Innovation in healthcare: leadership perceptions about the innovation characteristics of artificial intelligence- a qualitative interview study with healthcare leaders in Sweden

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Abstract

Background

There are substantial challenges in the implementation of intelligence (AI) applications in healthcare. This study aimed to provide an insight into implementation preconditions by exploring the perceptions of leaders and managers in Swedish healthcare concerning the intervention characteristics of AI as an innovation to be implemented into their organization.

Methods

The study had a deductive qualitative design, using constructs from the domain of intervention characteristics in the Consolidated Framework for Implementation Research (CFIR). Interviews were conducted with 26 leaders in healthcare.

Results

The participants perceived that AI could provide relative advantages in solutions for the management of care, for clinical decision-support and for early detection of disease and disease risk. The development of AI in the organization itself was perceived as the main current intervention source. The evidence strength behind AI-technology was questioned by the participants, who highlighted a lack of transparency and potential quality and safety risks. Although the participants perceived AI to be superior for humans in terms of effectiveness and precision in the analysis of medical imaging, they expressed uncertainty about the adaptability and trialability of AI in other clinical environments. The participants perceived that user and end-user views on design quality and packaging would impact implementation at all levels. Complexities such as the characteristics of the technology, the lack of consensus about AI as a concept, and the need for many implementation strategies to achieve potentially transformative practice change were spoken of, and the participants also expressed uncertainty about the costs involved in AI-implementation.

Conclusion

The leaders saw the potential of the technology and its use in practice, but also perceived that AI’s opacity limits its evidence strength, and that there was a high level of complexity both in AI itself and in introducing it in healthcare practice. More research is needed about the perceptions of AI implementation in other stakeholder groups and about outcomes from the implementation of AI in real-world situations. New theories, models and frameworks may need to be developed to meet the challenges related to the implementation of AI.
Background

Artificial intelligence (AI) is a promising tool for enhancing healthcare in many high-income countries through improved efficiency, quality, and clinical and health outcomes (1, 2). However, there are substantial challenges to implement AI-based applications in healthcare as in the case of innovations in healthcare in general (2). The European Union sees itself as having the potential to be the potential global leader in the safe introduction of AI in healthcare and plans to develop a regulatory framework based on human rights and fundamental values to benefit people, businesses, and governments (3). There is a “buzz” around AI in healthcare in Sweden with expectations of novel solutions entailing better cost-effectiveness, a better workflow for staff, and greater empowerment for patients (4). The Swedish Government identified in a recent national approach document that Sweden must create the enabling conditions for AI-related work in order to increase economic growth, find solutions to environmental and social challenges, and strengthen Swedish competitiveness and enhance welfare (5).

An AI system can be defined in a technical sense as “a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy” (6). AI-based applications use one or more machine-based systems to achieve a specific end in specific circumstances. However, the implementation of AI extends beyond any specific intelligent technology and encompasses the socio-technical system that surrounds and supports it (7).

Whilst interest in AI is on the rise and the number of pilot projects are growing, “the level of diffusion is still relatively low and most projects are just at an initial stage to “test the water” (2, 8). The Diffusion of Innovation theory proposes that five innovation attributes (also referred to as intervention characteristics) influence the adoption of an innovation: relative advantage (is the innovation perceived as being better than the idea it supersedes?); compatibility (does the innovation fit with the existing values, past experiences and needs of potential adopters?); complexity (is the innovation perceived as difficult to understand and use?); trialability (can the innovation be experimented with on a limited basis?); and observability (are the results of the innovation visible to the adopters?) (9). The knowledge field of implementation science has adopted a broader approach towards the implementation of innovations, expanding upon Rogers’ innovation attributes. The widely used implementation science framework Consolidated Framework for Implementation Research (CFIR) adds attributes such as the cost and source of the innovation (10). However, understanding how different innovation attributes influence the implementation of AI remains unexplored (1, 11, 12).

Implementation science highlights the importance of accounting for stakeholder views in the initial phase of the implementation, as it is key to know how different stakeholder groups perceive the characteristics of an innovation and its potential impact on population health and value for patients (13). The importance of leaders for successful implementation in healthcare is recognized in implementation science (14) yet this is one of the stakeholder groups that has received relatively little research attention (15). Understanding how leaders in healthcare perceive the intervention characteristics of AI will provide
an insight into preconditions for implementation from the perspective of this important stakeholder group.

Methods

Aim

This study aimed to explore the perceptions of healthcare leaders in clinical and administrative roles concerning the intervention characteristics of AI as an innovation to be implemented into their organization.

Design

The study uses a deductive qualitative design. Constructs from the domain of intervention characteristics in the Consolidated Framework for Implementation Research (CFIR) are used as a deductive tool in this “directed approach” (16). The study is reported in accordance with the Consolidated Criteria for Reporting Qualitative Research 32-item checklist in order to ensure trustworthiness (17) (Additional File 1).

Theoretical framework

The intervention characteristics of CFIR consist of eight constructs (Table 1).

<table>
<thead>
<tr>
<th>No.</th>
<th>Construct</th>
<th>Definition</th>
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<tbody>
<tr>
<td>1</td>
<td>Relative Advantage</td>
<td>Perceptions of leaders about the advantages of implementing AI versus current solutions for healthcare organization and delivery.</td>
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<tr>
<td>2</td>
<td>Intervention Source</td>
<td>Perceptions of leaders about whether AI is or will be externally or internally developed.</td>
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<td>3</td>
<td>Evidence Strength &amp; Quality</td>
<td>Perceptions of leaders about the quality and validity of evidence supporting the belief that AI has or will have the desired outcomes.</td>
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<tr>
<td>4</td>
<td>Adaptability</td>
<td>Perceptions of leaders about the degree to which AI can be adapted, tailored, refined, or reinvented to meet the needs of different care-processes and work-units.</td>
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<tr>
<td>5</td>
<td>Trialability</td>
<td>Perceptions of leaders about the possibilities for testing AI on a small scale in the organization and to be able to reverse course (undo implementation) if warranted.</td>
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<tr>
<td>6</td>
<td>Design Quality and Packaging</td>
<td>Perceptions of leaders about excellence in how AI is bundled, presented, and assembled.</td>
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<tr>
<td>7</td>
<td>Complexity</td>
<td>Perceptions of leaders about the difficulty of the implementation of AI reflected by duration, scope, radicalness, disruptiveness, centrality, and intricacy and number of steps required to implement AI.</td>
</tr>
<tr>
<td>8</td>
<td>Cost</td>
<td>Costs of AI and costs associated with implementing including investment, supply, and opportunity costs.</td>
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Table 1. CFIR descriptions of the eight constructs from the domain of intervention characteristics (adapted to the intervention of AI).

Setting

The study was conducted in southwest Sweden. Participants were employed in a regional health authority with a strong focus on developing infrastructure to support the implementation of AI into practice. The region has since 2009 invested in a strategic healthcare analysis and research platform to enable agile management and analysis of clinical and administrative data (18).

Participants and recruitment

The recruitment of the participants from the regional health authority started with members of high-ranking management levels. The number of interviewees was consequently increased organically through a snowballing technique until a sense of the multiple types of leaders emerged and no further roles in the representation of leadership functions within the regional healthcare organization were identified. Twenty-six of the 28 participants who were invited (18 men and eight women) were willing to participate in interviews. Fourteen participants worked in top-level management functions in healthcare. Two participants were politicians at the regional top-level. Two participants had a technical advisory function. Eight participants had a quality development portfolio in their remit and worked in a strategic role either at an intermediate level or in local quality development roles. Two participants worked in primary healthcare and two in secondary care.

Data collection

The interviews, which were performed via telephone or video communication at a timepoint that was agreed upon by e-mail, were conducted by a female researcher (LP, trained in health education) and a male colleague (trained in management research). Both were experienced interviewers and had a research interest in the study topic. Although some formal collaboration existed between the university and the healthcare organisation, relationships with the participants were only established when the study started. The interviews were conducted with each participant on a one-to-one basis on one occasion. They had a semi-structured approach and the informants were asked to share their perspectives of AI as a phenomenon, their experiences with AI, and their perceptions of what could hinder or facilitate implementation of AI in their workplace (Additional File 2). Although AI systems are designed to operate with varying levels of autonomy, the interview questions did not differentiate between different kinds of AI technology. The terms that the participants used reflect the general immaturity of the language describing different forms of AI and their perception of AI as a “general purpose technology” (Samoili, 2020) (19). Interviews were pilot-tested, but no changes were deemed necessary and the pilots were included in the data. The interviews took place between October 2020 and May 2021 and lasted between 30 and 120 minutes, with a total length of 23 hours and 49 minutes. Field notes were taken and the interviews were audio-recorded and transcribed verbatim.

Data analysis
The analysis of the qualitative data was undertaken with the software program Nvivo (NVivo 1–14). This involved a qualitative content analysis with a directed (deductive) approach, using a stepwise method described by Hsieh and Shannon (2005) (16). The analysis starts with a theory as guidance for the initial coding when applying a directed approach, which in this case was based on constructs related to the Intervention characteristics as described in CFIR (10). Following this method, the researchers moved back and forth through the steps in order to validate, revise, and refine the findings, and discussing saturation of the data in each step.

All the transcripts were read in their entirety by all the authors in the first step of the analysis process. PN and MN constructed a codebook (Table 1) for the analysis of the data in the second step. The definitions of the eight constructs of the characteristics of the intervention in the CFIR framework were adapted to the study context. While the definitions adhered closely to the original content of the constructs, the adapted definitions were designed to serve as codes and facilitate the qualitative analysis of the data in this study. The definitions were iteratively discussed and ultimately finalized by the authors. The codes based on these constructs formed the main categories. The codes were applied to each interview in the third step. The first author (MN) allocated meaning units to the main categories, using the descriptions for each construct in the codebook. The preliminary allocation of meaning units to the main categories was iteratively and repeatedly discussed between all the authors until consensus was achieved. The content in each main category was collated by the first author (MN) and carefully abstracted with the conscious intention of preserving the variation in the scope and depth of the data. Quotes from the data were chosen to illustrate and add depth to the descriptive text in each category and translated verbatim (Table 2). All the authors participated in the discussions leading to the final results.
Table 2
Findings, quotations sorted by Intervention Characteristics based on the Consolidated Framework for Implementation Research and defined for the study (in Table 1).

<table>
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<tr>
<th>Relative advantage</th>
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<td>“…understand our operation in a better way so that we can make wise decisions about how we can develop our operation…. We can understand the medical development … and we can have a better comprehension of the financial links and relationships … when we can integrate the operations we run … a little tighter than we have been able to previously” (2)</td>
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<td>“The clinics have many such ongoing projects that are registered in the electronic records system. The different records systems vary in how good they are at providing such support but these information systems for healthcare generally work to help the clinics present such things. This will just be another matter, a warning triangle really” (10)</td>
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<td>“We've got all the data in situ, we've got a department for systems development that can build things, we have a lot of knowledge in house and a healthcare administration that is brave and looks to the future, we have the possibility to prioritize things, that it should happen, no it’s feasible to build today, I think.” (5)</td>
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<td>“It’s the preparatory work that’s important and puzzling and that’s what’s probably also time-consuming. That’s what many medical tech companies are so frustrated about. Because many of them think that they have solutions that are ready. All you need to do is to start the process, “look, you can save money or save lives” or whatever. Yes, that’s very good and then I’ll look through it because I've made my own little checklist.” (2)</td>
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<td>“Today, you can go to the library and start digging into research reports. It can take hours, days, weeks but then at least it’s you who has worked your way to some form of understanding. Then there’s the volume … We’ll never find all the research reports in this field of course, but it’s still this that I can stand up for. I have read about this, I trust this, that’s my assessment. I’ll also take responsibility for it if it doesn’t turn out well.” (7)</td>
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## Relative advantage

“We've already got decision support in the form of various risk scores where we calculate point scores into different levels of risk. The first six of these are already part of the medical records system that we will launch in 18 months to two years. But that's because they are already in use, then we come back to the question that we previously talked about. When is decision support sufficiently ethical and evidence-based to be applied? It is still unfortunately a bit of assessment sport. But when somebody says that now's the time, then it can be quickly incorporated in the medical record system. Because it's already been prepared.” (2)

## Design quality and packaging

“One doctor of all the doctors I've met since we started to work with the cancer process wanted to have the routines printed to have on his/her desk. Only one doctor of all those I've met. All the others wanted a digital version to access it quickly and easily. This indicates that a simple way of accessing this support is needed and that you need to ask a few questions in order to get the right information in return. But then it can't be too complicated and can't take too long as it won't work at all.” (4)

“Then it can perhaps say honestly that “I can't do that”. I think that would also be a good thing. It's perhaps not always necessary that an answer or a suggestion is provided. Then it can't always be like that, but then it must also be very clear that you can use “Doctor John” in this field [AI]. He's a good urologist, but useless as a cardiologist” (7)

“It could even be the case that “Doctor John” [AI] works as an adviser to the nurse. Instead of running into Sara (a doctor) whose office is opposite his/hers, she starts with “Doctor John” [AI] first for the first advice or perhaps even for more advanced advice. Then I hope that in certain circumstances the nurse can also be short-circuited, that this [AI] provides the same as the nurse.... We are dealing with people who are ill and you have to have respect for that because everybody won't be able to use these tools” (7)

## Complexity

“These are very important discussions that the administration management needs to have so that there is a consensus .....Shall we invest in those fields where we know there are many assessments of a subjective nature or where we have very high numbers of patients in the system, I mean that we have large numbers in some cases, or should we focus on fields where we have very small numbers because that's there we have more unambiguous experiences ... there are so many perspectives”. (9)

“The unavoidable fact is that our co-workers’ everyday life changes ... greater demands will be put on those who can take care of their own health, in order to prevent illness in the future. There's a limit to how much we can produce, we'll only have this much resources and that’s why we have to manage this in a different way in the future. There won't be a lack of treatment alternatives or medication or other ways of taking care of the illness, but the difficult thing is to prevent illnesses instead”(14).

## Costs

“Resources and time need to be allocated. It needs to be financed as well. We often forget about that and think that it will be sorted out in the current budget, no that won't be done. Resources and time have to be allocated in order to be successful”. (04)

## Findings

Participants believed that a **relative advantage** of AI as an innovation to be implemented in healthcare lies in its effective and comprehensive management of large volumes of data from different sources, and in particular, data from the data-warehouse of the organization itself. Participants saw AI as part of a
necessary development as healthcare would not, in the long run, be able to keep up with the population's healthcare needs. The application of AI technology was thought to enable decision-makers to allocate resources where they are most needed in the organization. Management decisions for organizational changes in primary care units and hospitals were considered to be supported through the aggregation of data on outcomes from various care activities at multiple sites.

The participants also perceived AI’s potential for supporting professional decision-making in clinical care. AI was specifically perceived to be able to contribute by its ability to analyze images from digital imaging systems with a high level of precision and time effectiveness. The capacity of AI was perceived to be superior to the human analyzing ability of even very clinically experienced professionals in that it was not only more efficient and precise but also less biased.

AI was not perceived as replacing the need for human interaction between caregivers and patients, as this would provide other information, such as the patient's preferences and state of mind. On the other hand, the participants thought that AI could be equivalent to a colleague as a “second opinion” in situations of uncertainty.

The participants described that AI could serve as a warning or a “yellow flag” for alerting healthcare professionals to clinical data that needs to be taken into account given a certain situation and specific conditions. The participants considered this uncontroversial, as they saw AI as just another tool to help healthcare professionals in their clinical work.

The participants had great expectations for the possible AI-based applications that could come in the future. “Digital triage” was perceived as an attractive idea to empower patients in their own care and to achieve a more effective care as self-help for some patients. This was expected to generate more time for vulnerable patients. They also envisaged that standard health information could be collected from the patient and an AI-informed selection of laboratory tests could be completed prior to the primary healthcare visit, making the patient-provider encounter more informed and time-efficient.

Another aspect of perceived relative advantage was the potential of AI for discovering previously unknown patterns of care flow and its early detection of disease, facilitating health predictions for individual patients or groups of patients at risk. The participants highlighted the AI algorithm's ability to impartially discern clinical patterns based on multiple data sources without the need for prior clinical training, preunderstanding, and assumptions.

Regarding intervention source, the participants thought that AI would primarily be internally developed in the near future. They thought that their organization had some readiness to develop AI because of a relatively long history of investing in AI. Strategic leadership in the county council was perceived to have supported the AI development and research early on, which led to a perception of local ownership of the AI development in the county council. AI as an innovation was perceived as a “hot topic”, and collaborations with universities and other actors such as companies were seen as strategic for the county council to take advantage of this “window of opportunity”. Some even expected local healthcare
professionals to actively participate in the development of AI-based applications for use in their own field of interest.

Networking around the use of AI within the larger national healthcare system was perceived as a slower and more cumbersome process than regional collaboration with specific tech companies. However, the participants believed that many tech companies were not equipped to follow the accepted quality and safety standards in healthcare, which led to hesitations about relying on them.

Although the participants rated evidence strength and quality to be of key importance for the implementation of AI they perceived this to be highly questionable. The participants felt they lacked control over the long chains of data processing and perceived that they had no insight into which process decisions were made along the way, for which reasons, and by whom. The participants thought that due to data being transformed between systems, aggregated and repackaged, then the original data would be increasingly difficult to retrieve and use.

The participants perceived that the mathematical complexity of AI prohibited an easy understanding of the reason that lay behind the information presented by AI; they characterized AI as a “little black box”. One of the reasons for questioning the evidence strength of AI-based applications was that the knowledge-base and data behind AI could not be verified in traditional and transparent ways like reading up on relevant scientific research findings.

The participants perceived AI to have a degree of adaptability, but they also believed it to fit more naturally in some clinical contexts than in others. Care units with medical imaging techniques as an important work tool were perceived as being especially prepared for making changes towards AI-based diagnostic support. Areas that were highlighted were radiology, pathology, clinical laboratory medicine, and dermatology. The participants thought that using AI would encounter barriers in other work units because of the perceived need to protect sensitive personal data.

AI was perceived to be a potentially useful tool in the future when healthcare professionals meet a patient with diffuse symptoms that have been presented in different forms over time, such as in mental illness. Through tracking a patient’s history, AI could provide a comprehensive picture of the patients’ health status, which in turn could facilitate a better understanding of the problem.

When discussing trialability, the participants suggested testing AI on a small scale in the organization but did not discuss any ways of retracting the implementation if necessary. The current use of AI for managing care in the organization was experienced as gaining importance and was tested in an ongoing process. The participants expected to be able to test a small number of AI-based applications in clinical contexts within the next few years, partly due to them having observed that IT-systems had prepared the technical infrastructure for AI “behind the scenes”.

Diagnostic tools in the shape of digital imaging tools based on AI were seen as being feasible for testing in clinical use, but the participants also perceived it would be necessary to create more opportunities for
testing other AI algorithms developed for use in care processes in clinical practice. The participants tentatively discussed where new AI-based applications could be appropriate and feasible, e.g. in situations that are a step away from patient-provider encounters. They also reasoned about the usefulness of AI in situations of broader diagnostic uncertainty, for example, in primary care consultations. Some participants perceived that AI is already more or less informally present in some clinical contexts.

The participants perceived that the design quality and packaging of AI will be important for the future implementation. They imagined that AI applications in healthcare need the AI component to be as simple to use as possible while at the same time being designed to target complex problems that healthcare professionals need help in solving.

The participants perceived that most healthcare professionals currently had little knowledge about AI, with the technology having “brave new world” connotations for them. The participants mentioned that limited trust in AI technology could be circumvented by providing objective background information about the product, including its limitations.

The participants were not convinced that the healthcare organization itself could manage to design the AI applications without external expertise. They perceived that developing the AI models and algorithms was not sufficient and that the technical functions of AI needed to be integrated into user-friendly products for healthcare professionals to use. They also perceived that future IT infrastructure development was necessary for integrating AI into IT systems for ease of use. The participants believed that AI could have different designs based on the same data but tailored to users of different professional backgrounds and patients with different levels of digital literacy and health literacy.

The participants perceived multifaceted complexity in the implementation and use of AI. They believed that there are many competing and occasionally conflicting opinions about what AI is and is not. Decisions about investments in AI were the remit of top-level management, but the participants expressed a lack of guidance for decisions connected to AI. They wanted their decisions to be based on a thorough knowledge of the AI technology itself and which type of problems it can be expected to solve. However, they did not find it clear which criteria should be used for decision-making about how and where to start applying it.

The participants highlighted that collecting large volumes of data was not realistic at present, as health data were fragmented in the system, and current IT systems were not mutually compatible. Sharing data and exchanging knowledge between county councils was expected to be difficult, as different county councils make independent choices concerning how to build the data warehouses and which technologies and suppliers to invest in. The participants perceived risks of privacy violation during managing, monitoring, and storing large volumes of sensitive health data from many different data sources, involving different IT systems and numerous staff in technical and medical capacities and storage in commercial facilities. They also said that current legislation prohibits data sharing between different caregiving agencies in county councils and municipalities.
The participants perceived that implementing AI is complex and will impact patients and healthcare professionals. AI will need to be adapted to many factors, including different levels of digital literacy, professional fields of interest and levels of technological know-how and will involve leadership at all levels. The participants experienced that processes of change tend to move very slowly in healthcare. In addition to professional change resistance and organizational barriers, a high level of skepticism around AI was to be expected. They thought that healthcare professionals could experience AI as alien and as challenging to their professional role.

Not being fully cognizant of the scope and depth of knowledge in AI was thought to have consequences for patient safety in clinical practice. The participants perceived that there were risks of staff becoming overly reliant on knowledge provided by AI, which could lead to more limited use of clinical reasoning. They highlighted that repeatedly exercising professional judgment was necessary for developing clinical expertise over time. This was seen as especially important for younger professionals, but even more experienced clinicians could risk becoming overly confident in AI-informed decision support.

Some participants perceived that it was possible to take the positive results of using AI as proof of its effectiveness but highlighted the risk of bias in the data that feeds into the technology and how health data were processed. They felt strongly about the need for quality and safety control of AI-based applications, considering the consequences of faulty and skewed data-processing in AI and the large potential impact of AI imperfections on management and health outcomes.

The participants expected that societal debate would need to precede some of the transformative changes for healthcare professionals and patients. The complexity also included that AI might provide healthcare professionals and patients with previously unavailable information, which they are currently unequipped and unprepared to deal with. They thought that healthcare would change profoundly towards being more prevention-focused in the future, with citizens expected to be in charge of managing their own health.

The participants could not estimate the costs of AI technology at present but perceived that no state-allocated resources were available for more large-scale implementation and roll-out of AI. The participants had varying perceptions of the success of the organization's efforts in developing AI so far, with some applauding the current and past AI development efforts, while others instead doubted what the outcome was of the resources that the organization had used for AI-development so far.

The participants were uncertain about the level of costs involved in the future larger-scale implementation of AI but feared that some currently ongoing research and development projects could suffer. Although the purchase of AI-products and IT-system capacity was thought to be costly, some participants thought that the IT technology infrastructure was ready and able to accommodate AI, which would alleviate costs. The cost of product development by external companies was perceived as a barrier to implementation in the short term, as procurement procedures at present do not apply to AI. In the longer perspective, the participants expected that the organization could incur financial costs for purchase, support, and
maintenance of AI technology. Future projections of costs were perceived to include recruiting AI-competent staff potentially.

Discussion

The study explored the perceptions of leaders in healthcare concerning the intervention characteristics of AI of relevance for the adoption, implementation and use of AI in their organization. Their perceptions were categorized in accordance with the eight intervention characteristics constructs of CFIR. The results show that participants had high expectations of the relative advantage of AI even though they were not convinced of the evidence strength and quality. The leaders were more tentative in their perceptions of trialability, adaptability, design quality and packaging, and costs, because of the relatively early stage of deployment of AI in their organization. Participants' expressions concerning intervention source and complexity were indicative of conflicting perceptions.

The participants perceived that AI could offer relative advantage in the management of care, clinical decision-support, and early detection of disease and disease risk. It is interesting to note that, in spite of their positive expectations of the advantages of AI in healthcare, the evidence strength and quality of AI were questioned by participants. They highlighted opacity in AI and technological weaknesses. The lack of intuitive understanding of the theory underlying AI model development and the high level of mathematical and statistical complexity has been termed as the “black box problem” of AI (20). Similarly, the ways in which these AI models achieve their results are not always comprehensible (21). Among the most important weaknesses in AI are potential biases embedded both within algorithms and within the data used to train algorithms (22). Furthermore, social human fallibility and implicit values and biases, carried into the development of AI algorithms could potentially cause a lack of generalizability and perpetuate systemic inequities (22–24). These biases and flaws come with a risk of catastrophic consequences in life and death situations when implemented in practice (20). Indeed, research clearly indicates that weaknesses in the design and quality of the studies investigating the implementation of AI in practice limit any generalizability, so there still is insufficient evidence to advocate the routine use of AI in healthcare (8, 12, 25).

Concerning adaptability, the participants described that certain practice arenas would be more amenable to AI implementation because of the nature of the work. They perceived AI to be superior to humans in terms of effectiveness and precision in medical imaging and thought that this was the area of AI use that is closest to implementation. Other studies confirm this perspective, noting that AI in healthcare has two potential advantages to human performance; AI can learn from big data more efficiently than clinicians and can untiringly perform predefined tasks with higher precision (2, 20). A recent literature review shows that AI applications with a relatively narrow scope and simple rule-based design were potentially more implementable because they do not disrupt current practice (8).

In relation to their perceptions of trialability, the participants perceived that the county council has prepared the technical infrastructure for AI development and has the ability to test a small number of AI-
based applications in clinical contexts. Others have described that a necessary foundation for delivering AI in healthcare is having medical health records and a high degree of interoperability between IT systems (26). The first condition is met by healthcare organizations in several countries, including Sweden, but there are marked problems with the second condition of interoperability. Legislation protecting health data, limited technological standardization, ethical issues and supporting legal infrastructure for data-sharing are barriers to tackle if the ambitious Swedish eHealth goals are to be realized (27). Deciding in which clinical contexts and where in the organization the future application of AI-technology is most appropriate and likely to succeed was perceived as a difficult task for the leaders. Developing the capability to perform a qualitative needs-assessment and prioritization seems necessary (28). Still, is not clear how this capability should be developed, who is responsible for this “leadership-capacity leap”, and how it should be financed. Previous research has shown that policymakers' decision-making in the introduction of eHealth poses similar challenges (29). In decision-making, Costs is an important aspect related to AI implementation. However, the participants found that many aspects are unclear about the trade-off between costs and profits. The initial investment and operational costs for infrastructure and service delivery has to be included in future studies, and other options to achieve a similar impact must be benchmarked to inform strategic planning (30).

In relation to the intervention source, the participants perceived that the development of AI should be done internally. However, the leaders also perceived that there is a need to collaborate with external partners and that the views of users (such as healthcare professionals and patients) on design quality and packaging could impact implementation at all levels. While participants are motivated to improve care quality and cost-effectiveness in the long run, they feel uncertainty regarding how to balance the organization’s need for external AI know-how against the companies’ “business dynamics” that focus on profit. Contrary to the preference expressed by leaders, research points out the need to incorporate expertise and knowledge in the development of AI-based applications, combining the expertise of both computer scientists and healthcare professionals to make meaningful use of the data (2). Furthermore, collaboration between levels and parts of systems and between organizations is needed to counter the disruptiveness in care flows (31).

The participants’ described Complexity in relation to conceptual ambiguity and mistrust of AI. They expressed uncertainty about definitions and the key characteristics of AI. The general understanding of AI is diffuse for several reasons. Firstly, the term AI is used in many different ways in computer science, engineering and healthcare (32). Secondly, the characteristics of AI are continually evolving, and different types of “AI” exist in parallel (20, 21, 33). Thus, how we use the term AI needs to be clarified to identify nuances and differences of the AI technologies and AI systems, and study the specific challenges involved in their safe and effective implementation (21).

The participants also expressed Complexity of the whole “manufacturing process”, from data-acquisition to data management to data-warehousing and modelling of AI-based applications. Not being able to understand and follow the logic of decisions was perceived to cause uncertainty not only in the leadership role, but also with regard to the clinical uses of AI. The perceived opacity of AI had
consequences for the participants’ trust in AI. Trust is a psychological mechanism that deals with the uncertainty between the known and the unknown (34) and trust is described as a key to adoption and use of AI (20–22, 24). Increasing the explainability and transparency of AI systems in practice is thus essential. Explainability is highlighted as necessary with regard to professionals’ ethical principles of beneficence and non-maleficence (23). Ethical issues related to privacy, data-security, accountability, and responsibility are important as AI-based applications that are trained using personal health information in a long and complex process involving many stages and actors (24). Safe, secure, and appropriate use of personal data, with informed consent from the individuals concerned, is a prerequisite for ethically sound AI (2, 24, 33, 35). Moreover, explainability and transparency are necessary for professionals to evaluate performance measures regarding algorithmic fairness and for them to be able to confidently communicate with patients (23, 36, 37). Some authors point to these ethical issues as an important caveat to employing AI in the front lines of clinical practice at all (38). Other authors propose that some strategies may counter-balance some of the complex ethical problems with AI linked to biases in AI, and to limit the potential consequences on social equality (22). However, more research is needed on how AI systems can be implemented in daily practice in an ethical way and how AI impacts healthcare practice (19). As yet, the limited numbers of published empirical studies to date indicate that real-life implementation of AI is in its early stages and AI’s promise to “meet future challenges in healthcare in new ways” has not yet been realized and evaluated (2, 11, 12).

Study limitations and Methodological considerations

The study has some limitations that must be considered when interpreting the results. Participation in the study was voluntary, which means that the leaders who were interviewed may have been particularly interested in the topic, although it is difficult to determine how this might have affected the results. The intervention itself (i.e. AI) appeared to be interpreted by participants in different ways, although this was concurrent with the study’s aim to focus on perceptions from the leadership perspective. However, this also reflects the topic’s relative novelty for the participants. Future studies could benefit from a clearer delineation up-front of the different applications of the technology to understand more in depth how each application is perceived by leaders in healthcare.

We found that the eight attributes covered aspects of perceptions that were relevant to the study aim. However, it was occasionally difficult to classify the “flipside” of the attributes (when the data reflected more negative participant perceptions), but this was managed by classifying these types of perceptions in the sub-category “Complexity”. Although this choice on the part of the research team facilitated the analysis, this way of proceeding may point to a need to develop the theoretical framework.

The transferability of the results is limited to Swedish healthcare. However, key characteristics of AI may be generalizable beyond the Swedish context to inform stakeholders about possible facilitators and barriers for the adoption, implementation and use of AI (39). Communication around these determinants in a standardized manner may facilitate dialogue (40). It should be remembered, however, that the attributes of an intervention are not stable features, nor are they the only determinant of adoption and
implementation. The interaction between the innovation, the intended adopters and the context influences the adoption and implementation of interventions (10, 41, 42).

Conclusions

In conclusion, participants see the potential of the technology and its use, but also its opacity related to evidence strength and a large degree of complexity regarding both the technology itself and the intricacies of introducing AI in practice. A better general understanding of the attributes of AI may facilitate regulations to curb its potential of harm, and strategies may be devised for its safe and effective adoption, implementation and sustained use in healthcare. More knowledge is needed about the perceptions of AI implementation in other stakeholder groups and about outcomes from implementation of AI in real-world situations in order to develop implementation strategies. Although implementation science has many theoretical tools to describe, analyze and propose strategies for practical implementation, new theories, models and frameworks may need to be developed to meet specific challenges of AI-implementation. This is an area for future study.

Declarations

Contributions to the literature

- This theory-based study probes deeper into the understanding of the main attributes of AI, as it explicitly and systematically highlights CFIR’ s “Intervention Characteristics”.
- The views of leaders, an under-researched stakeholder group, are of key importance for the research about the implementation of AI.
- The findings reflect perceptions by technically and clinically experienced leaders that may challenge some of the prevalent general views concerning AI-implementation in healthcare.
- The study contributes to Implementation Science knowledge by testing the applicability of one of the CFIR framework domains in a deductive approach, with the potential for developing the CFIR-framework itself.

Ethics approval and consent to participate

The study conforms to the principles outlined in the Declaration of Helsinki (43) and was approved by the Swedish Ethical Review Authority (no. 2020-06246). The study fulfilled the requirements of Swedish research: information, consent, confidentiality, and safety of the participants and is guided by the ethical principles of: autonomy, beneficence, non-maleficence, and justice. Participants first received an e-mail with a short information of the research project and, at the same time, were asked if they wanted to participate in the study. If they agreed to participate, they were verbally informed at the beginning of the interview about the purpose and the structure of the study and that they could withdraw their consent to participate at any time. They were also informed of their right to decline participation altogether or to exit the interview and the study at any time. Participants were informed that the interview was confidential.
and that any personal data obtained in the interview would be protected during the entirety of the research process and in the final publication. Participation was voluntary and the respondents were informed about the ethical considerations of confidentiality. Informed consent was obtained from all participants prior to the interview.

Consent for publication

Not applicable

Availability of data and materials

Empirical material generated and/or analyzed during the current study are not publicly available, but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no potential conflicts of interest with respect to the research, authorship, and publication of this article.

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Authors' contributions

All authors together identified the research question and designed the study. Applications for funding and coproduction agreements were put in place by PS and JMN. Data collection (the interviews) was carried out by LP and DT. Data analysis was performed by MN, LP and IL and then discussed with JN, PN and PS. The manuscript was drafted by all the authors, and all of them have read and approved the final submitted version.

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References


**Supplementary Files**

This is a list of supplementary files associated with this preprint. Click to download.

- AdditionalFile1COREQchecklist.doc
- AdditionalFile2Interviewguide.docx