to ensure an adequately sophisticated representation of the complexity inherent to the phenomenon under study (Braithwaite et al., 2018; Greenhalgh and Papoutsi, 2019). Our primary source of data was one-on-one interviews with representatives of the participating companies. In total, we conducted 17 of these interviews with an average length of 50 min between April and December 2022. Interview partners were selected based on their strategic role in the company. We developed a semi-structured interview guide comprising questions about the process of ensuring patient access, the specific value proposition of the product, the management of user interactions, and the strategic goals of promoting AI-driven tools in healthcare. All interviews were conducted online in English and were audio-recorded and transcribed with the consent of the interviewees.

We triangulated our data by complementing these interviews with multiple data sources. The first of these was interviews with two directors at a leading pharmaceutical company partnering with AI providers to diagnose rare disease patients, as well as with a hospital that had previously used AI-enabled diagnostics supplied by one of the interviewed companies. By including these adopters in our analysis, we aimed to reflect the dyadic relationship and its inherent interdependencies (Yin, 2003) and thus provide a multidimensional view of the practices of technology developers. We abstained, however, from exclusively collecting dyadic data because identifying the appropriate technology adopters would have required a snowball technique that depended on the recommendations of the participating technology providers. We considered that such an approach would potentially introduce bias to our study because technology providers might tend to refer us to successful cases of implementation.

As an alternative way to introduce the clinician’s perspective to our research and thus critically reflect on our interview data, we organised an online focus group with six physicians who had practical experience using AI-enabled diagnostics. The physicians were from different European countries and practised different specialties, and all of them had indicated during an earlier online survey on the use of AI to diagnose rare diseases that they would be willing to take part in a follow-up focus group. For 90 min, participants discussed the spread of AI-enabled diagnostics in healthcare and their experiences cooperating with AI providers. The discussion was facilitated by the research team and guided by prompts to identify aspects such as the biggest hurdles to embedding AI technology in healthcare, the potential of AI to improve clinical practice, and the role of the physician in the implementation of AI tools. Mini focus groups have been shown to be particularly well suited for prompting discussion about specialised experiences and creating an intimate atmosphere, thereby limiting negative group effects (Onwuegbuzie et al., 2009).

Lastly, we collected archival data, including 74 online blog posts by the participating AI developers, public guidance on the use of automated diagnosis tools, and white papers and peer-reviewed articles published by the technology developers that provided evidence on the performance or use cases of their algorithms. All data sources are listed in Table 1.

3.3. Data analysis

We conducted a thematic analysis of our qualitative data following the recommendations of Gioia et al. (2013). Through multiple iterative rounds of analysis and theory building, we critically examined our findings with the aim of faithfully depicting the complex and variable context of our research setting (Golden-Biddle and Locke, 2007). Adopting an inductive approach, we began with a first round of “open coding” (Corbin and Strauss, 1990) that centred on actors’ subjective reality (Gioia et al., 2013) and allowed us to derive rich first-order concepts. Subsequently, we aggregated and abstracted these concepts into second-order themes. This process was guided by an iterative method that involved continuous challenge and restructuring as we compared the fit of each new data fragment into the existing categories (O`Reilly et al., 2012). The emerging themes related to different processes and ideas for embedding AI technology in healthcare systems. We then used the ontology of complexity science to identify three aggregate dimensions, which captured the highest level of abstraction in our data structure. Our final data structure is illustrated in Fig. 1.

Lastly, we established links between the different levels and dimensions of our data structure. This process required a high level of agreement between the coders and familiarity with the precise

Table 1
Data sources.

17 interview transcripts
10 CEOs of AI providers 1 Business & Product Lead of AI provider 1 Co-founder and Deputy Director of AI provider 1 Global Business Developer of AI provider 1 Innovation Program Leader of AI provider 2 Directors of large pharmaceutical company 1 Physician in adopting organisation
1 focus group transcript (5 attending physicians; 90 min)
2 whitepapers on AI use for diagnosis **3 public guidelines** on AI use for diagnosis **74 blog posts** by AI providers

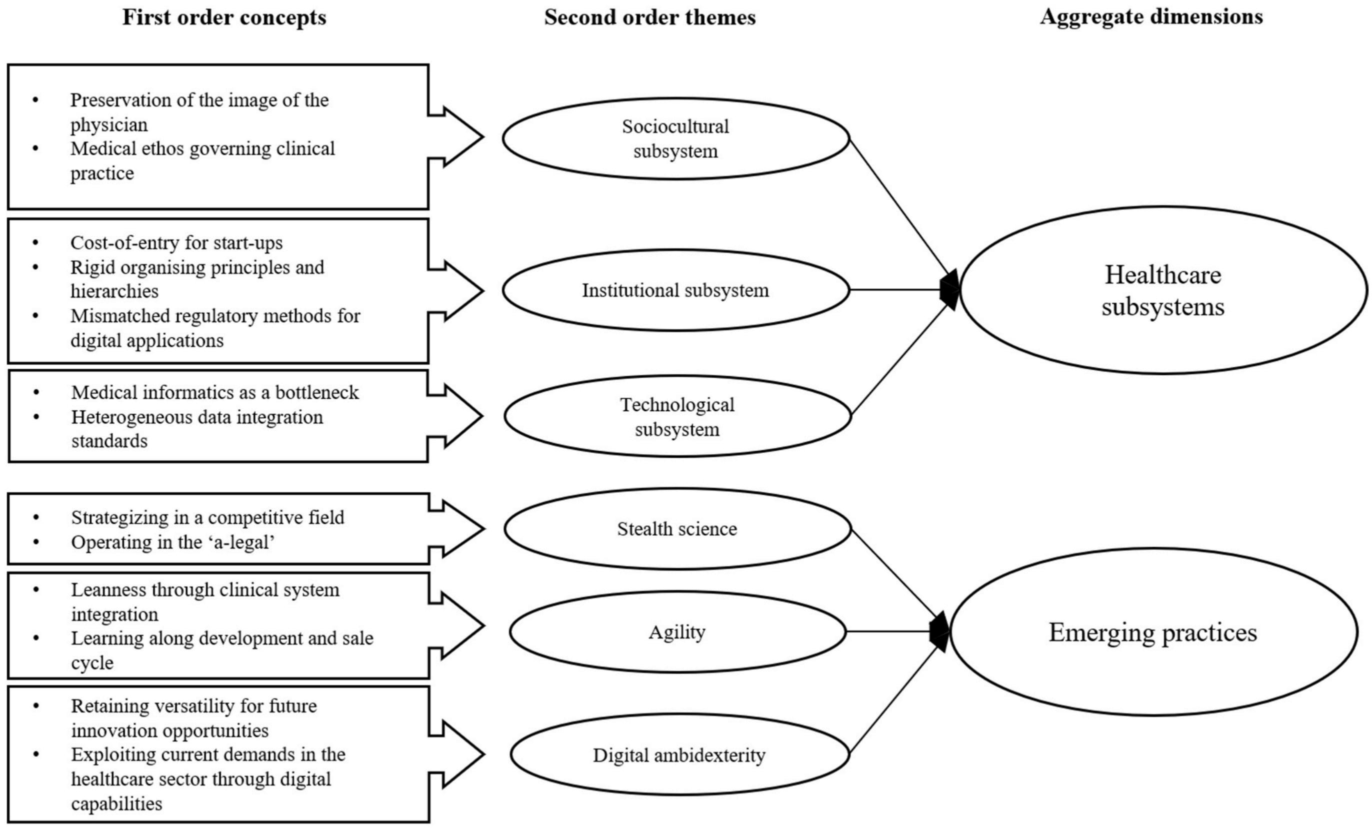

Fig. 1. Data structure (own illustration).

definition and scope of each concept, theme, and dimension. Because theory mainly emerges from the links between categories (Gioia et al., 2013), we frequently revisited the source material to uncover how different categories related to each other. This practice enabled us to establish a theoretical abstraction of a provider-centric perspective on promoting AI spread in healthcare.

4. Results

In the first part of this section, we present how the participating AI providers made sense of complex healthcare systems as they operated within three distinct subsystems of healthcare: sociocultural, technological, and institutional. Subsequently, we illustrate how the challenges they perceived in these subsystems contextualised their agency. Lastly, we describe how their responses to these challenges culminated in emergent practices.

4.1. Subsystems of complex healthcare systems

4.1.1. Sociocultural subsystem

In their interviews, AI providers discussed various mental models and belief systems related to healthcare delivery. Their views encompassed ethical and moral codes, as well as perspectives on the roles of different agents in healthcare systems. We classified these perspectives as part of a *sociocultural subsystem* of healthcare. A dominant theme among AI providers was the current medical ethos, a set of jointly agreed and implicitly codified rules about how healthcare is to be practiced. In particular, certain role interpretations and related processes of sense-making by physicians were seen by AI providers as restricting the spread of AI in healthcare. While AI providers recognised that healthcare professionals bear considerable responsibility in their daily decision-making, they also believed that the prevailing medical ethos influenced physicians' willingness to embrace risk and disruptive change in clinical practice. Because black-box decision-making is an inherent characteristic of advanced AI, the blurred boundaries between clinical responsibility and the opacity of diagnostic results were considered by the AI providers to be incompatible with the medical ethos. One interviewee explained how discussions of diagnostic errors elicited negative feedback from physicians.

> "In the early days, we would focus on diagnostic error. We'd say the problem is loads of diagnostic errors. And, of course, people interpret that, and they get very prickly: 'I'm comfortable that you're talking about diagnostic error because it's always somebody else.' It's not ever them that makes a diagnostic error – it's always somebody else. And if you talk to the GPs, they say, 'Yeah, it's not really for me. But I think the guys at the hospital would actually love it. Can you talk to the guys at the hospital?' So we did. [But then the people at the hospital said,] 'But the GPs, they would really love this.' So there's always somebody else that would use it […]. It's a bit like when seatbelts came out, you know? It was always, 'My brother is a terrible driver. He needs it, but I don't need it.' It's basically the same thing. So, in the early days, we did talk about diagnostic error, and that was a mistake." (CEO AI provider No. 14)

AI providers also appeared to attribute the small error margins that physicians allow themselves in their work to medical ethos. For example, one interviewee believed that the high stakes associated with accurate diagnoses act as a barrier to advancing digital innovation.

> "I think doctors know what they want, but they are difficult to work with in innovation because they normally want perfection, and they don't accept error a lot. That's the kind of thing that really kills innovation when you talk about pilots and these kinds of things. So I think it's a difficult environment to innovate in. It's great, you can do it, but it takes a lot of time and effort. It's exhausting." (CEO AI provider No. 9)

Furthermore, AI providers perceived a potential fear among physicians that using AI-enabled technology in front of patients might harm their reputation. AI providers interpreted the resulting tension as physicians' attempt to retain their expert position and reproduce patient–physician hierarchies. AI's potential to empower patients and thus shift the balance of power in the patient–physician relationship was seen as a root cause of this tension.

> "Culture is always a problem in medicine. So, for example, clinicians are scared of patients getting a symptom checker. [For them it's] just like opening a Pandora's box, because normally there's this relationship of the doctor and the patient. […] The phrase that I keep coming back to that encapsulated it so beautifully: the doctors need to get off their pedestals, and the patients need to get off their knees. It's this cultural difference." (CEO AI provider No. 14)

While this fear was not echoed by the physicians who participated in our focus group, the introduction of AI implies potential shifts in power dynamics beyond the patient–physician relationship. Indeed, focus group participants spoke of power redistributions between themselves and the technology, suggesting that the role of the sociocultural system in accommodating autonomous technology in healthcare requires further exploration.

4.1.2. *Technological subsystem*

We defined the second subsystem of complex healthcare navigated by AI providers as the *technological subsystem*, pertaining to technical infrastructure, standards, and processes in healthcare. Here, AI providers referred to two main barriers to AI-enabled diagnostics: a bottleneck in medical informatics and the heterogeneity of data integration standards. Medical informatics encompasses the medical informatics staff, resources, infrastructure, and capabilities of healthcare organisations. Medical IT departments rather than physicians were perceived by AI providers as gatekeepers due to their control over system integration processes and *de facto* data ownership. One technology provider described how medical informatics departments fulfil their gatekeeping role by regulating data and technology access.

> "I would say that the first thing the IT department has to do is to anonymise the information and give us access to it, even when it's not ours. I will repeat it one hundred times: It's theirs, but we need to read it. Otherwise, we cannot apply our algorithm. So they have to do some informatics activities to be able to provide us access to it, and that takes a bit of time. And the IT departments are always overwhelmed, so we have to be sure that they see the benefits long term because it's a one-time effort, and then it's forever." (CEO AI provider No. 9)

The second barrier identified by AI providers was the diversity of rules and practices related to data formats across healthcare systems and jurisdictions, resulting in heterogeneous data integration standards. At the lowest levels of integration, healthcare data were not yet fully digitalised, thus preventing their use by AI-powered diagnostic support tools. At the other end of the spectrum, fully integrated IT systems were seen by AI providers as preventing the integration of externally developed algorithms.

4.1.3. *Institutional subsystem*

We found that by referring to the distribution of power and formal regulation of the system, AI providers were describing an *institutional subsystem* in healthcare. One frequently perceived barrier to technology spread in this subsystem was the perseverance of rigid organising principles. Providers of AI-enabled diagnostics advocated a preventative approach to medicine, which they interpreted as being incompatible with the prevailing curative paradigm in healthcare. Slow sales and R&D cycles were often attributed to this incompatibility.

Interviewees also highlighted the rigidity of regulations governing the use of AI in healthcare as a barrier. In a European context, AI-enabled software is regulated as a medical device, which implies strict requirements for developing and commercialising the technology. This was seen as being in stark contrast to the 'fail fast and break things' approach of AI-enabled innovation. Due to institutional and regulatory hierarchies in healthcare, AI providers described a considerable cost of entry, particularly for start-ups, which prevented them from interacting with regulators and thus from pursuing change. Because AI presents an extremely fast-moving technological domain, one respondent described their frustration in navigating this subsystem from the lower hierarchical levels and with such high costs of entry.

> "I've been in think tanks where I'm frustrated by the fact that when I say what we do, people seem to think it's something that's going to happen in five or ten years' time. We're doing it now, so why not ask us what to do? Because if you still think it's happening in the future, you've missed the boat already. So this is the problem: Policy-makers will talk to the big people […] with big money. And they don't talk to people who can actually implement it. […] So the only people that really engage seem to be the big pharmaceutical companies because they've got plenty of capacity to spend on that. The cost of entry for conversations about regulation is so high because you have to have people literally dedicated to it." (CEO AI provider No. 10)

4.2. *Emergent practices of AI providers in healthcare*

Our findings suggest that by linking and scaling local implementation efforts, technology providers seek to *embed* AI in healthcare. During this embedding process, AI providers are confronted with negative system feedback whereby AI is perceived as incompatible with the context of different healthcare subsystems. The resulting tensions slow down or even prevent the boundary-spanning work of spreading AI across organisations. In turn, our findings indicate that these perceived tensions give rise to *emergent practices*, or patterns of self-organisation by AI providers, in the joint pursuit of overcoming negative system feedback.

4.2.1. *Stealth science*

First, we observed *stealth science*, defined as a lack of transparency around the development of scientific and technical capabilities and motivated by the desire to protect trade secrets or avoid regulatory scrutiny (Sendak et al., 2020). Among the AI providers participating in our study, the use of stealth science was justified by the need to strategise in an increasingly competitive field – indeed, as part of an arm's race to develop the most scalable, user-friendly, and reliable AI-enabled diagnostic support on the market. Moreover, technology providers pursued stealth science by operating in the 'a-legal'. One respondent explained how stealth science from their point of view is, in fact, an inherent part of technological innovation.

> "The majority of the great achievements in innovation, they happen in the grey areas, in the 'a-legal', where [things are] not legal or illegal. If you really want to innovate, you have to assume that for some time you're going to work in a grey area – not doing anything unethical or illegal – but in a grey area until things are legislated. And that's great. If you're playing in a place that isn't legislated, you're probably innovating. If you're playing somewhere where [things] are black and white, you're probably not innovating, because it means someone has thought about it already." (CEO AI provider No. 9)

In short, stealth science can emerge as a practice in contexts where the institutional subsystem is seen as threatening to impose rules on technology providers regarding the use and commercialisation of their technical capabilities. Importantly, the inhibitory effect of strict top-down regulation was exacerbated, in the view of AI providers, by the lack of opportunity to interact with regulators.

4.2.2. Agile practices

We additionally observed the emergence of *agile practices*, which can be defined as project management and software development approaches anchored in the principles of learning and leanness. Both of these principles featured prominently in technology providers' descriptions of their efforts to spread AI-enabled diagnostics. The principle of learning was evident throughout the sales and development cycle of AI tools: Because large training data sets are needed to power predictive AI models, simultaneously selling and developing the technology was standard practice among interviewed providers. This dual approach facilitated the continuous integration of feedback from clinicians and IT departments, fostering continual product improvement. The principle of leanness was manifested primarily through system integration. AI providers took deliberate steps to ensure that operational barriers to using their AI tools would be as low as possible. As one respondent pointed out, this emphasis on leanness was crucial for circumventing technological barriers.

> "I think by now we've seen all systems that exist, and we're able to extract the data in the format that you prefer. Some organisations want to give us raw information. Sometimes organisations want to give us access to the database. Some organisations even gave us plain text, and we really adapted to this. We have different methodologies to transform all this data into one single common data model. So we're not really playing the game of data standards because we don't really need them." (CEO AI provider No. 8)

Agile practices appear to have emerged because AI providers had to navigate different technical implementation settings. We found that they frequently encountered heterogeneous data integration standards and bottlenecks in medical informatics. However, AI providers felt that these challenges presented opportunities for transferrable and scalable learning, even though this learning must be adjusted to different contexts.

Because organisational contexts in healthcare are typically diverse, collaboration between technology providers and healthcare organisations demands an agile approach to implementation. The emergence of agile practices enables providers to accommodate the fragmented digital and data landscape in different healthcare settings. At the same time, providers appear to adjust their communication strategies when interacting with collaborating physicians, allowing them to navigate the sociocultural system more easily.

4.2.3. Digital ambidexterity

The third emergent practice revealed by our data was *digital ambidexterity,* which describes the dual pursuit of efficiency and innovation through digital capabilities (Magnusson et al., 2021). Achieving and maintaining this balance is generally considered extremely challenging due to resource constraints (O'Reilly and Tushman, 2008). We observed digital ambidexterity emerge among participating AI providers as they succeeded in pursuing two seemingly opposed strategies: the short-term aim of exploiting their technological capabilities to make themselves invaluable stakeholders for healthcare providers, and the long-term aim of exploring innovation opportunities. One respondent described how AI providers can exploit other agents' high opportunity costs of accumulating AI capabilities.

> "And that's another reason why hospitals partner with [AI provider], right? Because I mean, you don't want trained physicians to develop machine learning and AI applications by themselves. There is a very high cost when you ask people to do something they haven't done before. I mean, look at us. We are one of the biggest pharmaceutical companies, and although we do have some machine learning and AI capabilities in-house, we prefer to work with [AI provider] because of the time it would take us to reach the levels at which [software name] is today. It would be associated with a great opportunity cost. So at the end of the day, you need to find the right mix of partners and make sure that each one of them focuses on what they can do best." (Director pharmaceutical company No. 1)

A similar sentiment was shared by physicians in the focus group, as highlighted by one participant.

> "I think [physicians] don't need to be experts in the process behind the algorithm, but we need to be sure that the algorithm itself is valid and gives results that we can rely on. We don't need any training per se for developing these tools. [But] we [do] need, of course, collaboration with [AI] experts, who know what machine learning can give us." (Focus group participant No. 4)

We also observed long-term strategies for exploring innovation opportunities. Participating AI providers emphasised their intent to exploit the versatility of their data analytic capabilities. Most of them had developed several distinct product versions of their algorithm yet maintained an open stance on which product direction to pursue in the future. One respondent noted how retaining this versatility broadened the market reach to a wider spectrum of potential technology users.

> "The technology always works the same way. I would say that the way that it is integrated for each customer can be different because the goals of each customer are different. So, for example, an insurance company might just like to get faster triage and access for their members to in-network services. And a pharma company maybe just wants to find these undiagnosed patients around the world and point them towards information about the disease or patient associations." (CEO AI provider No. 5)

We found that digital ambidexterity emerged predominantly due to tensions in the sociocultural system. Participating AI providers perceived physicians as being resistant to AI technology due to a fear that it might harm their reputation or that using it might violate the prevailing medical ethos. Our data suggest that digital ambidexterity allows technology providers to surmount such barriers by exploiting short-term needs dominating the healthcare market, such as demands to resolve inefficiencies in healthcare provision, knowledge fragmentation, and the lack of automatisation of time-intensive routine processes. It would seem that ambidextrous practices simultaneously enable AI providers to explore new use cases with higher social acceptance rates in the long term. This is either achieved by exploring innovation opportunities in the clinical setting or by targeting other customer bases such as health insurance or pharmaceutical companies. Such collaborations typically receive less public attention and may therefore open revenue streams less subject to regulatory scrutiny.

5. Discussion

This study investigated how providers of AI-enabled diagnostics perceive and navigate AI spread in complex healthcare systems. Our theoretical model is rooted in complexity science and analyses the perspective of AI providers operating across local implementation contexts to embed their technology in depth and at scale. Fig. 2 summarises and illustrates our findings. Overall, our results reveal that stealth science, agility, and digital ambidexterity emerge as practices among AI providers to mitigate tensions arising from the introduction of AI in the sociocultural, technological, and institutional subsystems of healthcare.

We present healthcare as a complex system comprising different subsystems. In this way, we build on previous literature that has sought to disentangle implementation complexity by defining different dimensions of technology spread (Sittig and Singh, 2010; Tornatzky et al., 1990; Yusof et al., 2007). We regard the three subsystems as an abstraction of the highly interdependent implementation context perceived by the technology providers. Our theoretical model also considers how interdependencies between the subsystems affect the context in which AI providers' agency is situated within each subsystem (Long et al., 2018). For instance, the perceived culture of risk avoidance

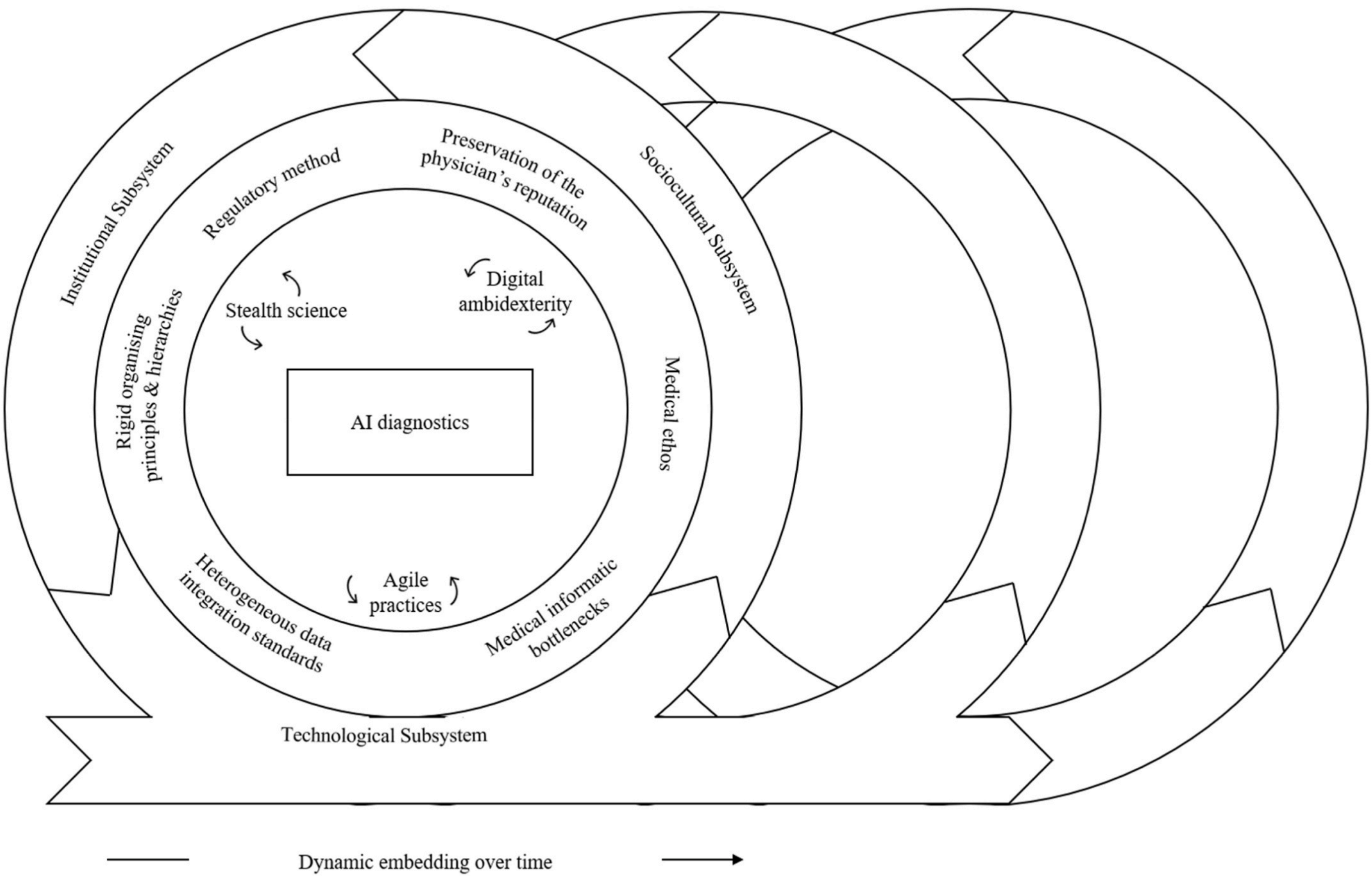

Fig. 2. Theoretical model illustrating the dynamic embedding of AI-enabled diagnostics in healthcare (own illustration).

characterising the sociocultural subsystem determines patterns within the institutional and regulatory subsystem; these patterns are then interpreted by AI providers as rigid and conservative regulations. In turn, the rules set by authorities influence the technological context of data integration practices across healthcare organisations. Importantly, our model anticipates a dynamic perspective, illustrated by system loops. AI spread is an ongoing process that assumes the continuous embedding of technology in a changing healthcare system context. This implies the emergence of new practices over time that cannot be fully anticipated.

Overall, our results suggest that AI providers perceive complex healthcare systems as difficult to navigate. Adopting a complexity science approach, we initially contrasted the healthcare system's unpredictable uptake of a new technology with AI providers' ambition to promote and perpetuate technology spread. Our results suggest that AI providers' local practices, which are aimed at achieving what is needed 'on the ground', culminate in new patterns of self-organisation. Indeed, the emergence of stealth science is a remarkable illustration of how the opposing forces of cooperation and competition described by Bahar (2018) can lead to systemic patterns of self-organisation among locally operating AI providers: At the micro level, each AI provider seeks to protect its competitive advantage in a tightly regulated market by guarding its technical capabilities. At the macro level, however, the aggregation of competitive behaviour, fuelled by collective discontent with current regulatory methods for AI in healthcare, incentivises providers to evade or precede regulation, thus jointly engaging in stealth science. Our results also imply that rather than seeking to exercise control over the complex implementation environment or its inhabitants, AI providers tend to develop common practices that afford them more latitude in their work of embedding AI across organisations. Stealth science, agility, and digital ambidexterity each extend their adaptability to variable conditions across implementation settings.

AI providers' use of these practices has several implications for the healthcare system as a whole and for AI spread in particular. Similar to Essén and Lindblad (2013), we observed how a state of "bounded instability" (Plowman et al., 2007) permits a system to oscillate between positive and negative system feedback. Our results illustrate the negative feedback perceived by AI providers in each subsystem of healthcare. Without reaching stability, the system *in flux* is caught in a paradoxical state: the spread of AI is stuck between acceleration and inertia. Emergent practices among AI providers work to shift the balance towards accelerated technology spread. At the same time, their own practices inadvertently render healthcare even more complex: technological advances are obscured through stealth science, and ambidexterity entails the constant re-definition of the technology itself.

Previous research has found that the implementation of clinical decision support tools requires the demystification of the system (Liberati et al., 2017); however, our results suggest that the practices employed by AI providers may work to the contrary. Moreover, recent ideas of applying a 'systems' regulation approach to AI entail assessing AI in a clinical environment while considering the human and organisational factors that influence its performance (Gerke et al., 2020). Such an approach could reduce the flexibility and ability to improvise that AI providers seek because it would require much stricter adherence to an implementation protocol. Lastly, emerging practices may lead to unintended consequences due to interactions between system parts (Greenhalgh and Papoutsi, 2019). While some emergent practices are momentarily successful at resolving immediate tensions in the system, they can cause negative effects as the system dynamically evolves. For example, the constant re-balancing of innovation and efficiency through digital ambidexterity currently allows AI providers to avoid resistance in the sociocultural system but may, in the long run, dilute the value creation and value capture propositions necessary to engage other agents in the spread of AI.

Our results underscore that different agents are currently in the process of negotiating their own and AI's respective roles in healthcare (Sun and Medaglia, 2019). On the one hand, this implies continuous boundary setting through technological and regulatory means. Restricting access to data and maintaining conservative regulation of AI are examples of efforts to define the limits of AI in healthcare. On the other hand, the process of negotiation entails adapting the characteristics of AI in terms of transparency and agency to establish clear accountability towards patients. Although AI technology is already capable of fully automated decision-making, in the case of AI-enabled diagnoses, the final decision tends to rest primarily with healthcare professionals (Lupton and Jutel, 2015). Our results highlight how AI providers seek to mediate this process by resolving emergent tensions and, in doing so, promote the spread of AI. However, as part of a complex system, AI spread is equally influenced by other sources of agency, which might work for, against, or in parallel with the agency of AI providers.

We consider our model specific to the spread of AI and therefore not applicable to general technology spread. As Hund et al. (2021) point out, there is a "remarkable interconnectedness between social actors and digital technologies". Our model accordingly seeks to reflect how AI technology, which is characterised by unprecedented technological agency, defines the action context of technology providers, and leads to unique emergent behaviours. While insights from complexity science may benefit general models of technology spread, its application requires a rich and nuanced exploration of the research artifact (Greenhalgh and Papoutsi, 2018).

Our study has implications for future research on the topic of AI spread in healthcare. We have contributed to current theories of emergence in healthcare (Essén and Lindblad, 2013) by illustrating emergent practices among AI providers directed at perpetuating technology spread. Due to market failures and the need to protect patients against the self-interest of different stakeholders, top-down healthcare regulation is valuable and needed. Future research should acknowledge emergent phenomena in healthcare and explore how they can be reconciled with necessary regulatory methods. This is particularly true for AI, where legislative efforts are relatively young, and more knowledge is needed to guide regulation to overcome risks of confirmation bias and avoid stealth science. Furthermore, we encourage our peers to embrace the idea of healthcare as a complex and dynamic system. While there will always be merit in boxes-and-arrows models where appropriate, opportunities to employ complexity science should be recognised more often, particularly when the available body of research reveals seemingly inexplicable tensions and paradoxes.

While our study makes important contributions to the literature on AI and technology spread in healthcare, it has several limitations that must be considered when interpreting its results. First, more use of dyadic data could have revealed a richer picture of the interactions between AI providers and healthcare organisations (Morgan et al., 2013). Our study therefore only represents the perspective of technology providers. Researchers with access to adopting organisations may wish to enrich our findings with accounts of interactive processes from both perspectives. Moreover, our study is situated in one moment in time. We highlighted this aspect of our research by pointing out the novelty and rapidly evolving nature of the studied phenomenon. However, while our model anticipates dynamic changes, we cannot currently predict which new practices will emerge or how these will interact with other sources of agency. A longitudinal study could add content to the system 'loops' of our model and thereby contribute insights into how healthcare systems and the spread of AI-enabled technologies dynamically evolve.

6. Conclusion

In this study, we provide the first account of AI spread in healthcare from the perspective of AI diagnostics providers. Drawing upon a complexity science view that technology spread is probably unpredictable and difficult to manage, we contrasted AI providers' agenda of promoting AI use with the challenges they perceive when navigating healthcare systems. Our results suggest that AI providers, rather than attempting to exert direct control over adopters or AI adoption pathways, rely instead on strategies of stealth science, agility, and digital ambidexterity. While these strategies provide AI providers with flexibility when seeking to embed their technology across different implementation settings, they may raise concerns about future regulation and wider acceptance of AI in healthcare.

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Disclaimer

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Data availability

Data will be made available on request.

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