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From Half-Truths to Situated Truths: Exploring Situatedness in Human-AI Collaborative Decision-Making in the Medical Context

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Abstract: *While the introduction of artificial intelligence (AI) solutions has large potential to improve organizational decision-making, it requires a further understanding of how humans and AI can collaborate. Through the lens of situatedness, this paper attempts to provide insight into the wider nature of human-AI collaborative decision-making. Based on a case study on AI-assisted breast cancer screening, two important findings can be highlighted. First, decomposition and decoupling through temporal division of action with either humans or AI dominating enable an advanced human-AI decision process to be decoupled while enabled by a foundation of shared situatedness. Second, decision-making emerges as a dynamic sensemaking process with each additional human-AI interaction evolving the decision-making process until a final decision outcome is reached.*

Keywords: Decision-making, situatedness, organizational context, human-AI collaboration, personalized medicine, breast cancer screening

1. Introduction

Decision-making has long been considered a topic of interest in organizational studies (Cyert and March, 1963; Gavetti et al., 2007). With the emergence of artificial intelligence (AI) being able to support decision-making in organizations, a renewed focus can be observed (von Krogh, 2018). AI solutions have been associated with large potential to assist human decision-making, due mainly to their ability to quickly process and analyze large amounts of data (Shrestha et al., 2019). These solutions are usually not implemented in isolation but increasingly integrated into critical managerial tasks in specific contexts, such as in IoT (internet of things), energy systems, and healthcare. This requires an understanding of the context as well as the underlying logics of human- and AI-based decision-making (Trunk et al., 2020). Humans tend to make decisions based on bounded rationality (Simon, 1997), i.e., guided toward satisficing rather than optimal decisions, as they are bounded by time and information constraints. In other words, humans make decisions based on what could be referred to as 'half-truths' as the decision premise. Such half-truths are dependent on the available information, but also largely on mental models that are formed through personal experiences, and, in organizations, also related to a contextual understanding (Weick, 1996). Understanding human-AI collaborative decision-making thus not only requires opening up the black box of how humans and AI collaborate in decision-making, but also an understanding of the wider contextual impact referred to as 'situatedness' in this paper.

Inspired by the Neo-Carnegie call for understanding organizational actions and decision-making as embedded in a larger context (Gavetti et al., 2007), this paper uses the lens of *situatedness* for understanding human-AI collaborative decision-making in organizations. Situatedness refers to the idea that knowledge, reasoning, and decision-making are closely tied to the context in which they occur (Elsbach et al., 2005; Gavetti et al., 2007). By including a contextual understanding, situatedness broadens the understanding of decision-making beyond bounded rationality, and even to an extended rationality when AI solutions potentially provide an opportunity for extending the amount of information that can be processed and form the basis for a decision. Situatedness potentially provides a more holistic understanding of how the emergence of AI solutions affect decision-makers and decision processes in organizations, reflecting the complex reality of organizational decision-making due to the many interconnected elements that need to be considered, including bounded rationality, high-stake choices, and potentially conflicting interests (Klein, 2008; Gavetti et al., 2007).

While AI is expected to make a difference in such complex organizational settings (Yu et al., 2023), currently, research on the role of situatedness in human-AI decision-making processes in complex organizational contexts seems to be scarce. Through the lens of situatedness, this paper attempts to provide insight into the wider organizational implications of decision-making with AI. *Following this, the purpose of this paper is to explore situatedness in human-AI collaborative decision-making in complex contexts.*

To address this purpose, we have studied the emergence of AI-assisted breast cancer screening as an empirical case shedding light upon human-AI collaborative decision-making. A practice of AI-assisted breast cancer screening is emerging in the larger context of personalized medicine, i.e., reflecting an emphasis on an individual's own unique characteristics (Johnson et al., 2021). As such, it represents an example of human-AI collaboration where situatedness increasingly plays a role. The AI-assisted breast cancer screening case illustrates a relatively complex context including the emergence of AI, imaging and diagnostic tools largely supported by academic research as well as clinical implementations (Jairam and Ha, 2022; Agarwal et al., 2023). Based on the insights from this case study, we open up the black box of situated human-AI collaboration by outlining the role of decoupling, temporality, and dynamic sensemaking as central for understanding the evolvement of human-AI collaborative decision-making that could evolve the field from half-truths toward situated truths.

2. Theoretical background

2.1. Decision-making and bounded rationality

Much of contemporary understanding and practices in organizational contexts relies on Herbert Simon's conception of bounded rationality (Puranam et al., 2015). But the focus on decision-making as one of the cornerstones in organizations is often attributed to organizational theorist Chester Barnard and his work "The Functions of the Executive" published in 1938 (Buchanan and O'Connol, 2006). Barnard described decision-making as an important starting point of organizational action. As one of Barnard's successors, Herbert Simon has further laid the foundation for individual and organizational decision-making by explaining how individuals and groups of individuals make daily decisions and how these decisions have fundamental implications for the achievement of organizational goals (Simon, 1990). Contrary to the popular utilitarian-centered ideology of the time, Simon pointed out in his book "Administrative Behaviour," originally published in 1947, that individuals in organizations are incapable of making perfectly rational decisions because of several limitations, including cognitive (in)abilities and lack of resources, such as information and time (Simon, 1990). This model of decision-making is referred to as "*bounded rationality*" and explains that decision-makers in organizations tend to make decisions that favor *satisficing* options as opposed to optimized ones. It represents a decision-making process where generated alternatives, goals, and outcomes are not weighed simultaneously, but instead, choices are made based on subjective and heuristic inferences (Simon, 1997; Kahneman, 2003). According to March and Simon (1958), decision-making modes in organizations vary from problem-solving search activities to fixed sets of responses that are activated based on stimuli in the environment (Gavetti et al., 2007).

Kahneman (2003) expands upon Herbert Simon's ideas by outlining that decision-making is affected by factors that lie beyond humans' bounded rationality. He identifies the role of *framing*, reflecting that the way problems are presented and formulated is an important determining factor in human decision-making (Kahneman, 2003). The importance of framing can be even better understood when considering the characteristics of real-world problems. Such real-world problems are also referred to as ill-defined problems (Simon, 1997) that need to be transformed into well-defined problems to be able to be solved through a process of search. The seminal work of Simon and others in organizational and cognitive theories has created a great interest in decision-making, not only in the field of organizational theory, but through his contributions to cognitive science (Simon, et al., 1992) organizational psychology (Simon, 1986), and interestingly also contemporary AI (Simon, 1995; Simon, 1996). He understood early on the importance of computers and believed in their capability to surpass human abilities.

2.2. Decision-making embedded in the context

In parallel to his contributions in organization science, Simon, together with his colleague Newell, built the hallmarks in computational cognition with the "physical symbolic systems hypothesis" (Newell and Simon, 1976). This theory is built as an analogy to the natural cognitive and decision-making models, where

symbolic systems can solve any problem, if they have the right resources (ibid). This view stipulates that cognition (natural and computational) is based on formal rule-based representations inside the brain (or machine) and is essentially detached from the environment (Clark, 2013).
However, emerging cognitive perspectives such as dynamic and extended cognition view cognition as a process that goes beyond the boundaries of the human mind and into the context in which it exists. In contrast to the view of the brain as a computational, pattern-forming device, the dynamic systems ‘behavior is “… fixed by complete encoded instruction sets and ones whose behavior emerges as a sequence of temporarily stable states of a complex system with richly, interdependent intrinsic dynamics” (Clark, 2013, p. 155). The novelty in these systems is in the fact that the knowing, perceiving, and acting processes have evolved through dynamically interacting with the context, rather than just passively being impacted by it (Thelen et al., 2001). This process explains how unique components of a cognitive system (be it human or artificial) work and evolve in close relation to the context. A great example of a dynamic system is Thelen and colleagues’ work on the “A not B” experiment (2001), which explains that the failure of infants to successfully allocate the hidden objects is not because they have deficits in specific cognitive components (object knowledge, localization, memory, etc.). On the contrary, their failure derives from the collective dynamic processes integrating brain (looking, remembering), body (reaching) and environment (planning for action) that have not developed in parallel as a multiprocessing system (Thelen et al., 2001). This experiment is very important for illustrating dynamic cognitive systems, for many reasons. Firstly, they highlight the roles of body and the environment in learning and problem solving (Clark, 2013), a notion that, in a way, already was prevalent in the work of Chester Barnard in 1938, as he noted that decision-making is accompanied by an extended process of deliberation bounded by the organizational and social context. Secondly, the system components like seeing, remembering, acting, and planning do not function separately, but are instead intricately interconnected in dynamic causal processes. Dynamic systems are useful in the context of complex systems, where they can deal with different parts of the systems interacting and emergent behaviours in different parts of the systems (Clark, 2013). These complex systems often involve high levels of cognition that support developed, real-time action for real world challenges, as opposed to individual representations (ibid). This approach is based on the idea that perceptions are connected to actions in the brain, and information about either process flows in different directions. This approach is built on getting input from the environment through different sensors and behaving accordingly (outputs) to these inputs. Dynamic systems show that the uniqueness about human rationality “… may depend on a much broader focus than that to which cognitive science has become most accustomed, one that includes not just body, brain, and the natural world, but the props and aids (artifacts, sociocultural rules, institutions) in which our biological brains learn, mature, and operate” (Clark, 2013, p.167).

2.3. Situatedness in organizational decision-making

Organizations often represent, function in, and deal with complex contexts which cannot be navigated through neither simplistic nor linear decision-making models (Langley et al., 1995). Under conditions of uncertainty, time-pressures, and high-stakes choices, decision-makers cannot rely only on analytical problem solving, like Simon proposes (Klein, 2008). Rather, organizational decision-making can be understood as “networks of decisions” (Langley et al., 1995), with individuals and their decision-making capabilities at the center of decisions. It has been suggested that different types of decision-making models could be combined, including those that build on decision-making as problem solving and pattern-matching as well as naturalistic (Gore et al., 2006) and sensemaking models (Weick, 1996), building on organizational memory, shared knowledge, and mental models.

New theoretical developments in organizational science and decision-making suggest the increasing importance of situatedness in organizational decision-making, representing a lens for understanding the role of the interaction of organizational actors with their context for decision-making in organizations (Ocasio and Joseph, 2005; Gavetti et al., 2007). This represents an understanding of decision-making based on a situated rationality, that builds on a social psychology concept known as situatedness (Lave and Wenger, 1991). Situatedness refers to the notion that cognition and learning are *situated* in socialization processes and interactions with the external socio-cultural context (ibid). Through communication and interaction between the organizational actors and the socio-cultural artifacts, organizational actors create certain values and knowledge that are shared among them, forming what Lave and

Wenger (1991) refer to as communities of practice. “The contingence of action on a complex world … is no longer treated as an extraneous problem with which the individual actor must contend, but rather is seen as an essential resource that makes knowledge possible and gives actions sense … the organization of situated actions is an emergent property of moment-by-moment interactions between actors, and between actors and the environments of their action” (Suchman, 1987, p. 179; Lindblom, 2001).

The interaction of cognitive schemas of organizational actors with the dynamic context leads to the process of sensemaking (Weick, 1996) and situation awareness (Endsley, 1995), which consecutively affects decision-making (see also Figure 1). According to Elsbach et al. (2005), situated rationality thus involves both processes and action: process in terms of the trajectory of understanding, attributing and predicting the situation in hand, and action in terms of acting accordingly to the specific complexity of the situation (ibid). Moreover, given that organizations are complex systems (Gavetti et al., 2007) that continuously evolve and adapt to their context, a feedback learning loop can be integrated into original cognitive schemas, updating and evolving them.

The framework of situated rationality presents an understanding of how decision-making can occur, given that the process of sensemaking and situated rationality affects critical prerequisites for decision-making, including problem framing (Kahneman, 2003), decision premises, evaluation of outcomes, and influencing factors, to name a few (Gavetti et al., 2007). This perspective creates new opportunities for understanding the role of the context in decision-making beyond bounded rationality in relation to human-AI collaborative decision-making.

With the emergence of AI, not least in relation to certain managerial and operational tasks, organizational decision-making processes and structures will possibly need to alter. Raisch and Krakowski (2021) discuss the potential of AI to either automate (replace humans) or augment (close collaboration between humans and machines in managerial tasks) them. Studies have also pointed at situatedness to show that the nature of human-AI collaboration is task-dependent (Shrestha et al., 2019) as well as context dependent (Jarrahi, 2018). It has been argued that, for some tasks or problems, algorithms may outperform humans, in others, humans may outperform algorithms, or the aggregation of humans and AI may outperform either of them (Puranam, 2021). At the center of creating a new understanding of potential human-AI collaboration thus lies a perspective on situatedness, expressed in situated sensemaking as well as situated decision-making guiding organizational action (cf. Raisch and Krakowski, 2021; Puranam, 2021).

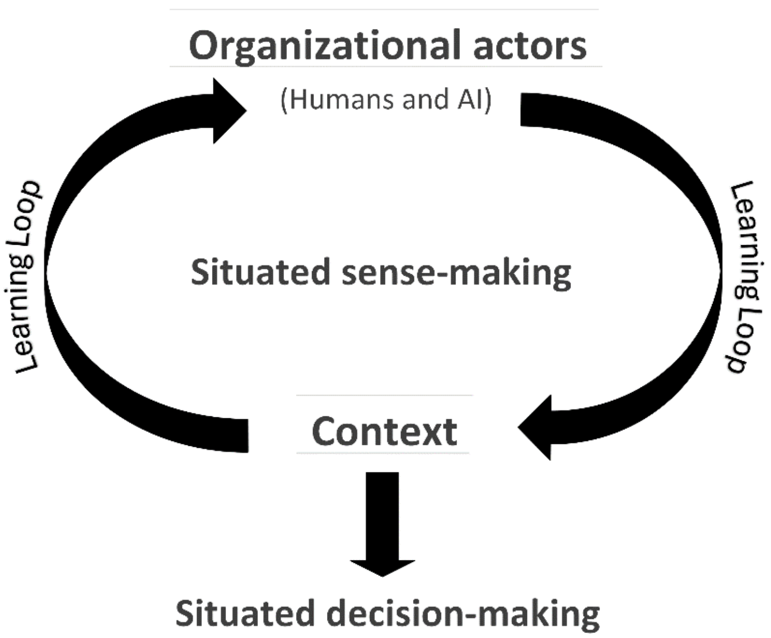

Figure 1 Framework of situated decision-making

3. Methods

This paper uses a case study methodology (Yin, 2016) as an opportunity for an in-depth investigation of the contemporary phenomenon of emerging human-AI collaborative decision-making in a real-world context, as well as using relevant circumstances to create theoretical insights. Our research is phenomenon-driven, i.e. representing an anomaly from existing decision-making practices that may possibly challenge existing knowledge and the scientific discourse (von Krogh et al., 2012). The rapid emergence of AI has particularly been identified as providing opportunities for phenomenon-based theorizing (von Krogh, 2018). This paper aims to make a contribution by distinguishing the emerging phenomenon of human-AI collaborative decision-making from current decision-making practices and observing and exploring this phenomenon to eventually contribute to a new theoretical understanding (Fisher et al., 2021).

We carefully considered the choice of empirical context for this study, as we aimed at being able to observe human-AI decision-making in its organizational context. Although AI is much discussed, the actual implementation and uptake of AI solutions in relevant decision-making contexts is proceeding rather slowly. With this in mind, we found that the field of personalized medicine in general and breast cancer screening in particular has progressed relatively far in creating a systematic understanding of human-AI decision-making in a situatedness perspective. Personalized medicine reflects a new emerging field where physicians to a large extent are supported by extended information, diagnostic technical solutions, predictive AI and connected devices for sometimes making life-saving health decisions based on their patients' unique characteristics (SwedenBio, 2018). In a new era of personalized medicine, breast cancer screening in particular seems to be evolving rapidly toward new approaches involving deep learning models that can assist in diagnosing cancer based on medical images as well as on a possibly expanded situatedness by including women's individual lifestyle and risk factors in personalized medicine. The field of radiology has always been known for adopting new technologies, particularly in imaging (Barley, 1986). The emerging new approaches are systematically evaluated and well documented in scientific articles as well as in popular science publications and policy documents. There is an outspoken ongoing development toward integrating AI imaging solutions into the breast cancer screening process, as well as a high degree of stakeholder collaboration in the field (Topol, 2019; Lebovitz et al., 2022; Jairam and Ha, 2022; Lång et al., 2022). A quick search for "breast cancer screening"' and "artificial intelligence" in Web of Science (performed March 8, 2024) returns 729 results from Web of Science Core Collection with a rapid increase in the number of publications from 2019 onwards. Out of these 729 articles, 60 mention decision-making, while only four articles have decision-making in their title. Most of these articles are either in the medical field or in the field of computer science.

We confined the focus of our study mainly to the developments taking place in Sweden as an example of a country with a systematic screening program offered for free to all women between 40 and 74 years of age. We have collected and analyzed over a period of more than two years both primary and secondary data sources, such as policy documents and the results from published scientific studies outlining new approaches to human-AI collaborative decision-making and personalized medicine. This method of scientific inquiry allowed us to create a deeper understanding of the phenomenon in its context, as also suggested by von Krogh et al. (2012). Supported by Langley (1999), who noted that studies on organizational decision-making require the combination of both retrospective and historical data, with current data collected in real time, we used diverse and multiple sources of evidence including interviews with key informants in the field. Using multiple sources of evidence has been suggested to also create additional support for construct and external validity, which may allow for careful investigation and decrease the risk of misinterpretation (Yin, 2016). Our primary data consists of 11 interviews with key informants in the field of personalized medicine and radiology in Sweden. The interviews, focusing on experts working within radiology, are conducted with individuals that hold key positions in national research and practical healthcare initiatives in their respective regions in Sweden, including Stockholm, Östergötland and Skåne region. The other interviews focus on key experts in AI in Sweden, both in healthcare (region Halland), research in AI and societal implications, as well as on private companies supplying breast imaging solutions involving AI. Key informants were chosen as one of the central data sources, not only for their valuable knowledge (cf. Goetz & LeCompte, 1984) and experience within the application of AI in radiology specifically and healthcare in general, but also because of their interpretations (cf. Spradley, 1979) around potential future implications of integrating AI into medical decision-making and healthcare and shared sense of societal and research relevance (cf. Bogner et al., 2009) in the topic. Most importantly, the choice to interview key informants for this study is tightly connected to the central phenomenon of AI implications in management and organizations, which is ongoing and under development, and for most organizations a phenomenon that is still hard to grasp completely. Giddens (1990), who is cited in Bogner and colleagues (2009), states: "… experts become important when people find themselves having to deal with abstract systems (whose internal workings they do not understand). It is up to the expert here to convince them to trust such (primarily technical) abstract systems, for example by means of appropriate self-staging strategies" (p. 5).

We combine the primary interview data with extensive secondary data in the form of scientific publications, and perform qualitative document analysis (von Krogh et al., 2012) of national strategies in the field of personalized medicine. This expands the case around the organizational and societal challenges that emerge as a result of AI systems integration in decision-making, which according to Eisenhardt (1989), provide a richer context for theory building. Some of these secondary data includes three policy documents published by the Swedish national innovation agency (Vinnova) in collaboration with Swelife (2020), AI Sweden and SwedenBio (2018), annual reports (CMIV, 2022) as well as a national strategy on life science document launched by the Swedish government (2020). Additionally, the secondary data includes extensive publications on current AI-assisted breast cancer on a national, regional, and international level involving retrospective and prospective studies, literature reviews on AI-assisted breast cancer screening and studies in human-AI collaboration in radiology.

The analytical strategy for this research is a mix of a descriptive approach, which is represented by the development of a case description, as well as an abductive approach (Dubois and Gadde, 2004), which combines elements of iterating between inductive and deductive approaches. In the former, the case serves to illustrate the new decision landscape and provide initial evidence to formulate a characterization outlining perspectives necessary for exploring human-AI collaboration in decision-making in the studied context specifically, and that potentially can be transferred to other contexts of human-AI decision-making. We study the phenomenon emerging in real time, responding to the need to study the infusion of intelligent technologies before they have become fully established (Bailey and Barley, 2020) and aiming at anticipating and influencing the type of managerial knowledge needed to deal with coming societal and organizational concerns (Corley and Gioia, 2011, p. 13). Although we consider this necessary, given the state and importance of the field, it can also be considered as a methodological limitation, as it is more difficult to capture proven processes and practices.

4. The case study

4.1. The context of personalized medicine

Medical practice has long largely relied on clinical guidelines and protocols that are based on assessments of groups of patients with similar symptoms (Ziegelstein, 2017). Such guidelines and protocols have been guiding physicians in diagnosis and treatment decisions but provide little opportunities to take into account an individual patient's unique characteristics. Rather, most of the decisions are guided by evidence-based studies on smaller or larger groups that provide the basis for decisions for a whole population (Mesko, 2017). It is an emerging practice and induced by new technology development such as genome sequencing, advanced biotechnology, health sensors, and the increasing availability of a vast amounts of data. This has sparked the emergence of what is sometimes referred to as a new paradigm in medicine, i.e. personalized medicine that partly transforms the focus from reactive treatments toward proactive prevention, (Duffy, 2016; Mesko, 2017; Denny and Collins, 2021). Personalized medicine is sometimes also referred to as 'precision medicine.' While precision medicine is often more linked to genomics, personalized medicine can be defined as more holistic by pointing to its focus on making healthcare smarter by using a variety of information sources about an individual, including environment and lifestyle factors, to tailor medical treatment and/or prevention of illness to the individual characteristics of each patient[1]. AI is central in realizing the benefits of personalized medicine (Mesko, 2017).

[1] See also report from The Joint Committee of the Nordic Medical Research Council's NOS-M, "Personalized Medicine in the Nordic Countries",http://norden.diva-portal.org/smash/get/diva2:1347257/FULLTEXT01.pdf (retrieved on 28 september 2023)

With the help of AI solutions and data-driven approaches that provide additional contextual and individualized patient information like medical history, age, and lifestyle, it is expected that healthcare institutions can increase prevention and the quality of treatment for patients (Swelife, 2020).

The field is not new, starting with early experimentations from the 1960s (Duffy, 2016); however, it was not until the last decade that it really started to become the focus of policy-makers. In 2015, the United States launched the PMI (personalized medicine initiative) and in Europe the ICPerMed (The International Consortium for Personalised Medicine) represents the effort of 40 European countries in research and clinical advancement in the field of personalized medicine. This has given rise to the formulation of national strategies as well as ‘bottom-up’ initiatives to build competence networks, infrastructures crossing traditional disciplinary boundaries and the forming of a non-siloed ecosystem that has the potential to benefit patients and society at large (Stenzinger et al., 2023).

4.2. Breast cancer screening within the context of personalized medicine

As part of the ongoing transition from traditional medicine to personalized medicine, new approaches relying on AI-assisted breast cancer diagnosis are emerging. Breast cancer screening through regular mammograms is an important preventive measure, lowering the risk of dying from breast cancer. In Sweden, residents between the ages of 40 and 74 are offered a free mammography every two years (Bröstcancerforbundet, 2023). These mammograms are sent for assessment, where, traditionally, two radiologists (referred to as a ‘reader’) review the images and decide whether there may be indications of cancer in the breast tissue (Figure 2). If one or both readers suspect cancer, the case is sent onwards in the decision-making process to a consensus meeting involving two radiologists. These then together make the decision as to whether a patient is to get a recall for a new screening or will receive a healthy letter or a recall. This process enables early detection, and as a result, a chance of better prognosis and treatment. However, this decision process is not without challenges. The interviews reveal that radiologists’ decision-making involves making ‘educated guesses’ based on observations and initial diagnosis and limited time and resources. It is rather common that the decision-making is based on imperfect diagnoses or, as one of the interviewee’s phrased it, “half-truths,” reflecting a degree of bounded rationality. Among several concerns, radiologists highlight the challenges such as confirmation bias that may have an impact on the accuracy and efficiency of the decision. Another concern that has been highlighted during our interviews is that, despite having multiple sources of input for decision-making, information from one source does not always correlate with information from another source, or is even incomplete and contradicting. Decision-making thus seems to involve a degree of sensemaking.

Key informants in radiology and AI-assisted breast cancer research in Sweden, describe that there are several underlying logics in the consideration of implementing AI solutions. First, the AI solutions can be considered as an independent reader, along with radiologists, in the double reading step (Figure 3) or may be even potentially replacing one of the human readers. Second, the AI solution is used as a triaging tool in collaboration with human radiologists, preceding human assessment and creating an initial stage in the assessment of mammograms (Figure 4). In this process, The AI algorithms generate a score reflecting a risk of having detected anomalies which is matched to a threshold decided by the hospital. If the AI score is below the assigned threshold, the mammogram is deemed to be normal, while if it is above the threshold, the mammogram is considered to deviate from normal, which indicates a risk of cancer. This provides an opportunity to assign different risk groups with different workflows, e.g. a low risk could simplify the workflow and resource investment with, for instance, only one reader, while a high risk could warrant a more complex workflow and even the consideration of additional factors in the assessment.

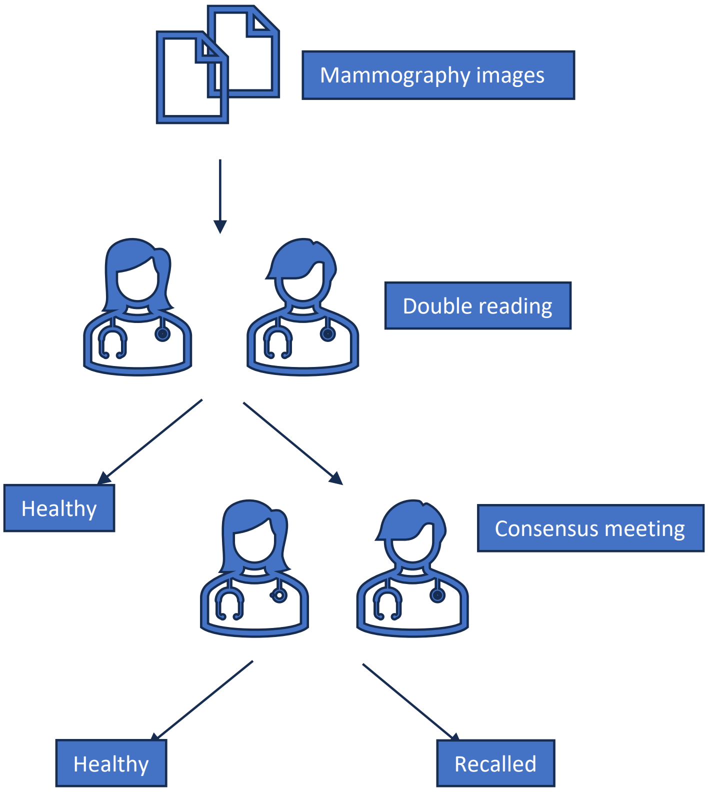

Figure 2 Traditional breast cancer screening in Sweden

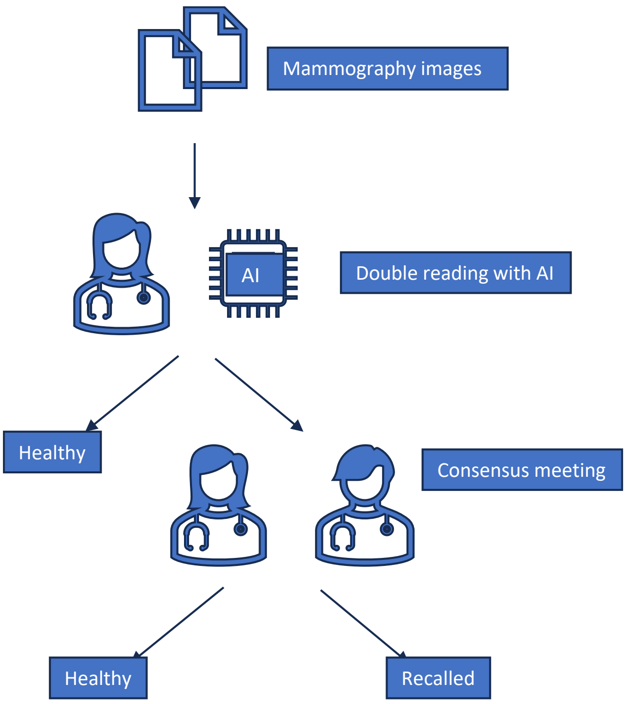

Figure 3 Breast cancer screening with AI as one of the readers

Recently, with the advancement of imaging technologies and AI, several regions in Sweden, including the regions of Stockholm, Östergötland, and Skåne, have started to test and to carry out studies and initial implementations of AI-assisted breast cancer screening (Lång et al., 2023; Dembrower et al., 2020). As an example, and reflecting the varying logics, at Capio S:t Görans Hospital, in Stockholm, Sweden, the following process is considered. Initially, the mammogram images are reviewed by one radiologist and the AI solution independently. If both these readers, i.e. the human radiologist and the AI solution, assess with a negative result, the case is dismissed as healthy. If any of the readers indicate a possible positive result for cancer, the case moves to a next stage, which is a consensus meeting involving two radiologists. They can either decide on dismissing the case as healthy, or recall the individual. This involves additional workup, i.e. getting more images, e.g. from different angles of the breast as well as an ultrasound examination. Once those images are reviewed, the radiologists decide to proceed with a biopsy or not.

Another example of human-AI collaborative decision-making that is being tested and studied at Skåne region and Östergötland region, is the potential of using AI as a triaging tool for the decision-making (Figure 3). In this case, the AI solution is programmed to assign a risk score (usually from 1 to 10) to each mammography image screened. Consequently, a score from 1 to 7 (following the MASAI randomized study) means low risk, 8–9 moderate and 10 high risk (Lång et al., 2023).

Similarly, Dembrower et al. (2020) found in their retrospective study that the AI solution can be implemented as a complementary assessment tool in the screening process, both by filtering low-risk cases (60% according to the study) and by being, potentially, a concurrent assistant to the radiologist for higher-risk cases, later in the screening stages. In the Östergötland region, a similar workflow implementation is being tested, with the use of an AI solution not only as a triaging tool, but also as a third reader for different score levels.

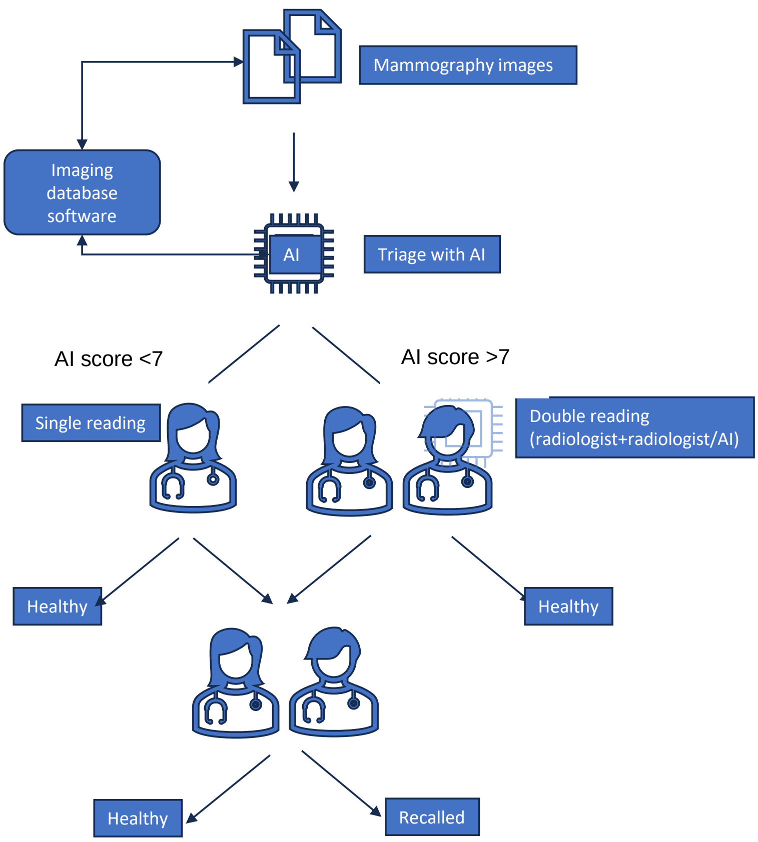

Figure 4 Breast cancer screening with AI as a triaging tool

While developments are ongoing, our interviews show that more advanced cancer detection algorithms and potential human-AI collaborative decision-making workflows are under way. As one interviewee describes, an improved quality of breast cancer diagnosis is expected, not least by connecting an imaging database software to the diagnostic AI tool (Figure 4), providing opportunities for ongoing feedback and learning in the system.

Regardless of the variations, the use of AI as a triaging tool is primarily intended to be a complementary decision tool for radiologists in several aspects (Dembrower, 2023). Firstly, it has been shown that human-AI collaborative decision-making potentially provides an acceptable triaging and cancer detection rate, as good as or even outperforming current workflows. Second, radiologists may, in a consecutive single reading stage, and based on a more situated sensemaking (e.g. based on education, experience and broader medical knowledge), have an opportunity to pick up any potential indications of cancer that might have been left out from the AI solution (Lång et al., 2023), not least if they are relieved from reading a very large number of mammography images. Third, this may also imply that additional contextual factors such as those central in the personalized medicine approach may become part of the decision, increasing the situatedness of the overall decision. Third, a considerable gap is observed between ambitions in policies on precision medicine and current implementation efforts, as we have found no indications in current efforts of extended consideration of contextual aspects like lifestyle and genomics when selecting who and when to screen.

5. Analysis and discussion

Currently, the case of AI-assisted breast screening in Sweden is colored by interesting findings, and already many regions in the country are beginning to implement it in their hospitals. The study shows that there are several potential ways for integrating AI solutions into the existing diagnostic workflow, reflecting human-AI collaborative decision-making. It seems that there is an opportunity for integrating AI in an organizational process in many ways. Different integration points of AI result in different ways of interaction between radiologists and AI, resulting in a different dynamic in the decision-making process. Related to situatedness, the findings highlight two aspects of human-AI collaborative decision-making: temporality and dynamic sensemaking.

5.1. Temporality

An observed characteristic of situatedness in human-AI decision-making is the temporality aspect. In the example of the breast cancer screening where the AI algorithm is placed as an independent reader in the initial screening phase, the decision whether the patient is to be declared as healthy or as a potential cancer case is taken independently by the algorithm. In the next stage, for the potential cancer cases, a discussion among a consensus group takes place, presenting a new decision involving human organizational actors. Temporality seems to play a central role likely explaining the early success in the way breast cancer scanning is implemented as a human-AI collaborative process. Each interaction with a specific contextual element happens in a specific moment in time, making the sensemaking temporarily bounded (Elsbach et al., 2005). This suggests that decision-making is also temporary bounded to a specific context and situation in time (ibid). The evolving decision-making process relies not only on a network of smaller decisions (Langley et al., 1995) made by each actor in several stages of the screening process, but also on iterations that refine or adjust decisions as more informed decisions are enabled. In a general iterative decision process, each iteration is based on a situatedness that may differ or overlap between individual human and AI actors, providing conditions for the actors to contribute to a dynamic sensemaking process. Different actors and types of actors contribute in different ways, enabling an updated and hopefully more informed decision.

It seems that, first, the process has been successful in allocating action (Elsbach et al., 2005) in different iterations between either humans or the AI solution, rather than having both active simultaneously. This temporal division of action enables a conceptually advanced human-AI decision process to be decomposed into non-complicated iterations with either human or AI dominating. Second, the situatedness is largely based on information that is common between humans and the AI solution (as the AI-system is largely trained on pictures being analyzed by radiologists). This shared situatedness relying on information that is interpretable by both human and AI solutions probably contributes to the opportunity to switch initiative for action between human and AI without the need for advanced dialogues between the types of agents, in turn opening up for a temporal decomposition.

5.2. Dynamic sensemaking

Framing of the patient condition is an essential part of the sensemaking and decision-making process for the patient's health. AI, whether it is implemented in triaging or as an independent reader, applies its own `sensemaking` for scoring the images. Radiologists review the mammography images for each patient and use their expertise in flagging potential cancers in the images. At the same time, radiologists apply sensemaking while interpreting the score that is assigned by the AI solution. In addition to interacting with the mammography images, radiologists will get input from the patient's individual symptoms and medical and other characteristics that are relevant to the case and will interact with each other in several stages of the screening process. The interaction between radiologists themselves and the screening AI can be considered a form of dynamic system (Clark, 2013) where sensemaking is evolving beyond the human cognitive boundaries, in relation to dynamic interactions with other organizational actors, AI, and situatedness. Additionally, it can be observed that both radiologists and the AI solutions have (at least partially) shared situatedness. The context where the sensemaking is situated is similar, given that both radiologists and AI solutions analyze mammography images; thus, the data used to train the AI solution is coming from the same contextual domain (radiology imaging). This implies that the underlying logic for the sensemaking is similar. From the findings, it can be said that a form of dynamic sensemaking emerges in the process of AI-assisted breast cancer screening process through the shared situatedness, allowing for a combination of sensemaking between humans and AI. The process of dynamic sensemaking between humans and AI characterizes the decision-making that emerges. With each additional interaction, radiologists' sensemaking is transformed, and with the continuous input from AI, the decision-making process is evolving until the final decision of whether the patient is to be recalled or healthy. Shared situatedness between humans and AI creates further opportunities for making sense of complexity, by learning and adapting in increased complexity (Gavetti et al., 2007).

6. Conclusion

With the purpose of exploring situatedness in human-AI collaborative decision-making in complex contexts, we set out to advance our understanding of the introduction of AI in decision-making processes, striving to strengthen situatedness by accelerating and/or expanding the knowledge available. In both cases, this would imply pushing the bounds of rationality toward an expanded rationality, making decisions situated rather than based on half-truths. Our study reveals that such improvements are possible and currently emerging, but also shows that the progress is heavily dependent on how well framed the problem is.

The main overall contribution of this paper is linked to two aspects in human-AI collaborative decision-making: (1) the role of temporality, and (2) dynamic sensemaking. While representing a complex decision-making task, decoupling of the AI solution and the human(s) has been central to facilitate implementation in a less complicated way, partly involving augmentation and partly automation (cf. Raisch and Krakowski, 2021). Such decoupling may be an important strategy in complex contexts (Perrow, 1999) and can provide organizations with a structure to design for human-AI collaborative decision-making (Puranam, 2021).

An important prerequisite is the shared situatedness of the AI solution and the humans, as AI is trained by data generated in the same context of breast cancer screening by radiologists with similar backgrounds and experience, rather than depending on data that is not contextually embedded in the application area. This may have important implications for the way human-AI collaborative decision-making can be understood and how the benefits of AI might be achieved. It also has important implications for the data that is underlying the AI solution, something that has been lifted forward in the emerging literature on human-AI decision-making in particular and in the emergence of AI in general (Lebovitz et al., 2022; Panch et al., 2019). While previous research has pointed to potential problems related to the quality, relevance, and accuracy, etcetera of data used to train the algorithm (von Krogh, 2018), we have found that one way of mitigating these potential problems is by relying on contextual data strongly related to the domain it will be used in, creating a shared situated sensemaking. This expands previous insights, reflecting that, while human-AI collaborative decision-making is heavily influenced by framing and sensemaking, organizations need to consider the risks and limitations of problem framing from AI, especially related to data bias and reliability (Glikson and Woolley, 2020) and provides a potential way forward to realize the benefits from AI.

By studying efforts for improving healthcare systems using a personalized medicine approach, and in particular the role of breast cancer screening, we have opened the black box of how humans and AI collaborate in decision-making. Our case decomposes into two distinctly different characters of Human-AI collaborative decision-making, breast cancer screening, and precision medicine.

When studying the breast cancer screening processes and outlining temporality as well as dynamic sensemaking, it has been rewarding to open the black box of human AI collaboration, as the case reveals important aspects. The situatedness in this temporarily bounded problem is largely common between human and AI actors, which makes it possible to shift the initiative between human and AI actors iteratively when progressing toward satisficing decisions based on situated truths. All workflows studied for this case of human-AI collaboration have lent themselves to a temporal decomposition where the dynamic sensemaking has either resided with a human or AI initiative, when looking sufficiently in detail. Consequently, conceptually advanced processes of human-AI decision-making are decomposed into non-complicated iterations.

The precision medicine ambition aims at giving better care to individuals and to use healthcare resources in a more efficient way. Such an effort needs a widely expanded situatedness during decision processes to be meaningful, and it is expected to be based on much and many types of data, which does not easily lend itself to modeling and should hence be a natural candidate for application of AI. Our study has not revealed any substantial progress at this level when it comes to breast cancer treatment. The findings indicate that abstract mapping between underlying data and outcome creates a gap between human and AI situatedness that is difficult to bridge, and dynamic sensemaking processes benefiting from both types of actors do not straightforwardly lend themselves to decompositions or iterative variation over the time of the initiative between actors. Further research is necessary to unravel this less straightforward and more challenging situation in achieving expanded situatedness in human-AI collaborative decision-making.

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