Original Article

Implementing artificial intelligence in clinical practice: a mixed-method study of barriers and facilitators

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Background: Though artificial intelligence (AI) in healthcare has great potential, medicine has been slow to adopt AI tools. Barriers and facilitators to clinical AI implementation among healthcare professionals (the end-users) are ill defined, nor have appropriate implementation strategies to overcome them been suggested. Therefore, we aim to study these barriers and facilitators, and find general insights that could be applicable to a wide variety of AI-tool implementations in clinical practice.

Methods: We conducted a mixed-methods study encompassing individual interviews, a focus group, and a nationwide survey. End-users of AI in healthcare (physicians) from various medical specialties were included. We performed deductive direct content analysis, using the Consolidated Framework for Implementation Research (CFIR) for coding. CFIR constructs were entered into the Expert Recommendations for Implementing Change (ERIC) to find suitable implementation strategies. Quantitative survey data was descriptively analyzed.

Results: We performed ten individual interviews, and one focus group with five physicians. The most prominent constructs identified during the qualitative interim analyses were incorporated in the nationwide survey, which had 106 survey respondents. We found nine CFIR constructs important to AI implementation: evidence strength, relative advantage, adaptability, trialability, structural characteristics, tension for change, compatibility, access to knowledge and information, and knowledge and beliefs about the intervention. Consequently, the ERIC tool displayed the following strategies: identify and prepare champions, conduct educational meetings, promote adaptability, develop educational materials, and distribute educational materials.

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Conclusions: The potential value of AI in healthcare is acknowledged by end-users, however, the current tension for change needs to be sparked to facilitate sustainable implementation. Strategies that should be used are: increasing the access to knowledge and information through educational meetings and materials with committed local leaders. A trial phase for end-users to test and compare AI algorithms. Lastly, algorithms should be tailored to be adaptable to the local context and existing workflows. Applying these implementation strategies will bring us one step closer to realizing the value of AI in healthcare.

Keywords: Machine learning; innovation; deployment; qualitative; quantitative

Introduction

The start of the Information Age in the mid-20th century has been a catalyst for the use of data in medicine (1). The early days were characterized by limited datasets, created to answer specific questions, but developments were accelerated with the widespread introduction of monitoring devices and Electronic Health Record (EHR) systems around the turn of the century (2). This enhanced labeled big-data, together with increased computing power and cloud storage, boosted the use of artificial intelligence (AI) in medicine (3). Today's healthcare professionals often feel overwhelmed by vast amounts of data from various sources (4). As medicine enters the Age of AI, there is great potential for algorithms to help make sense of all the data and augment clinical decision-making (3,5). Algorithms can use data points from large numbers of patients to detect subtle patterns that healthcare professionals may overlook (6). These insights can support the clinical assessment of a patient, decrease diagnostic uncertainty, and improve the overall quality of care. However, medicine has been slow to adopt AI tools. Up until 2020, only 222 AI tools were approved by the US Food & Drug Administration (FDA) and 240 in Europe (of which 124 in both) (7).

The low number of approved medical AI tools is surprising considering the fact that over 50,000 studies of clinical AI model development were available in through MEDLINE alone as of October 2022, according to an interactive dashboard (8). There seems to be a significant gap between the development and deployment of AI in the healthcare industry (6). Recent reviews have shown that about 95% of the published studies on AI only address the development of a particular algorithm (9,10). In comparison, only 1–2% of those studies evaluate the use of the algorithms against clinically relevant outcomes, and few are integrated in practice. It has been suggested that a key factor of the poor implementation of AI algorithms is the lack of inclusivity and engagement of the end-users and their domain knowledge during the development of these tools (11).

Barriers and facilitators to clinical AI implementation among healthcare professionals are ill defined, nor have they been linked to appropriate implementation strategies to overcome them. The Consolidated Framework for Implementation Research (CFIR) is a tool to identify these types of contextual influences and explain the strikingly low implementation rates of medical AI (12). Furthermore, the barriers identified by the CFIR can be entered into the Expert Recommendations for Implementing Change (ERIC) tool for implementation strategies, to create a well-

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Highlight box

Key findings

• The current tension for change in healthcare is insufficient to facilitate AI implementation. Implementation strategies are needed to facilitate sustainable adoption.

What is known and what is new?

• A wide variety of AI algorithms have been created for the healthcare industry, but few make it into clinical practice. Barriers and facilitators in this process are ill-defined.

• This study revealed barriers and facilitators healthcare professionals may experience with AI (implementation) and suggests implementation strategies.

What is the implication, and what should change now?

• The introduction of AI tools in practice should systematically be supported by various implementation strategies, such as increasing knowledge and information through local leaders, using a trial phase to let users test and compare AI algorithms, and tailoring the tools to the local context and existing workflows.

tailored approach (13).

In the current study, we applied the CFIR framework to identify barriers and facilitators to AI implementation in the clinical practice. We aim to find general insights that could be applicable to a wide variety of AI-tool implementations, so that this information can be used to facilitate implementation of future AI tools in medical practice, and realize their potential to improve patient care. We present the following article in accordance with the COREQ reporting checklist (available at https://jmai.amegroups.com/article/view/10.21037/jmai-22-71/rc).

Methods

We conducted a mixed-methods study consisting of three inclusion phases: individual interviews, a focus group discussion, and a nationwide survey. The Amsterdam University Medical Centers' (UMC) local medical ethics review committee waived the review of this study as the Medical Research involving Human Subjects Act did not apply (IRB number: IRB00002991; case: 2021.0396). All participants provided informed consent. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013).

Inclusion phase I—individual interviews

The first phase of this study encompassed semi-structured individual interviews with the end-users (physicians) of potential AI algorithms in healthcare, regarding barriers and facilitators to clinical AI implementation. We designed a topic list for the interview, based on CFIR literature and expertise of the research team (physicians and a psychologist) (12). The topic list was structured as an hourglass: started broadly with questions and prompts on AI in healthcare in general. Then the topic narrowed down to a clinical case vignette about an AI blood culture tool to provide physicians with specific details, questions and prompts. This AI tool was recently developed by our research group and it predicts the outcomes of blood cultures in the emergency department, which may help avoid unnecessary testing and associated harmful effects (14). During the time of interview, focus group and survey (and to date) the blood culture tool was not implemented in clinical practice. We included this tool as clinical case vignette to provide interviewed physicians with real examples from a real project, and enhancing discussions. The topic list ended with AI in healthcare in the broad sense. The topic list

can be consulted in Appendix 1 (translated, English). The first few interviews were used to pilot the topic list, and we then concluded that the list was comprehensive, hence no additions or revisions were made to the initial list.

We included physicians from the emergency, internal medicine (including infectious disease specialists), and microbiology departments of our Amsterdam UMC hospitals (location VUmc and AMC). We chose to target these specific specialties as they will be the main end-users of our developed AI algorithm, and they represent a substantial percentage of all hospital physicians (15). Physicians of all experience levels were eligible for inclusion, to gain a broad and generally applicable picture.

Physicians were recruited through the department secretariats with an invitational email. When interested in participation, a research team member provided additional information regarding the study, and scheduled a date for the interview. Interviews were conducted face-to-face at one of the two hospital locations, in a private room (either a meeting room, or a personal workspace). All interviews were conducted by two researchers: a female psychologist (BS) and a male medical doctor (MS). Both interviewers had interview experience, gained through previous qualitative research projects and their education. Interviewed physicians were not close colleagues of the interviewers, nor was there a prior (work) relationship. The duration of the interviews was approximately 45 minutes. Interviews were recorded with an audio recorder and field notes were taken during interviews.

We aimed to include until data saturation for this phase was deemed to be reached. The inclusion of the individual interviews ran between August 2021 and September 2021.

Inclusion phase II—focus group

To complement the information that emerged from the individual interviews, the second phase of this study encompassed a focus group. The expected complementary value of the focus group was that it enables and stimulates interaction and discussion, which could therefore provide additional information. By performing both individual interviews and a focus group, we have the information on the topic that people are willing to share both 'publicly' and 'privately' (16). For this phase we used equal inclusion-criteria and processes as for the individual interviews. The topic list used in the focus group was identical to the individual interviews. The physicians included in the interviews were not allowed to participate in the

focus group. The focus group discussion was led by an experienced focus group interviewer (MvB), and supported by BS and MS. There was no prior relationship between MvB and the focus group participants. Due to COVID-19 restrictions, the focus group was conducted online and audio recorded through Microsoft Teams. The focus group took place in September 2021 and took 90 minutes.

Inclusion phase III—nationwide survey

Based on the themes identified in phase I and II, we created a quantitative survey (Appendix 2). The aim of this survey was to rank the most prominent barriers and facilitators from the interviews, and identify those endorsed by a large population of potential AI end-users. To keep the survey concise, we only incorporated questions on important topics identified in the interviews. A power calculation for the number of survey participants was irrelevant since we did not plan to perform any statistical tests. However, we aimed to include at least 100 survey participants, to ensure we had a variety of medical specialists of different ages. The survey thus ran between December 2021 and February 2022. An anonymous link was distributed to practitioners across the country through hospital secretariats, medical associations, and social media.

Data collection and privacy

Audio recordings of the interviews and focus group were transcribed. Transcripts or study results were not returned to participants for review and feedback. Audio recordings and transcripts were stored digitally at the Amsterdam UMC location VUmc. Characteristics data on the participants were stored in a separate file, and not included in the audio files nor transcripts. All data materials could only be accessed by the local study researchers.

As for the survey, no directly identifiable data were collected, and participants could stay completely anonymous.

Statistical analysis

Qualitative data analysis

We performed deductive direct content analysis (16), using the CFIR (12) to code the interviews and focus group transcripts. Transcripts were coded independently by both BS and MS. After two independently coded transcripts, an interim consensus procedure followed, to ensure inter-coder agreement. After which both coders continued independently coding all transcripts, followed by an extensive consensus process, leading up to the final codes. Coding was performed in MaxQDA 2022 (VERBI Software, 2021).

To match the barriers to implementation of AI algorithms in healthcare to implementation strategies, we used the ERIC tool (13).

Quantitative data analysis

The survey was conducted using Phase Zero (Phase Zero Software, 2021). The cohort of participants was described using means and medians when appropriate. The answers to the survey questions were reported using counts and percentages. Some questions were not answered by all participants. The number of answers and total number of responses are presented with all results.

Results

We first conducted ten individual interviews with physicians, and one focus group with five physicians. Interim analyses showed data saturation was reached after these interviews and the focus group, as no novel information emerged. *Table 1* reports demographic characteristics per interview- and focus group participant. The total sample consisted of 15 physicians, 33% of whom were female, with a median age of 40 (IQR, 34–45). The most prominent constructs identified during the qualitative interim analyses were incorporated in the nationwide survey. The demographic characteristics of the 106 survey respondents are presented in *Table 2*. Most respondents were aged between 31 and 40 (49%), they had a median of 9 years of experience (IQR, 3–17), and were mostly associated with Internal Medicine (77%).

Figure 1 shows a word cloud of CFIR constructs, coded based on the interview and focus group data (minimum frequency of 2). In the following section we will elaborate on the relevant CFIR constructs. Some CFIR constructs were rarely or never coded. Therefore, they were deemed irrelevant to the topic and are not included in the results. For constructs which were also addressed in the survey, the qualitative data were enriched by the corresponding quantitative data.

Intervention characteristics—evidence strength

Interviewed physicians found evidence strength an

Table 1 Demographic characteristics of the interview and focus group participants

Participant No.	Age, years	Sex	Specialty	Experience level
Interview				
1	33	Female	Internal Medicine	Resident
2	43	Female	Internal Medicine	Specialist
3	31	Female	Microbiology	Researcher
4	37	Male	Emergency Medicine	Specialist
5	60	Male	Internal Medicine	Specialist
6	43	Female	Internal Medicine	Specialist
7	33	Male	Emergency Medicine	Specialist
8	35	Male	Microbiology	Resident
9	38	Male	Internal Medicine	Resident
10	28	Male	Intensive Care	Resident
Focus group				
1	47	Male	Internal Medicine	Specialist
2	54	Male	Internal Medicine	Specialist
3	51	Male	Microbiology	Specialist
4	40	Female	Internal Medicine	Specialist
5	43	Male	Emergency Medicine	Specialist

important facilitator, although they did not agree on the type of evidence that would be sufficient. Some voiced that comprehensive retrospective and prospective validation of an algorithm would be sufficient, while others wouldn't settle for less than a high impact intervention study: *"conduct a rigorous study and publish in [high impact journal] that will be adopted worldwide."*—physician in interview 7, hereafter I7. All interviewed physicians agreed that an internationally published RCT indicating the AI tool X led to better outcomes for patient category Y would provide the best evidence and could facilitate AI implementation by enhancing trust: *"a randomized study would be a good result. That way you'll have to accept that AI has added value."*—I4, and: *"building trust in an AI algorithm has to be based on scientific research."*—I5.

There was no consensus regarding which study outcomes should be pursued in such a trial to best facilitate implementation. Some interviewed physicians considered cost-effectiveness and/or process optimization valuable outcomes, whereas others would only be willing to deploy AI if evidence shows benefits on patient outcomes.

To study the potential benefits of AI that would be considered valuable by a large population of physicians, we asked the survey participants to rank the following topics according to importance: cost-effectiveness, work process optimization, and patient outcomes. Surveyed physicians most often ranked these items in the following order of importance: patient outcomes, work process optimization, and cost-effectiveness (56/105; 53.3%). Some found costs to be more important than work processes, ranking them: patient outcomes, cost-effectiveness, and work process optimization (25/105; 23.8%). Among those who selected a ranking in which patient outcomes were not the most important potential benefit, the most common selection was: work process optimization, patient outcomes, and cost-effectiveness (17/105; 16.2%).

Intervention characteristics—relative advantage

To evaluate the potential benefits of AI, many interviewed physicians compared AI to their current practice. Often, AI was compared to the brain of a medical specialist, and put forward as both an influential facilitator and barrier. Some interviewed physicians argued that healthcare professionals

Table 2 Demographic characteristics of the survey participants (n=106)

Characteristic	Value
Age, years, n (%)	
18–25	2 (1.9)
26–30	16 (15.1)
31–35	26 (24.5)
36–40	26 (24.5)
41–45	15 (14.2)
46–50	5 (4.7)
51–55	6 (5.7)
56–60	5 (4.7)
61–65	5 (4.7)
Specialty, n (%)	
Internal Medicine	82 (77.4)
Microbiology	15 (14.2)
Intensive Care	3 (2.8)
Emergency Medicine	3 (2.8)
Orthopedics	1 (0.9)
Pulmonology	1 (0.9)
Other	1 (0.9)
Experience with AI*, n (%)	
None	25 (23.6)
Clinical use	17 (16.0)
Research use	18 (17.0)
Research development	22 (20.8)
Personal interest	42 (39.6)
Use in daily life	44 (41.5)
Clinical experience, years, median [IQR]	9 [3–17]

*, total exceeds 100% since multiple answers were possible (except when "None" was selected). Totals per question may not add up to the total of 106 participants, as some questions were not answered by all participants. AI, artificial intelligence; IQR, interquartile range.

Figure 1 Code cloud of all CFIR constructs mentioned during the interviews and focus group discussion. CFIR, Consolidated Framework for Implementation Research.

AI has relative advantage over experienced healthcare professionals. However, for the less experienced physicians, AI was thought to be beneficial: "*old-school physicians are like encyclopedias, they see a patient and instantly know what is wrong. (..) Less experienced physicians do not have the benefit of this pattern recognition due to less experience. For them, AI can be useful.*"—focus group.

Relative advantage can also be a facilitator, as some interviewed physicians voiced that the ability to analyze complex data, endless opportunities for combining data, and the speed that AI is capable of, could never be reached by the human brain. For example: "*[AI] establishes links that we cannot establish. The computer associates observations, and is less dependent on cause-effect. So when we as physicians cannot consider a logical solution because of this dependency, the model can actually draw logical conclusions.*"—focus group, and: "*we figure things out after three hours, while AI could figure it out within the first hour.*"—I4.

Intervention characteristics—adaptability

The adaptability of an AI algorithm has two important aspects for the interviewed physicians. An algorithm has to be adaptable to their patient population (regarding predictive performance), and be easy to integrate with existing workflows.

Currently, adaptability is a barrier as many interviewed physicians tend to believe an algorithm would not be applicable to their patients, even when it is validated in their specific patient population. A few examples: "*I would be stubborn, (…) and think: this is not applicable to my patient.*"—focus group, "*you would worry about this, even though you know*

base their decision making on certain aspects which are hard to capture in algorithms: "*the computer has not seen that patient, and I have.*"—I1, and: "*The gut feeling [that physicians have], (…) is intangible and not easily measurable. You cannot put that in an algorithm.*"—I2. They see this as barrier for implementing AI, as they do not believe

[the algorithm] has really been researched in this population."—focus group, and: "*I need to know how my patients fits into the picture.*"—I1.

Intervention characteristics—trialability

An important facilitator for sustainable implementation of AI is trialability. All interviewed physicians argued that having a trial-and-error phase to get used to an algorithm, and compare the outcomes of an algorithm to their own clinical decision making, would enhance trust. An example from I10: "*Look, everybody is talking about AUC's and how well [their algorithm] performs etc. But, in the end of the day, that does not show me what it adds in clinical practice. It needs to be implemented, it needs to be tangible. You need to see for yourself what it adds. (…) You need time to learn to trust the algorithm.*". Another example is: "*I want to see an algorithm work in practice. To be able to work with it, and know exactly how it operates. I need to build trust. (…) If we can try an algorithm for a while, we can quickly see the benefits*"—I4.

Similar results were found during the survey. When asked whether the surveyed physicians would trust an algorithm more if they would first be able to use it next to their own judgement, 76/106 (71.7%) agreed or strongly agreed, while just 18/106 (17.0%) disagreed or strongly disagreed.

Inner setting—structural characteristics

Structural characteristics (e.g., the social architecture or maturity of an organization) also play a role during the implementation of AI algorithms in healthcare. Although all interviewed physicians believed AI has some value in healthcare, they were not unanimously convinced that the traditional character of hospitals in general is well suited to its implementation in the short term: "*hospital care is highly conservative. We as physicians are highly conservative. So, I don't know whether [implementation of AI] will go fast to be honest.*"—I9.

Inner setting—tension for change

Tension for change, either positive or negative, was one of the most influential constructs on implementation of AI algorithms in healthcare. Some interviewed physicians did not feel the need for AI algorithms, because they rather continue working in the status quo. They explain that they learned certain ways of diagnosing/treating patients during

medical education, which has become a behavioural habit that is hard to deviate from: "*it is habit. We are used to doing things a certain way. It is hard to learn something new. It has to do with trust also. Because you trust the things you already do, but if you need to implement something new you need time in order to trust such an algorithm.*"—I1. Another example was voiced by the physician in I10 about the blood culture algorithm: "*I could definitely accept that prediction, because 1% is a low chance so then we won't perform the blood culture because that would be unnecessary care. But, it is so deeply rooted in our workflow, so actually I would still just perform the blood culture.*".

However, many interviewed physicians did see potential value of using in AI algorithms in healthcare: "*there sure is room for improvement [in ED diagnostics], AI could play a very important role in this.*"—I4, and: "*modern physicians need to be open to the idea that computers might perform better than they do (…). We only have experience of a couple of years, while the computer could have experience of thousands of human years.*"—I5.

For the interviewed physicians, the potential benefits of AI in healthcare lie within process optimization, time-efficiency, cost-efficiency, and enhanced patient-centeredness, patient safety, and quality of care, as voiced by I7: "*for example at the ED, but also at multiple wards. The shortage in nurses is a substantial problem, AI could help with this. But also with regard to timeliness of processes, efficiency, and maybe costs. For example, if you would perform less blood cultures, that would help. That is of course a small example, but you could broaden the scope. I think [AI] could have value in many different areas.*". Another example is: "*you could see more patients: perform the same work with less staff. That way you can spend more time on each patient, that is very important. Patients currently get way too little time with physicians. Especially on the wards, they lie in bed for 24 hours and the physician comes to see them for 5 minutes. That is too little. While the patient and their families have many questions, and need for conversation. If we would gain more time for these things, that would be golden.*"—I9.

Since the qualitative results showed that interviewed physicians can feel tension for change, but that this could be both a barrier and a facilitator, we asked the survey participants specifically how they felt about our blood culture prediction tool. In 81/104 (77.9%) answers, the surveyed physicians agreed or strongly agreed that the use of our AI algorithm for blood culture indication could add value, while just 7/104 (6.7%) disagreed or strongly disagreed.

Inner setting—compatibility

Another influential construct is compatibility. Interviewed

physicians found it important that AI algorithms are implemented to support their clinical decision making, while they keep their autonomy (to overrule an algorithm) and the responsibility for their patients. In other words, AI algorithms need to be compatible to existing workflows and decision-making and enhance/support this, as opposed to taking them over completely. For example: *"in the end the physician or nurse decides what they adopt from the algorithm. But keeping that autonomy is very important."*—I10, *"I think [AI] can be of value and support us, but we shouldn't just blindly trust it."*-I1, and: *"[AI] should become some sort of advice, and not an obligation. Because, well, advices are there to sometimes not be followed."*—I7.

All interviewed physicians believed that the responsibility for patient outcomes is always that of the physician, regardless of whether they followed or deviated from the algorithm: *"the physician has the final responsibility. For example when it comes to a medical disciplinary court, the computer is not the one to get the reprimand."*—I5.

Inner setting—access to knowledge and information

To enable trust in AI algorithms and facilitate proper implementation, the interviewed physicians felt they need access to knowledge and information about the algorithm. More specifically, they voiced the need to be informed regarding: the overall evidence, the data used (which patient populations and variables), the validation, how it operates, and how this translates to their clinical practice. This is particularly evident for highly complex algorithms. Examples are: *"I would like to receive some sort of package: what is the rationale, what are the studies, which datasets is it developed and trained in, what is the aim."*—I6, and: *"of course AI can sometimes be challenging to explain. So you have to take end-users by the hand. I think it is most important that we understand how the model is functioning in practice."*—I3. Another example is periodic feedback information to end-users: *"to show results and effects of the AI based decisions periodically. This way we can create trust in the algorithm."*—I3. In addition, some interviewed physicians felt that they would sooner use decision support provided by algorithms when they understand how the predictions are made. An example is: *"But if I would understand why it would predict a certain outcome, then I would be more inclined to consider whether I would or would not use it."*—I1.

In the survey, we followed-up with this frequently mentioned construct and asked how surveyed physicians would like to be informed about future AI algorithms.

There was a clear preference for information integrated in the existing workflow (41/106; 38.7%) [e.g., in the EHR system where the algorithms is implemented), or frequent reminders and presentations during handover moments and teaching sessions (41/106; 38.7%)]. Documentation stored in separate systems, or training periods prior to implementation were less favoured with 11/106 (10.4%) positive answers each. When asked specifically how the participants would prefer AI algorithm outputs to be presented, there was no clear preference for absolute risk percentages (31/106; 29.2%), binary suggestions to take or not take a certain action (37/106; 34.9%), or risk categories (38/106; 35.8%).

Characteristics of the individual—knowledge and beliefs about the innovation

Knowledge and beliefs about AI algorithms in healthcare was also one of the most influential constructs. There was a wide variation of attitudes, values, familiarity with facts, etc. related to AI algorithms both between and within individual interviewed physicians. Even though there was this wide variation, many interviewed physicians voiced to have little to no prior experience with AI, especially not in their clinical work: *"Maybe there are algorithms that play a role in my life. But I don't use them myself. No, not at all."*—I9.

During the nationwide survey, 25 out of 106 (23.6%) surveyed physicians shared the belief that they had never come into contact with an AI algorithm, either in their work or outside.

Worst case scenarios

To identify out of the box barriers, additional to the CFIR constructs, we asked interviewed physicians about potential worst case scenarios in the clinical use of AI. Interviewed physicians mostly worry about adverse outcomes for patients, i.e., delayed or wrong diagnosis, suboptimal treatment, inappropriate discharge, or even death. The physician in interview 4 voiced: *"harm to the patient. Like missing an important diagnosis, that has major negative outcomes for the patient. This could turn into a complication or even adverse event."*.

Other worst case scenarios were regarding the professional stature of physicians. This includes that deployment of AI could lead to losing their job altogether, lose the enjoyable aspects of the job, or to become a 'lazy' physician. For example: *"if all you have to do is follow the [AI]*

model you don't have to go to medical school. Then you will just sit behind your desk and approve everything [the AI model predicts]. That would be completely worthless. At least for the physician. Although maybe it would be better for patient care." (I10).

The survey results do not fully match the findings from the qualitative part of the study in this instance. When we asked surveyed physicians whether they were worried that AI would take over the enjoyable and interesting parts of job, 74/105 (70.5%) disagreed or strongly disagreed, while just 14/105 (13.3%) agreed.

Implementation strategies—ERIC tool

We used the CFIR to identify potential barriers to implementation of AI algorithms in healthcare, and then linked these barriers to implementation strategies using the ERIC tool. We included all nine CFIR constructs that are described above, leading to a top 3 of the following implementation strategies: *identify and prepare champions* (cumulative percentage: 280%); *conduct educational meetings* (258%); *promote adaptability* (235%). Two other important strategies are: *develop educational materials* (153%) and *distribute educational materials* (149%), due to their high individual endorsement percentages. For the total output of ERIC strategies, see Appendix 3.

Discussion

This study identified barriers and facilitators to AI implementation in clinical practice. Through individual interviews and a focus group with end-users (physicians), we found nine CFIR constructs important to AI implementation: evidence strength, relative advantage, adaptability, trialability, structural characteristics, tension for change, compatibility, access to knowledge and information, and knowledge and beliefs about the intervention (12). When linking these constructs to implementation strategies using the ERIC tool, we found that the following strategies should be used for AI implementation: identify and prepare champions, conduct educational meetings, promote adaptability, develop educational materials, and distribute educational materials (13).

AI has the potential to change medicine through its ability to augment clinical decision-making by detecting subtle patterns in vast amounts of patient data, and do so tirelessly for 24 hours a day. To reach this potential, physicians need to see the *relative advantage* of integrating AI in their current practice, and feel a *tension for change*. In general, physicians

acknowledge the potential value of AI in healthcare, which is a facilitator for implementation. However, physicians in our study expressed that current behavioural habits and standard practices are hard to deviate from. To create new norms and behaviour, we need to go beyond sole awareness creation (17). As highlighted by the ERIC tool, local champions are the key to success in this process. One needs committed local leaders to inspire and actively remind others to use a specific AI tool. Lasting change and sustainable implementation of AI can then be achieved through several key CFIR constructs. Firstly, *evidence strength* is important, because physicians view a peer-reviewed and internationally published article as a facilitator to AI implementation. As described in the introduction section, there are many published papers on AI algorithms, but these are neither implemented nor deployed in clinical practice (10). This suggests that an international publication in itself is not sufficient for sustainable implementation. In addition, *access to knowledge and information* about the algorithm is essential. This was one of the most prominent CFIR constructs in our study. *Access to knowledge and information* about an AI algorithm can be realized through the following ERIC implementation strategies: *conduct educational meetings*, *develop educational materials*, and *distribute educational materials*, which can be expedited by local champions. Hence, to provide physicians with digestible information regarding an AI algorithm, it is important to develop a toolkit with manuals and other supporting material, to distribute these toolkits, and explain and educate further in meetings (13). Our data shows that physicians favour the following information in their toolkit: overall evidence, the data used, the validation, how it operates, and how this translates into clinical benefits. Both qualitative and survey data display that physicians prefer their source of knowledge and information integrated in the existing workflow, e.g., EHR system. This is in line with the CFIR construct *adaptability*, and ERIC strategy *promote adaptability* (18). Moreover, integrating AI in the EHR will promote sustainable implementation (19,20). Besides adapting AI to existing workflows, it is necessary to provide physicians with information regarding how well an AI algorithm is adapted to their patient population. We found that physicians tend to expect that a certain algorithm does not apply to 'their' patient, even when the algorithm has been validated in similar patients. This could be due to frequency bias in physicians, leading to the belief that the frequency of patients that will fall within the small margin of error of the algorithm (and therefore lead to a wrong prediction) is much higher than it actually is. Moreover, even though evidence-based medicine is considered the gold standard in clinical

reasoning, the review by Nicolini *et al.* show the importance of local -context and knowledge for physicians when making clinical decisions, and how this is usually valued more than evidence from research (21). This could be overcome by *access to knowledge and information*, and *trialability* (22). Trust is another important dynamic in the interaction between AI and end-users, which has been well-studied in the literature. Factors such as explainability, transparency, and interpretability seem to be key to facilitate adoption (23). Our study further adds that physicians need a trial-and-error phase in implementation to experience these factors themselves, which has been described before (22). Besides increased trust, this will allow physicians to gain expertise with the algorithm, experience clinical benefits for patients, and will help further refinement and adaptation (24). Trialability also fits within the cycle of 'plan-do-study-act', which is a tool widely used in healthcare for quality improvement (25). The broad *range of knowledge and beliefs* regarding AI underpins the importance of *trialability* and *access to knowledge and information*. Lastly, *compatibility* emerged as a primary construct which may form a barrier to AI implementation. When end-users view an intervention as threat to their autonomy, it is less likely that implementation will be successful (12). In our study, physicians feel strongly about retaining their autonomy. They argue that they should always have the final responsibility over the patients, even when AI algorithms influence their decision making. Therefore, it is important for physicians to be able to deliberately deviate from the AI recommendations, like they can do with general clinical guidelines.

The results of this study should be interpreted in the light some limitations. Firstly, the interviewees and participants of the survey were mostly physicians from the Internal Medicine, Emergency Medicine, and Microbiology departments. However, we still feel these results are generalizable to a broader group of physicians, since most questions were not specialty dependent, and some of the themes we found have been described in other cohorts before (22). Still, it would be helpful to tailor any implementation of an AI tool to the local context and end-users, for which additional surveys and interviews in those settings are needed to confirm the generalizability of our results. Secondly, it could be possible that the survey was subject to self-selection bias, i.e., the physicians who chose to respond to the survey might have differed from the group of physicians that chose not to respond. Lastly, in our survey we included n=106 participants. We did not perform a-priori power calculation, as it was not feasible to make assumptions about effect sizes due to the novelty of the studied subject. It is therefore challenging to make a statement regarding the representativeness of our sample size. However, we do believe that this sample size is sufficient to ensure a range of variety in the participants.

Conclusions

The healthcare industry has been slow to adopt AI algorithms. We identified several widely endorsed constructs important to AI in healthcare and linked them to appropriate implementation strategies. Though the potential value of AI in healthcare is acknowledged by end-users (physicians), the current tension for change is insufficient to facilitate implementation and adoption. The tension for change can be sparked by conducting educational meetings, and developing and distributing educational materials to increase access to knowledge and information. Committed local leaders are indispensable to expedite this process. Moreover, a trial phase in which physicians can test the AI algorithms and compare them to their own judgement, may further support implementation. Finally, AI developers should try and tailor their algorithms to be both adaptable and compatible with the values and existing workflows of the users. As physicians have the final responsibility for the patient, they should be able to overrule any decision of the algorithm and keep their autonomy. Applying these appropriate implementation strategies will bring us one step closer to realizing the value of AI in healthcare.

Acknowledgments

Footnote

Reporting Checklist: The authors have completed the COREQ reporting checklist. Available at https://jmai.amegroups.com/article/view/10.21037/jmai-22-71/rc

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Appendix 1 Topic list—implementation AI. AI, Artificial Intelligence.

Topic list – implementation AI

Introduction
Do not record audio
- ➤ Introduction of interviewers
- ➤ Aim of study
- ➤ Procedure interview

Baseline
Do not record audio
- ➤ Introduction of participant
- ➤ Sex
- ➤ Age
- ➤ Medical specialty
- ➤ Experience level

TOPIC LIST
Start recording audio

Prior knowledge/opinion AI
Our definition of AI is: 'the use of complex algorithms and software to simulate human cognition.
- ➤ How would you describe your experience with AI?
- ➤ In what context was this
  - o Research
  - o Education
  - o Clinical practice
- ➤ What is your opinion on the use of AI in healthcare?
- ➤ What is the most important potential of AI in healthcare?
- ➤ What is the most important problem of AI in healthcare?

Case vignette
Start off with a short explanation of our prediction model, the context in which it can be used. Then explain that the case vignette will be used to gather the opinions about the use of our model, and that there are no right or wrong answers.

Read case vignette to participant + hand the case vignette to participant on paper (see below)
- ➤ What is your first impression of the case that was just drawn?
- ➤ Would you perform blood cultures for this patient?
  - o If yes: why?
  - o If no: when would you?

We developed a prediction model and implemented it in EPIC. It takes the values that are known for this patient, and predicts whether the blood culture will come back positive or not. For this patient the model predicted that the blood culture will come back negative, and you will be advised not to perform the blood culture.
- ➤ To what extent would/wouldn't you trust this prediction?
- ➤ Would you take this prediction into consideration regarding:
  - o Performing the blood culture

- o Starting antibiotic treatment
- ➤ Would your way of thinking or acting be influenced if the prediction is presented differently? For example in percentages/risk groups/positive vs negative?
  - o What is needed to optimize this?

Barriers

The next questions are not specifically about the case, but about AI in healthcare in general.

- ➤ Which barriers do you foresee regarding working with an AI model in your clinical practice?
- ➤ What would be needed to remove these barriers?
- ➤ In case of multiple barriers: how do these barriers relate to each other/prioritizing?
- ➤ What would be a worst case scenario when using an AI model in your clinical practice?

Facilitators

- ➤ Which factors would facilitate working with an AI model in your clinical practice?
- ➤ What would be needed to sustain these facilitating factors?
- ➤ In case of multiple facilitating factors: how do these barriers relate to each other/prioritizing?
- ➤ What would be an ideal situation when using an AI model in your clinical practice?

Implementation

- ➤ What does the future with regards to AI in healthcare look like?
- ➤ Who could make use of AI models in clinical practice?
  - o Medical specialists only?
  - o Also other physicians; residents etc.?
  - o Also other healthcare providers; nurses, etc.?
  - o The patient?
- ➤ Who would be end responsible for the outcome when using AI in healthcare?
- ➤ What would be the most important factor for sustainable implementation of AI in healthcare?

Closing question

Is there anything that you would like to share, that has not been discussed yet?

CASE VIGNETTE

Age: 64
Sex: man

Past medical history
Type 2 Diabetes
Hypertension
COPD

Medication use at home
Metformin (3x 500mg)
Perindopril 1dd 8mg
Amlodipine 1dd 10mg
Spiriva 1dd

History
The patient experienced pain in the lower abdomen last night. During the night, the patient developed a fever of 39.5 degrees Celsius, and he collapsed when getting out of bed. The patient has no history of diarrhea or vomiting, has not experienced any chills, and he does not cough more than usual.

Vital signs
Heartrate: 106/min
Blood pressure: 115/76 mmHg
Respiratory rate: 21/min
Temperature: 38.9 degrees Celsius
Saturation: 93% on room air
EMV max

Lab results
CRP: 40
Leukocytes: 14
Sodium: 142
Potassium: 4.1
Creatinine: 98

Microbiology
No previous culture results are available.

AI in clinical practice

Implementing Artificial Intelligence in Clinical Practice

Thank you for considering participating in this survey. It will take approximately 5 minutes to complete.

Participant information

We kindly ask you to participate in a survey on the use of artificial intelligence (AI) in clinical practice. Researchers have developed many AI tools for healthcare, but few have made it into practice. We suspect the low adoption rates may result from the fact that the end-user (you) is rarely involved in these projects. In preceding interviews and focus group discussions, we identified several barriers and facilitators to implementing AI. With this survey, we aim to quantify further the importance of these barriers and facilitators on a larger scale.

1. Do you consent to participating in this survey?

○

Yes ○

No

2. Do you ever order or process blood cultures as part of your medical practice?

○

Yes ○

No

2. What's your age?

Please select one category:

○

18-25 ○

26-30 ○

31-35 ○

36-40 ○

41-45 ○

46-50 ○

51-55 ○

56-60 ○

61-65 ○

>65

Required Field

3. What is your main specialty?

Selecteer er één

○

Emergency Medicine ○

Intensive Care ○

Microbiology ○

Internal Mediine ○

Longgeneeskunde ○

Gastro-enterology ○

Reumatology ○

Urology ○

Geriatrics ○

Neurology ○

Surgery ○

Orthopaedics ○

Gynaecology ○

Other

Required Field

4. How many years of experience do you have in that specialty (including residency)?

Please type a number here:

Required Field

Let's now talk about how your experience with Artificial Intelligence (AI)

For our definition, we think that AI entails the use of complex algorithms and software to emulate human cognition.

5. In what context have you ever come into contact with AI?

Select all that apply (except for when the final answer is selected).

☐

I have used AI in clinical practice ☐

I have used AI in research ☐

I have developed an AI algorithm myself ☐

I am interested in AI and read about it ☐

I come into contact with AI in my daily life ☐

I have never come into contact with AI

6. AI implementation in clinical practice could lead to cost effectiveness, improved workflows, and improved patient outcomes. Which of these benefits is most important to you?

Rank the items in order of importance (1 = most important; 3 is least important)

○

1. Cost effectiveness; 2. Patient outcomes; 3. Workflow ○

1. Cost effectiveness; 2. Workflow; 3. Patient outcomes ○

1. Workflow; 2. Cost effectiveness; 3. Patient outcomes ○

1. Workflow; 2. Patient outcomes; 3. Cost effectiveness ○

1. Patient outcomes; 2. Cost effectiveness; 3. Workflow ○

1. Patient outcomes; 2. Workflow; 3. Cost effectiveness

7. I would only trust an AI algorithm after I can first use it next to my own clinical judgement, to experience and judge the performance before fully adopting it.

○

Strongly disagree ○

Disagree ○

Neutral ○

Agree ○

Strongly agree

8. I worry that AI algorithms will take over the enjoyable parts of my wok in the future.

○

Strongly disagree ○

Disagree ○

Neutral ○

Agree ○

Strongly agree

The final questions will be specifically about our AI algorithm, which predicts the outcomes of blood cultures in the emergency department (ED)

9. I feel the number of blood cultures we draw in the ED is:

○

Very low ○

Low ○

Adequate ○

High ○

Very high

10. What percentage of the blood cultures drawn in the ED in the Netherlands do you think will turn out to be positive (disregarding contamination)?
Please provide a number between 0-100.

Imagine you are consulting on a patient in the ED and decide to order a blood culture. Is that really needed for that specific patient?

Our research group has developed an AI algorithm which predicts the outcomes of blood cultures drawn in the ED. The final questions are specifically about this scenario.

11. I see the added value of using such an algorithm to better use blood culture testing in the ED.

○

Strongly disagree ○

Disagree ○

Neutral ○

Agree ○

Strongly agree

12. I would like to learn about the algorithm and its use through:

○

An optional explanation when using the algorithm in the electronic health records ○

Separate documents on the hospital's intranet ○

Presentations during handovers and educational meetings ○

A training period, in which the research team is present on the floor to answer questions

13. I would like to see the algorithm's prediction for the individual patient as: ○

Categories: low, intermediate, or high risk of a positive blood culture ○

Absolute risk: the percentage change of a positive blood culture ○

Binary outcome: the recommendation to do or withhold blood culture testing

Appendix 3 Total output of ERIC strategies in Excel. ERIC, Expert Recommendations for Implementing Change

ERIC Strategies	Cumulative Percent	Evidence Strength & Quality	Relative advantage	Adaptability	Trialability	Structural Characteristics	Tension for Change	Compatibility	Access to knowledge & information	Knowledge & Beliefs about the Intervention
Identify and prepare champions	280%	41%	45%	23%	12%	27%	48%	21%	24%	40%
Conduct educational meetings	258%	47%	24%	12%	8%	5%	17%	10%	79%	56%
Promote adaptability	235%	3%	24%	73%	27%	23%	17%	45%	7%	16%
Assess for readiness and identify barriers and facilitators	235%	13%	24%	31%	35%	36%	35%	34%	7%	20%
Conduct local consensus discussions	224%	41%	24%	31%	8%	14%	43%	41%	10%	12%
Capture and share local knowledge	205%	25%	17%	35%	23%	23%	13%	14%	31%	24%
Conduct local needs assessment	201%	3%	34%	35%	19%	18%	43%	21%	3%	24%
Inform local opinion leaders	195%	38%	28%	15%	23%	14%	39%	3%	7%	28%
Conduct cyclical small tests of change	176%	3%	31%	23%	38%	23%	4%	38%	3%	12%
Tailor strategies	162%	6%	17%	35%	23%	18%	13%	38%	0%	12%
Create a learning collaborative	159%	16%	7%	23%	12%	18%	9%	14%	45%	16%
Identify early adopters	158%	22%	17%	27%	15%	23%	13%	10%	10%	20%
Develop educational materials	152%	28%	14%	12%	0%	0%	0%	3%	59%	36%
Distribute educational materials	149%	31%	10%	12%	12%	0%	13%	0%	55%	16%
Build a coalition	127%	6%	14%	15%	15%	27%	9%	21%	3%	16%
Facilitation	124%	0%	10%	27%	23%	9%	0%	24%	10%	20%
Conduct educational outreach visits	124%	34%	10%	12%	8%	0%	4%	0%	28%	28%
Visit other sites	118%	13%	21%	19%	12%	5%	13%	10%	14%	12%
Model and simulate change	104%	3%	10%	19%	31%	14%	13%	3%	7%	4%
Alter incentive/allowance structures	97%	3%	28%	0%	0%	18%	22%	10%	0%	16%
Stage implementation scale up	92%	3%	10%	0%	27%	14%	4%	10%	3%	20%
Develop a formal implementation blueprint	86%	0%	7%	8%	19%	18%	13%	3%	14%	4%
Organize clinician implementation team meetings	86%	3%	14%	8%	8%	14%	9%	14%	14%	4%
Use an implementation adviser	86%	6%	7%	8%	23%	5%	13%	10%	14%	0%
Provide local technical assistance	78%	3%	0%	4%	15%	18%	0%	14%	24%	0%
Audit and provide feedback	78%	13%	10%	4%	15%	5%	17%	7%	3%	4%
Provide ongoing consultation	78%	9%	3%	8%	19%	9%	4%	3%	17%	4%
Purposely reexamine the implementation	76%	6%	7%	12%	15%	0%	4%	28%	0%	4%
Facilitate relay of clinical data to providers	72%	6%	10%	4%	4%	0%	22%	3%	10%	12%
Involve patients/consumers and family members	68%	13%	3%	8%	0%	9%	22%	10%	3%	0%
Conduct ongoing training	67%	6%	3%	0%	8%	0%	0%	0%	38%	12%
Fund and contract for clinical innovation	62%	0%	14%	0%	8%	14%	9%	10%	3%	4%
Increase demand	61%	0%	24%	4%	0%	0%	13%	0%	0%	20%
Use advisory boards and workgroups	60%	9%	10%	4%	8%	5%	13%	3%	0%	8%
Develop academic partnerships	60%	25%	0%	0%	4%	5%	4%	0%	10%	12%
Shadow other experts	59%	3%	3%	12%	4%	5%	4%	3%	21%	4%
Use data experts	57%	6%	10%	8%	12%	0%	17%	0%	0%	4%
Promote network weaving	57%	0%	3%	4%	0%	23%	4%	0%	10%	12%
Obtain and use patients/consumers and family feedback	48%	6%	7%	4%	4%	5%	9%	10%	0%	4%
Involve executive boards	48%	6%	3%	0%	8%	14%	13%	3%	0%	0%
Change physical structure and equipment	42%	0%	3%	0%	0%	32%	0%	7%	0%	0%
Develop and implement tools for quality monitoring	41%	6%	7%	0%	12%	5%	9%	3%	0%	0%
Work with educational institutions	38%	16%	3%	0%	0%	5%	0%	3%	7%	4%
Recruit, designate and train for leadership	37%	3%	3%	0%	0%	18%	4%	0%	3%	4%