

**Table S4.** Excerpts from studies describing determinants to implementing artificial intelligence-based clinical decision support systems in healthcare with theoretical domains framework (TDF) mappings.

First Author	Excerpt	TDF Domain(s)
Abujaber	<p>“...the epistemic incommensurability between the EBM paradigm, which emphasizes theory-based knowledge, and the data science paradigm, which puts great emphasis on data-driven knowledge. They consider the paradigm incommensurability a key challenge to the willingness of the clinicians to adopt ML in informing their clinical decisions”</p> <p>“They recommended raising awareness as a measure to overcome resistance and to improve adoption. They suggested awareness campaigns to help reduce resistance and enhance knowledge about the potential benefits of adopting the technology to improve adoption.”</p> <p>"There is no formal training in modern analytical techniques in clinical school or healthcare organizations to orientate future clinicians about the use of ML to enhance the quality of clinical decisions [...] Several recent studies have stressed the importance of providing clinicians training and introducing AI in the clinical sciences curricula to prepare the healthcare industry."</p> <p>"...healthcare organizations enabling ML adoption by fostering a climate conducive to collaboration among different disciplines (i.e., clinical researchers, epidemiologists, biostatisticians, data scientists, ML experts, etc.). By achieving this, healthcare organizations can facilitate clinicians' access to data science and ML experts, who can help clinicians and clinical researchers unblock the ML black-box and help them better understand pertinent clinical evidence."</p>	<p>Knowledge</p> <p>Knowledge; beliefs about consequences</p> <p>Knowledge; skills</p> <p>Social influences; knowledge</p>

<p>“... the complexity of ML approaches, lack of procedural transparency, and lack of interpretability increase the ambiguity around the ML, which undermines clinicians' trust in ML outputs and raises questions about accountability for wrong decisions.”</p> <p>"...huge potential of ML and the risk of breaching patients' privacy, confidentiality, and anonymity [...] some scholars argued that the lack of transparency of ML procedures leaves patients with no choices and makes them feel pushed to choose certain treatment options, which jeopardizes the very principle of autonomy."</p> <p>“It is more likely that people will adopt a technology if they have the intention to use it.”</p>	<p>Knowledge; beliefs about consequences</p> <p>Beliefs about consequences; social/professional role and identity</p> <p>Motivation and goals</p>
Ankolekar	
<p>“...clinical guidelines determine the best treatment based on survival chances and that treatment decisions do not change often enough for a CDSS to add value. In addition, they noted that treatment choices are affected by factors, such as the patient's fitness level, so that even if a CDSS provides a prognostic prediction favouring a certain treatment, the clinician would still recommend a treatment based on what the patient can handle”</p> <p>“The lack of large-scale multicenter validation studies made three clinicians wary of using CDSSs in practice. They questioned whether CDSSs based on certain data could be useful in generating predictions for other populations or patients with a different profile.”</p>	<p>Knowledge; social/professional role and identity</p> <p>Knowledge</p>

	<p>“Time constraints were mentioned by two clinicians as a factor that might dissuade their peers from using a CDSS. This included the time taken to use the CDSS itself, such as filling in patient variables into the system, as well as explaining and discussing output in consultations with the patient.”</p>	<p>Memory, attention, and decision processes; environmental context and resources</p>
Baron		
	<p>“...an algorithm providing clinical advice (or even an automated diagnosis or treatment) may be held to a much higher standard than would a person providing the same function. A consequence of this philosophy is that health care systems may choose not to implement decision support systems that fail to reach a standard of perfection for every patient, even when such algorithms could clearly improve diagnostic quality or safety for the population as a whole.”</p>	<p>Knowledge; beliefs about consequences</p>
Bates		
	<p>“One major roadblock is that many EHRs include specific items, such as code status, in as many as 25 different fields, so reconciliation is problematic. Another problem is that EHRs have not generally been designed to allow extraction of real-time data, so that predicting an event, such as sepsis or clinical decompensation, requires setting up a new database. Every organization will need to address issues around data preparation.”</p>	<p>Environmental context and resources</p>
	<p>"Obtaining benefits from CDS in general demands that providers receive suggestions at specific times in their workflow and in ways that will help them make better decisions...In addition to being delivered in a timely way, it is critical how normative a suggestion is, and whether it interrupts the clinician in his/her workflow"</p>	<p>Environmental context and resources; nature of the behavior</p>

"The single most common barrier to the potential use of automated suicide risk-prediction models in routine care was the implication for liability. For example, many were concerned about being held legally responsible if they decided not to hospitalize a patient who was categorized as high risk and then went on to attempt or die by suicide."

Beliefs about  
consequences

"It was also fairly common to express concerns about low data quality in the EHR affecting the quality of model output (i.e., garbage in, garbage out)."

Knowledge

"Another frequent concern was the potential for alerts generated by automated suicide risk-prediction models to increase alert fatigue and, specific to this application, that providers may become desensitized to suicide risk alerts over time."

Emotion

"Providers were also concerned about the potential for such a tool to lead to increased rates of hospitalizing patients in health care systems already facing ED overcrowding and shortages of inpatient beds. The possibility for such a tool to further increase the (currently unmet) demand for outpatient mental health services was often raised, and participants noted that the system must offer additional resources if this tool were implemented. Indeed, some providers emphasized that the usefulness of the tool would depend on what next steps (e.g., interventions or referrals) are available."

Environmental  
context and  
resources

	<p>"Providers strongly believed that such a tool must have a good user interface and user experience to be helpful."</p> <p>"The need to establish clear, standardized workflows for both responding to suicide risk predictions generated by the tool and documenting interactions with the tool was a common theme."</p> <p>"Providers emphasized the importance of receiving systemic training on how to use the tool before it is rolled out clinically, including instruction on whether or not its use is mandatory."</p> <p>"Some requested having information available within the tool on how the algorithm works and key test characteristics (e.g., sensitivity and specificity). [...] Providers also overwhelmingly described an interest in being able to view the specific predictors (e.g., diagnoses, demographic characteristics, and treatment attendance) that contribute to an individual patient being identified as high risk for suicide via the model."</p>	<p>Memory, attention, and decision processes</p> <p>Nature of the behavior</p> <p>Skills; nature of the behavior</p> <p>Knowledge</p>
Benza		
	<p>"Our interviews suggest physicians require interpretable models and should be contextualized with traditional statistical calculators and the changes of patient risk over time. By visualizing such information, physicians also believe, in addition to prognosis, such tools can serve as a useful communication tool for patients."</p>	<p>Knowledge; social/professional role and identity</p>
Braun		
	<p>"In order to gain the trust of clinicians, AI should be user-friendly and based on adequate risk-benefit analyses."</p>	<p>Memory, attention, and decision processes;</p>

	<p>beliefs about consequences</p> <p>“Patients expect that AI enhances the care they receive, preferably without removing the clinician from the decision-making loop in order to maintain human interaction and interpersonal communication with a clinician who is in a position to evaluate the outputs of the system and to compare them with judgements arising from her own professional experience and training.”</p> <p>Social/professional role and identity; social influences</p> <p>“As with other data-intensive applications, adherence to data protection and privacy requirements such as the general data protection regulation (GDPR) will be essential. Moreover, it will be important that legally adequate levels of risk are being clarified beforehand in order to enable legal security for relevant actors and to give potential victims of damages the possibility to address transgressions of these risk levels.”</p> <p>Beliefs about consequences</p> <p>“...one specific epistemic challenge of AI-driven clinical DSS is transparency [...] despite these possible benefits, there remains a fundamental challenge which is discussed under the term of (epistemic) opacity. While the logic of simple algorithms can be fully comprehensible, the kinds of algorithms that tend to be relevant and useful towards practical applications are more complex. [...] The grounds on which the algorithm provides a particular classification or recommendation in a specific instance are bound to be opaque to designers and users, especially since it also depends on training data and user interactions.”</p> <p>Knowledge</p>
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	<p>“...since a plurality of agents contributes to decision-making guided by AI-DSS, it becomes less clear who is morally and legally answerable in which ways. With the involvement of autonomous, adaptive and learning systems, it becomes harder to ascribe individual responsibility and liability for singular decisions, especially those with adverse outcomes. [...] In the clinical setting, this raises a need for frameworks on medical malpractice liability resulting from deploying AI-DSS.”</p>	Beliefs about consequences
Buck		
	<p>“...participants expressed existential anxiety connected with AI-enabled systems as they perceive that this technology can take over some of their tasks. [...] This concept included the fear of no longer being useful and being replaceable by AI-enabled systems and the worry of losing their unique status as physicians.”</p> <p>“Participants mentioned the impairment of the physician–patient conversation through the use of technology as threatening to the physician–patient relationship. The concern is that, by using AI-enabled systems during patient consultations, a GP cannot devote all their attention to the patient sitting in front of them, but instead must also focus on the screen to follow an AI-enabled system’s recommendations. [...] concerned that AI-enabled systems would generally reduce physician–patient contact, which is a core component of GP care and is inevitable for successful treatment and patient care.”</p> <p>“Most participant statements that expressed demands of AI-enabled systems contributed to the minimum requirement of time efficiency. GPs need AI-enabled systems to be fast and easy to use, as they have limited time for each patient consultation. [...] Also, participants stated that AI-enabled systems must not take additional time, as this would keep a physician from performing essential tasks.”</p>	<p>Social/professional role and identity; beliefs about consequences</p> <p>Beliefs about consequences; social/professional role and identity; memory, attention, and decision processes</p> <p>Memory, attention, and decision processes; environmental</p>

	context and resources
<p>" Another environmental influence was stakeholder influences, which indicated how certain groups of people and organizations influence GPs' opinions. The interviews revealed that patients and institutions are key stakeholders in this context. [...] GPs place trust in these institutions and regard them as scientific and validated committees of their profession (participant 11). Supported by the fact that physicians wish to receive more recommendations on which technologies they should use in practice, the influence of these institutions' attitudes is evident."</p>	Social influences
<p>"In the event of technical problems, AI-enabled systems cannot be used properly or at all, which can undermine optimal patient care. Physicians are skeptical about AI-enabled systems in this regard and prefer the established ways of performing their routines, as they cannot rely on the overall infrastructure, which needs integration of AI technologies to function properly."</p>	Environmental context and resources; beliefs about consequences
<p>"...diagnostic quality was mentioned as another key requirement of AI-enabled systems. For physicians to consider the use of AI-enabled systems, the AI-enabled system must be validated, must not make mistakes, and must provide accurate diagnoses so that there is no threat to patient care. [...] In addition, AI-enabled systems must be evidence-based and must follow guidelines."</p>	Knowledge



	<p>“Participants also named guaranteed data security as a requirement for using AI-enabled systems. The physicians justified this requirement with concerns about privacy and misuse of data and they do not want patient and physician data to be accessible to anyone.”</p> <p>“... the participants expressed their willingness to use AI-enabled systems based on how the technology is financed and stated that the cost–benefit ratio must be consistent.”</p> <p>“Transparency and thus the comprehensibility of AI algorithms is another key requirement of AI-enabled systems. To trust AI-enabled systems, it was important to the GPs that the proposals submitted by the AI-enabled system are comprehensible.”</p> <p>“...an AI-enabled system must be self-managed by the providers. Using the technology is feasible only if a physician can continue to work autonomously and the next treatment steps are not decided by an AI-enabled system. However, the participants had a negative attitude toward intervention in a physician’s self-determined work.”</p>	<p>Beliefs about consequences</p> <p>Environmental context and resources</p> <p>Knowledge</p> <p>Social/professional role and identity</p>
Cartolovni		
	<p>"Privacy emerged as a major ethical and legal concern, often in the context of the misuse of electronic medical records and of the issue of data ownership."</p> <p>"Not disclosing the use of an opaque AI-based decision support tool may be unethical in that it may negatively impact the patient-physician relationship, undermine patient autonomy and trust, and potentially compromise informed consent."</p>	<p>Beliefs about consequences</p> <p>Beliefs about consequences; social/professional role and identity</p>

	<p>"The lack of appropriate regulation emerged as the most prevalent legal issue in our analysis."</p> <p>"When AI-based decision making tools are designed to suggest medical recommendations and guidance, another prevailing issue in the literature is liability and accountability for patient harm [...] most of the difficulties in establishing liability for AI-based tools stems from its opacity and black-box nature [...] the difficulty lies in demonstrating that the treatment was inappropriate, that the patient's rights were violated, or that the harm caused by the algorithms and the chain of legal causality has been impaired."</p> <p>"Safety and transparency constitute the two most pressing issues that pervade the entire AI-based medical decision-making process as an important and determining factor for trust in and acceptance of technology."</p>	<p>Beliefs about consequences</p> <p>Beliefs about consequences</p> <p>Knowledge</p>
Choudhury	<p>"Clinicians' positive perceptions toward BUC expectancy can lead to a lower perception of risk and, in turn, result in a higher intention to use BUC. Emphasizing the potential benefits such as (a) rapid calculation to determine the required units of blood needed for a transfusion, (b) accuracy of recommendation, (c) reliability of data analysis, and (d) consistency with the clinical requirements may increase clinicians' intention to use the technology."</p>	<p>Knowledge; beliefs about consequences</p>

	<p>"We also found that clinicians' perception of AI, in general, determines their risk perception towards BUC in particular and consequently reduces their intention to use BUC."</p>	<p>Motivation and goals; beliefs about consequences</p>
Ciecierski-Holmes		
	<p>"The 'Brilliant Doctor' clinical decision support system was found to require too much information from physicians, which was perceived as too time-consuming in a majority of cases."</p> <p>"Lacking integration with existing IT systems also resulted in critical laboratory information not being factored into the AI's decision making process. Physicians in Peruvian TB clinics also reported problems with an app-based TB-diagnostics tool utilising chest Xrays, including issues such as crashes of the app or mistranslations. Poor internet connectivity inside the clinics and the overall limited availability of X-ray viewers throughout clinics impeded the uploading of X-ray images to the TB diagnostic tool by nurses."</p> <p>"Physicians [...] expressed distrust in clinical decision support systems, as the basis on which diagnostic or therapeutic decision-making occurred was not sufficiently transparent. "</p> <p>"...the AI clinical decision support tool had not well accounted for rural primary-care physician workflows in its design, and its usefulness could have been improved as a triage assistant rather than a physician assistant."</p>	<p>Memory, attention, and decision processes; environmental context and resources</p> <p>Environmental context and resources</p> <p>Knowledge</p> <p>Nature of the behavior; environmental context and resources</p>

	<p>"...the US-based training of IBM Watson for Oncology using US medical literature has led to inappropriate treatment suggestions in the Chinese context. "</p>	Knowledge
Clement		
	<p>"The most common challenge, identified by 48 articles, was a lack of the generalizable, representative data to train the algorithm such that it would work well on the general patient population; the problem is exacerbated by data sets with large proportions of records with missing data. [...] Successful use of AI tools will require a validation process to certify that a model is "good enough" based on the data available and provides more benefit than harm."</p> <p>" A second frequently identified challenge to adopting AI relates to uncertainty with how to incorporate AI recommendations into clinical decisions. In particular, the "black box" nature of many AI algorithms is noted."</p> <p>"Authors also identified the need for ethical guidelines for incorporating AI recommendations and standardized accuracy criteria. For a commercial firm to sell a clinical AI agent in the United States, they will generally have to receive FDA approval for the tool under the Software as a Medical Device (SaMD) protocol, but the same is not necessarily true of "home grown" AI tools. For example, a hospital would not be required to follow the process before implementing an in-house tool used to stratify patients based on their risk for medication non-adherence if it were for research purposes."</p>	<p>Knowledge; environmental context and resources; beliefs about consequences</p> <p>Knowledge; nature of the behavior</p> <p>Beliefs about consequences; knowledge</p>

Couckuyt		
	<p>"Before adopting the ML model in the clinic, it first needs to be externally validated. The model needs to be tested on independent and larger cohorts, and on the other hand, it needs validation on a cohort from an independent institute. [...] It is also advised to compare the ML model performance with established clinical scores or existing ML models."</p>	Knowledge
	<p>"Even if the ML model is proven to be valuable and can generalize to unseen samples or other cohorts, clinicians might still favor slightly worse, but explainable and interpretable models over "black box" models. Lack of trust in these complicated models is at the root of this preference."</p>	Knowledge; beliefs about consequences
Emani		
	<p>"At sites without integrated patient record systems, some users found manual data entry to be a burdensome process...for physicians with a high patient load, the time needed to enter information into the system may be an issue."</p>	Environmental context and resources; memory, attention, and decision processes
	<p>"Users also want WfO to provide an explanation of its process for scoring and ranking treatment options; in doing so, users would feel more comfortable with trusting the information and recommendations provided by WfO."</p>	Knowledge
	<p>"Another important concern is that the data and training of AI tools may not incorporate local patient characteristics into treatment recommendations."</p>	Knowledge

	<p>"The technological challenges that are unique to LMICs and should be mentioned include access to the internet, technology training, and whether local technology teams would be able to address technical issues."</p> <p>"Providing a decision support tool that is user-friendly and aligns with daily workflows is essential for implementation in LMICs, where physicians' experiences with technology can vary."</p> <p>"There is also concern about whether AI tools would exacerbate the divide in health care access and use, especially with respect to socioeconomic status."</p>	<p>Environmental context and resources; skills</p> <p>Nature of the behavior; environmental context and resources; memory, attention, and decision processes; skills</p> <p>Beliefs about consequences</p>
Evans		
	<p>"Any system that operates in a nursing context is likely to be large, more extensively used, etc. [...] All of these scenarios imply extensive costs. Large aggregate costs due to the nature of the nursing constituency represent a challenging situation that systems implementors must address for nursing."</p> <p>"Nursing pods or stations already have hospital-supplied stations and terminals for a variety of purposes; there is a growing crowding condition already developing that impinges on new nursing applications."</p>	<p>Environmental context and resources</p> <p>Memory, attention, and decision processes; environmental</p>

	<p>context and resources</p> <p>Environmental context and resources</p> <p>Knowledge; beliefs about consequences</p> <p>Environmental context and resources</p>
Fujimori	<p>"Even over the intermediate term, externally developed stand-alone decision support systems will not take into account to any great extent local hospital idiosyncrasies or extensively interface with records and materials their nurses already utilize."</p> <p>"From the experience of using hospital-based MIS systems that are tuned to specific needs, there is an often overwhelming expectation by nurses that every system will be unrealistically "friendly." Indeed, system performance may be expected to surpass any reasonable expectations of even a human. The nursing experience with the hospital's MIS as well as the constant trumpeting of user-friendliness, coupled with nursing's lack of wide exposure to the limitations of systems in general, has created widespread unrealistic expectations. Often there is also the added expectation that all systems will be so advanced that learning will be immediate, and system mastery will be instantaneous."</p> <p>"The widespread practice to provide nursing systems through the hospital main-frame computers will also have to be reconsidered. As additional systems are introduced, the hospital main-frame will grow more overextended; new patient record features and cost accounting already strain many systems and data-processing budgets."</p>
	<p>"...informants stated that the system would not be useful for typical cases in that the differential diagnoses would not change with the alert."</p> <p>Knowledge</p>

	<p>“Ten informants talked about the design quality, and all of them considered the design to be neither interruptive for daily practice nor effortful and found it useful for medical practice.”</p> <p>“All informants noted that the system can be integrated with the existing workflow processes and practices. However, one informant stated that the system affected typing speed and could interfere with the clinical workflow if it were to stop working or freeze.”</p>	<p>Memory, attention, and decision processes</p> <p>Nature of the behavior; environmental context and resources</p>
Goldstein		
	<p>“Academic informaticians, health services researchers, physician domain experts, and hospital information system specialists typically have disparate disciplinary perspectives and cultures. Consequently, uniting them on the same team with common overall objectives requires effort and commitment to develop a shared vocabulary and patterns for handing-off tasks. We approached this challenge by starting with small tasks and using bridge personnel, i.e., individuals who had familiarity with at least two of the four disciplines. As our team gained experience in working together, we developed patterns of communication and identified the most effective role assignments.”</p> <p>“Early in the planning stage, we met with IRMS administrators and networking staff to outline our plans and obtain their input and approval, and we maintained close contact with the IRMS staff during planning and implementation. The IRMS staff provided support in several key areas including installing the project server in the IRMS server room so that it could benefit from backup power supply, air conditioning, and optimal network connections; programming the M patient data extract; and network support.”</p>	<p>Social influences</p> <p>Environmental context and resources; social influences</p>



<p>“Successful guideline implementation requires local clinical opinion leader “buy in” of the clinical content. Clinicians must be assured that the guideline recommendations are well founded. The recommendations presented should be based on sufficient backing.”</p>	<p>Knowledge; social influences</p>
<p>“Both San Francisco and Durham had on-site physician-investigators who were primarily responsible for overseeing implementation, but neither of these physicians had special training or experience in informatics.”</p>	<p>Skills; knowledge</p>
<p>“Since the VAPAHCS study site included clinics located in seven different cities across a wide geographic area, it was not feasible to bring the clinicians together for training”</p>	<p>Skills; environmental context and resources</p>
<p>“Clinicians receive many clinical reminders. One effective means to sustain clinician interest was to provide quarterly feedback on guideline–drug concordance for hypertension.”</p>	<p>Behavioral regulation</p>
<p>“The physician-investigators in San Francisco and Durham were not the original developers of ATHENA DSS and did not initially have a sense of “ownership” of the knowledge base. Lack of familiarity with the program could potentially interfere with their enthusiastic endorsement of it to their colleagues.”</p>	<p>Knowledge; social influences</p>
<p>“Clinical opinion leaders must also be confident that the guidelines apply well to their own patient population. We recruited several physicians to assist with review of our guideline implementation in ATHENA DSS. In addition to the physician-administrators described above (one of whom was also the medical center’s overall guideline implementation leader), we recruited the supervisor of the general medical clinics at the Palo Alto site and the primary care chief resident as physician-monitors. We shared the knowledge rules used in ATHENA DSS, gave them individual training sessions in use</p>	<p>Knowledge; social influences</p>

	of the system, activated the system at their clinics, and encouraged them to comment directly and to use the feedback features built into ATHENA DSS as described above.”	
Henry		
	<p>"Clinicians described that their overall willingness to trust the ML-based system was rooted in several factors that helped them build a mental model of how the system worked. None of the clinicians fully understood the machine learning behind the system; however, while some were curious to learn more, they did not perceive that understanding the system's logic in an individual case would change their decision making [...] although unconcerned with the specific statistical model behind the system, clinicians reported having come to better understand how the system operated by observing its behavior in different scenarios and with different patient types"</p> <p>"Clinicians valued external studies of the system and recommendations by colleagues and experts that allowed them to develop trust peripherally. [...] For instance, one ED physician said, 'I'd want to understand the population it was derived from...and then I'd want to see the population they validated it on afterwards...whether that group looks like the patients I'm treating.'"</p> <p>"Clinicians also valued that they were able to ask questions about the system design choices during educational sessions and customize the interface and alert sensitivity to their environment and patient population [...] interacting with the deployment team also allowed for input into the tool's operations, which was described as an improvement over prior CDSS deployments."</p>	<p>Skills</p> <p>Knowledge; social influences</p> <p>Social influences; nature of the behavior; environmental context and resources</p>

	<p>"Concerns that regulatory agencies might use these systems to standardize care even in scenarios where a clinician disagrees with the system, potentially leading to over-treatment and patient harm, especially in cases where the alerts occurred prior to clinical recognition. [...] when asked what would convince them to act on the system's recommendations prior to apparent symptoms, suggestions included clinical trial evidence, or personally experiencing scenarios where the alert was dismissed but the patient was later diagnosed as having sepsis."</p> <p>"Ultimately, the capacity of state-of-the-art ML systems to improve clinical care depends on clinicians' ability and willingness to incorporate the information provided by these systems into their work."</p>	<p>Beliefs about consequences; social/professional role and identity</p> <p>Motivation and goals; nature of the behavior</p>
Jauk		
	<p>"The expert group appreciated that there was no need of additional data entry and that the prediction was available within few seconds in the user interface of the HIS."</p>	<p>Memory, attention, and decision processes; environmental context and resources</p>
Jeong		
	<p>"Model deployment can be tricky because facilities need to understand where the model will benefit the most. Whether it be the floor units, emergency departments, or intensive care units, the clinicians and model developers need to discuss which cohort is most appropriate given the dataset model was trained on. Furthermore, the deployed unit must have the human resource to integrate the ML model into their workflow."</p>	<p>Environmental context and resources; behavioral regulation</p>

<p>“...for AI/ML in neonatal care to have a clinical impact, clinicians must be able to trust the model. While decision interpretation was an important factor, the model providing an “actionable item” is also important. For instance, rather than providing a raw probability (in percentage) for neonatal sepsis, an output of simplified colored categories of risk was found to be more actionable and intuitive for clinicians.”</p>	Knowledge
<p>“However, when a model trained in one environment is deployed into another environment, where neonates may have distinctive characteristics, e.g. racial, socioeconomic, etc., AI/ML models may fail to generalize. We quantify this performance (accuracy) through out-of-sample error, or the generalization error. CDSS often suffer from out-of-sample errors.”</p>	Knowledge; environmental context and resources
<p>“For a CDSS to be deployed in the model, we need to acknowledge the need for 1) an operating framework that can support large data collection, management, and communication 2) a method to optimize computing resources. In order to leverage the full advantages of data-driven CDSS, it is critical to implement a framework or architecture that can support real-time processing of temporal data and the data mining techniques.”</p>	Environmental context and resources
<p>“The clinical team’s perception of CDSS may have been positive, but the utility and its true impact in clinical setting depend on how well it fits to the established clinical workflow. [...] Firstly, too many alerts or inaccurate alerts from a clinical decision model could disrupt the clinical workflow and intensify alert fatigue in clinical staff as illustrated in Fig. 5. A poorly designed layout or display of the alerts could also add disruption when clinicians are reviewing patient charts.”</p>	Nature of the behavior; environmental context and resources; memory, attention, and decision processes; emotion

Ji		
	<p>“...the AI + CDSSs in Chinese hospitals, similar to systems explored in other studies, may suffer from a mismatch between clinical needs and system functions thus making the absence of translating users’ requirements into system function design and clinical pathway integration one of the major obstacles faced by AI + CDSSs implementation. Therefore, it is recommended to [...] generate the right recommendations to the right person in the right intervention format through the right channel at the right time and location.”</p>	<p>Nature of the behavior; environmental context and resources</p>
	<p>“The second challenge related to the implementation of AI + CDSSs highlighted by our analysis is posed by data quality and availability. This is a common global problem where the lack of high quality and available data creates a barrier for practitioners to receive the “right information” from an AI + CDSS. The complex nature of medical data makes data quality problems more evident because missing, incorrect, or vague information may lead to useless or even harmful results.”</p>	<p>Knowledge; environmental context and resources</p>

	<p>“The degree to which clinicians can understand how the AI + CDSS works and generates the information given and the basis for individual recommendations affects their trust in the system. The lack of methodological transparency inherent in many machine learning approaches (“black-box”) can impair user trust in the outputs produced by an AI + CDSS. This creates a distinctive phenomenon in the health care field where medical practitioners are less likely to adopt AI in clinical practice if they do not trust the technology or understand how it was used to support process of care or patient outcomes.”</p>	Knowledge
Jordan		
	<p>“The initial rollout of the new technology was met with some skepticism, because it could not actually “see” the patient, and so would not be able to accurately assign acuity. The reliance on cultural knowledge and skill as a factor in interpreting the meaning of vital signs and presenting concerns caused participants to question the appropriateness and effectiveness of the new technology.”</p> <p>“There was a widespread concern that having an AI program that provided an ESI triage level would reduce the need for nurses to actively consider their cases. Many of the nurses believed having a computer program provide a recommended ESI level reduced the drive for nurses in the ED to refine their analytic skills and maintain cultural competence. This feeling was especially pronounced when referring to the development of new nurses. The emphasis that nurses should rely on their own experience and intuition was widely expressed.”</p>	<p>Knowledge; social/professional role and identity</p> <p>Social/professional role and identity</p>
Joshi		

	<p>"Optimizing the alert to appropriately identify patients and trigger clinician response was the first major barrier to generating clinician acceptance. Optimizing the alert consisted of fine-tuning thresholds, content, and integration of the alert into the workflow. Themes focused on lack of consensus, tension between alert placement and disruption of workflow, and burden of optimization falling to individual institutions."</p> <p>"The most frequently cited concern for clinician buy in for both rule-based and machine learning models was avoiding alert fatigue, or over-alerting users. A few remarked that this concern was present with all their decision support tools."</p> <p>"Other themes focused on concerns about clinical relevance, difficulty explaining why models fire, confusion with understanding what an alert means, and distrust stemming from mismatched expectations."</p>	<p>Nature of the behavior; environmental context and resources</p> <p>Emotion</p> <p>Knowledge; beliefs about consequences</p>
Knop		
	<p>"...the development of a healthy trust relationship with algorithmic decision-making relies on the thoughtful design of system characteristics. In general, the resulting performance of the system and its ability to explain or justify its conclusions appear to be strong predictors of a positive relationship."</p> <p>"A human actor's trust in an AI-enabled CDSS appeared to be another important factor that directly influenced the quality of collaboration and adoption of technology [...] a lack of trust might result from different technological characteristics and their situational fit but always negatively impacts the overall performance of the human-AI team."</p>	<p>Knowledge; beliefs about consequences</p> <p>Beliefs about consequences; environmental context and resources</p>

	<p>“...the output of an AI-enabled CDSS in its dimensions of simplicity, granularity, and concreteness might affect the final decision of clinicians; the better an AI-enabled system’s output is adapted to the situational context of its use, the more precise the overall diagnostic performance of the AI and humans (e.g., clinicians facing multiclass diagnostic problems are supported by AI-based multiclass probabilities).”</p>	Environmental context and resources; knowledge
Kulchak Rahm		
	<p>"...testers initially expressed concern around 'too many clicks' and 'click fatigue' but noted as they progressed through the cases that the clicking was unavoidable and necessary [...] testers who commented on the cognitive load required to review flagged findings and choose age of onset noted the cognitive load was similar to completing the task without."</p> <p>"For a CDS to be acceptable and implemented by clinicians and organisations, it must fit with real-world workflow and must present a solution to perceived need."</p>	<p>Emotion</p> <p>Nature of the behavior; environmental context and resources; knowledge</p>
Kyrimi		
	<p>“Several authors reported that quality and availability of medical data was lacking. Regardless of the efforts on overcoming lack of data when developing BNs using medical expertise and/or literature (an important advantage of BNs over purely data-driven models) the poor quality and/or lack of medical data remain an issue for the model’s performance and usability.”</p>	Environmental context and resources; knowledge



<p>“Lack of clinical impact, shown in Fig. 5, was the main PO barrier for acceptance of BN-based systems in healthcare. Evaluating the system’s impact on clinical decision making, its usefulness in practice, and the degree of practitioner acceptance were considered important and necessary steps to aid adoption in practice. Further, BN-based systems should adhere with and be integrated into current clinical practice in order to be accepted by clinicians.”</p>	<p>Knowledge; nature of the behavior; beliefs about consequences</p>
<p>“Another barrier to widespread adoption of BN-based systems is the requirement for extensive development effort and subjectivity involved when relying on clinicians’ judgement. Clinicians can also resist processes that may interfere with their daily workflow or challenge their autonomy. And finally, another barrier related to clinician’s resistance arises when a model lacks credibility, also known as face validity.”</p>	<p>Social/professional role and identity; nature of the behavior</p>
<p>“Clinical involvement was considered an important facilitating factor for resolving both clinicians’ resistance and the lack of credibility. Cooperating with multiple clinicians has been considered beneficial to developing a credible BN-based system that captures medical knowledge, a property desired by clinicians. BN-based systems should be reviewed by clinicians in order to obtain their input and agreement if we are to achieve adoption in practice.”</p>	<p>Knowledge; social influences</p>
<p>“A BN-based system’s interpretability was also mentioned as a facilitator for overcoming clinicians’ resistance. Their graphical structure can make them more comprehensible, which is important in medical applications. An explanation of the system’s prediction could also be beneficial. The fact that BN-based systems can be easily understood is also one of their main benefits.”</p>	<p>Knowledge</p>

	<p>“Validating the system’s performance was considered as a necessary facilitating factor for assisting its adoption. In addition, even if the BN-based system has a good predictive performance, it will fail to be accepted in practice, if it has no generalisability. Thus, external validation must be undertaken in different cohorts and geographical areas before the BN-based system can be used routinely in clinical practice.”</p> <p>“In addition, development of a user-friendly interface was described as important element for assisting adoption.”</p>	<p>Knowledge</p> <p>Memory, attention, and decision processes</p>
Loftus		
	<p>"Dissemination and clinical implementation of AI models across healthcare systems requires data structures to be standardized across centers."</p> <p>"Mistrust hinders clinical implementation of AI-enabled decision support through skepticism regarding opaque, 'black-box' model outputs and recognition that AI models can make egregious errors."</p> <p>"Clinical application of AI-enabled decision support in nephrology should occur only after high-level evidence of safety and efficacy has been validated by a robust peer-review process. To avoid harm, models should be subjected to assessments of technology readiness, similar to those adopted by NASA after the Challenger tragedy."</p> <p>"The integration of AI models with clinical and digital workflows may also decrease the deployment costs associated with the organizational effort and resources required for clinical implementation."</p>	<p>Environmental context and resources</p> <p>Beliefs about consequences; knowledge</p> <p>Knowledge</p> <p>Nature of the behavior; environmental context and resources</p>

	<p>“...assigning accountability for medical errors and complications associated with SaMD remains challenging, especially when legal governance overlaps with ethical considerations. [...] The dynamic, complex nature of these dilemmas hinders the development of universal rules and policies for legal governance of medical AI.”</p>	Beliefs about consequences; social/professional role and identity
Matthiesen		
	<p>"The results also show that an actionable prediction tool is one that presents the reason for why the algorithm deemed as it did, such as in this study, by highlighting important data to be used for clinical evaluation and enabling clinicians to assess the algorithm's outcome against their own evaluation."</p>	Knowledge
Mezrich		
	<p>“Medical malpractice law covering physicians is well established and predictable; health care providers, insurers, patients (and their lawyers), and the courts are cognizant of the expectations and risks. Laws related to AI autonomy are not yet established; this uncertainty creates an inherent bias toward limiting the role of AI to that of a tool and holding the human user—the radiologist—primarily responsible.”</p>	Beliefs about consequences
Miller		
	<p>"Many providers suggested that education and consideration of workflow before and during implementation could facilitate programmatic success over time."</p>	Behavioral regulation; environmental context and resources;

		nature of the behavior
Mitchell		
	"We conclude that healthcare providers and decision support suppliers will have the best chance of meeting legal challenges if: they are first tested in translational research with the patients' explicit, informed consent; decision support system suppliers and healthcare providers are able to clarify and agree on their individual legal responsibilities, and; patients are properly informed about privacy risks and able to decide themselves whether their data can be used for other purposes, or are stored and processed outside the European Union."	Beliefs about consequences; social/professional role and identity; knowledge
Norrie		
	"The greatest challenge will be integrating these decision-support tools into multidisciplinary shared decision making, ensuring that all teams involved are comfortable with an increased reliance on decision aids; a further challenge is making sure that patients and carers are properly informed about the methods being used and approve of this increased reliance on data-driven clinical decision making."	Social/professional role and identity; social influences
Petitgand		
	"...the lack of interoperability between the DSS and the AHC clinical information systems (Electronic Patient Record and Emergency Information System) meant that medical histories had to be printed and handed to physicians in paper form. These tasks were assigned to nurses and clerks who were already overworked with their regular obligations. As a result, medical histories were often not printed and thus were not provided to physicians."	Environmental context and resources; memory, attention, and decision processes

	<p>"Some nurses were convinced that physicians were not using the medical histories because they had difficulty understanding patient information reported by the DSS. This was, in fact, a major barrier reported by several physicians. The physicians interviewed considered that the AI-based system was good at reporting simple complaints (a localized pain, a broken leg, etc.) but very poor at making sense of multi-complaint conditions (pain throughout the body, pain related to severe pre-existing conditions, etc.). This was a major concern, as most patients coming to the ED presented with the latter profile."</p> <p>"At the start of implementation, several physicians were positively disposed toward using an AI-based DSS to enhance their diagnostic practice. However, some reported having discovered "errors" in the medical histories. In particular, two physicians reported that reading the medical history led them down the wrong diagnostic path [...] Perceptions of DSS-induced errors were shared among physicians, and this led some to develop a persistently skeptical attitude towards the usefulness of the DSS. The AI system was thus viewed as introducing a real risk into clinical practice that was capable of causing harm to patients. This is a perception that tends to increase clinician resistance to health information systems."</p>	<p>Knowledge</p> <p>Emotion; beliefs about consequences</p>
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	<p>“...the research emphasizes the need to consider the unique challenges raised by AI integration into clinical processes and workflow. As shown in this study, actors’ perceptions of a technology influence their actions towards it, be they related to adoption or resistance. For this reason, it is essential that managers responsible for implementation deal with specific assumptions and expectations regarding AI systems. Since these can generate negative perceptions (e.g. distrust in the effectiveness of automated decision making), that can hinder testing and adaptation, it is necessary to develop systematic learning processes based on user feedback to ensure that AI systems are implemented effectively.”</p>	Behavioral regulation; social influences
Petkus		
	<p>"Concerns about professional practice, ethics and liability included that the legal liability of doctors following advice is unclear (17.5), that black box systems fail to provide explanation for their advice (15), that doctors may mistakenly follow incorrect advice (15; ‘automation bias’), and that CDSS can embed unconscious bias, leading to unfair care for some patients (12.5)."</p> <p>"Concerns about regulation included poor system labelling (total 22.5; including concerns that CDSS fail to describe their aim or scope of use (12) or the level of user experience required for safe use (10.5)); that CDSS require high-quality patient data that NHS systems rarely provide (13.5); and that study results on CDSS can become obsolete due to fast-changing algorithms (13.5)."</p>	<p>Beliefs about consequences; social/professional role and identity; knowledge</p> <p>Knowledge; skills</p>
Pumplun		

<p>"As one subfactor of ML features, the interviewees pointed out the lack of transparency of ML systems as a major obstacle for the clinic's adoption of ML systems."</p>	<p>Knowledge</p>
<p>"Another subfactor of ML features is the ability to adapt their functioning if being retrained on novel data. This can become relevant either when the ML system is transferred to another context (e.g., another clinic) or needs to be retrained after some time; for example, new medical research results are gained or the patient demographic structure shifts. Clinics thus have to deal with an opaque system that is able to change its reasoning, making the outcome of an ML system unpredictable."</p>	<p>Knowledge</p>
<p>"...the interviewed experts emphasize that small clinics usually have fewer resources than large clinics, which could hamper the adoption of ML systems (C-15). In the specific context of ML systems, larger clinics further care for a higher number of different patients and thus have access to more patient data, which are needed to train ML systems appropriately. [...] Some of the experts report that clinics frequently rely on a wide range of clinical legacy systems, which are often proprietary to the suppliers, not connected, and based on outdated software and hardware. This difficulty is not only present within the clinic itself but also translates to the interorganizational level."</p>	<p>Environmental context and resources</p>
<p>"The European Medicines Agency is also still in the early stages of defining and establishing an approval process for ML systems [73]. Therefore, legal ambiguities could represent a hurdle for clinics to adopt ML systems for diagnostics. [...] The experts interviewed indicated that it is questionable who takes over responsibility if the diagnosis prepared by an ML system is inaccurate (C-06, C-14, and S-05). It is also unclear who can be held liable—the HIT provider, the clinic, or the physician who is providing the medical diagnosis."</p>	<p>Beliefs about consequences</p>

	"The limited applicability of ML systems for the diagnosis of specific conditions will impede the adoption of ML systems in clinics."	Knowledge
Romero-Brufau		
	<p>"The most commonly-listed facilitator was that the CDS promoted team dialog about patient needs (N = 14, 52 %). Five users (19 %) listed integration of recommendations into workflow and 3 users (11 %) listed usefulness of patient risk factors."</p> <p>"The most commonly listed barriers were related to inadequacy of the interventions recommended by the CDS. Eleven users (24 %) were dissatisfied that the interventions were too similar between different patients and therefore were not sufficiently tailored to each patient. Eleven other users (24 %) felt that the suggested interventions were inappropriate or not useful. Eight users (18 %) were dissatisfied that the system inaccurately classified standard risk patients as high-risk (i.e., high false-positive rate)."</p>	<p>Nature of the behavior</p> <p>Knowledge</p>
Rost		
	<p>"Only if additional value coming from a predictive model is proven, will an implementation into a CDSSs lead to a successful supporting device. Biases in such systems, for instance, were shown to lead to underestimations of their effectiveness, high non-compliance rates among users, and even to wrong diagnoses by physicians."</p> <p>"Apart from data protection, which needs to be assured, questions regarding liability and responsibility for treatment decisions have to be addressed, especially when it comes to disagreement between physicians and support systems."</p>	<p>Knowledge; beliefs about consequences</p> <p>Beliefs about consequences; social/professional role and identity</p>



Sax		
	<p>"Among all surveyed physicians, only 8% disagreed or strongly disagreed that they would feel comfortable using an ML-based model to assist with decision-making after they were first educated on how the model worked. Many physicians recognized the benefits of ML-based models but expressed some fear using something they did not fully understand (concern over what variables were included and how the algorithm works). Clinicians would be more comfortable if the models were biased conservatively to decrease the risk of serious adverse events."</p>	Knowledge
	<p>"Receiving education on how the risk tool and CDS works and feedback on patient outcomes after use were seen as opportunities for increasing acceptance."</p>	Knowledge; behavioral regulation
Schleder Gonçalves		
	<p>"The results of this experience are in the improvement of the performance of healthcare teams by the use of the tool, and the improvement of the tool itself. These potential benefits occur despite technological challenges, such as infrastructure in relation to computer terminals, bedside data recording equipment, tablets, smartphones and Wi-Fi networks; challenges of individual proficiency of health professionals in the use of hardware and software; and distrust in the accuracy of technology, among other challenges that influence the success of projects like this one."</p>	Environmental context and resources; skills; beliefs about consequences

	<p>"In the actual implementation process, the nurses act conduct an initial moment of awareness-raising with the healthcare teams, when they explain the process of conception of the tool, its mission, its functionalities, its impact on the nurses' work process and the actions that are expected from the team so that the early identification of possible cases of sepsis is effective. Communicating the overall benefits of the implementation and of a new technology is fundamental to help the members of the staff – those who will effectively use the technology – to stay engaged and work together to achieve the success of a project. Among the skills to be built up by nurses in this implementation phase are communication, empathy, attentive listening, and technical knowledge about the tool and the nursing work process in that specific hospital context."</p>	<p>Social influences; knowledge</p>
Schwartz		
	<p>"Concordance between clinicians' impression of the patient's clinical status and CONCERN's prediction emerged as an important factor influencing clinicians' perceptions of the accuracy of CONCERN with (1) concordance builds trust, (2) discordance erodes trust, and (3) discordance impact depends on reliance on CDSS for decision-making."</p> <p>"Clinicians identified several limitations to predictive CDSSs relative to clinicians and emphasized that CDSSs were just one of many sources of information that they considered when making clinical decisions. This category is illustrated through three subcategories: (1) clinicians have acquired knowledge and instinct and can reason, (2) some patients may not fit the mold, and (3) data may not reflect real time."</p>	<p>Knowledge</p> <p>Social/professional role and identity; knowledge</p>

	<p>"Clinicians also wanted explanations for individual patient predictions provided at the point of care. A physician said they want to see “the vital signs or the whatever that is making the score change” (Physician 3). A nurse said they would look for “what piece of it is causing the algorithm to say that the person’s not stable” (RN 2)."</p> <p>"However, delivering an accurate and desirable explanation of machine learning logic remains a challenge. [...] When our team iterates on the CONCERN design, we will look to explanation design frameworks such as that outlined by Barda et al. to optimize the impact of explanations on understandability. However, long-term strategies aimed at increasing the education that clinicians receive on machine learning are also likely needed, as others have also reported from their investigations."</p>	<p>Knowledge</p> <p>Knowledge</p>
Seneviratne		
	<p>"The medical community is familiar with the rigorous regulatory process for vetting new pharmaceuticals and medical devices; however the safety of algorithms remains a significant concern for clinicians and patients alike. This mistrust is often pinned on issues such as interpretability (the ‘black box’ problem of inscrutable deep learning algorithms) and external validity (will an algorithm trained on external data apply here?)."</p> <p>"In order for an algorithm to achieve widespread use, we need empirical validation and a plan for ongoing algorithmic and technical resilience—that is, surveillance of a model’s calibration and performance over time, and robust infrastructure to ensure system uptime, error handling, and so on."</p>	<p>Knowledge; beliefs about consequences</p> <p>Environmental context and resources</p>
Shaw		

	<p>"The challenges associated with ML initiatives at the level of health policy and systems are extensive. These include broad legislative frameworks related to emerging health-related technologies more generally and to the innovation procurement systems that vary across health system settings. The policy issues presented by ML in health care are beginning to garner more attention, but here we present one issue that we have not seen addressed in health care or public health literature: the challenge of scalability."</p>	<p>Beliefs about consequences; environmental context and resources</p>
Shortliffe		
	<p>"Black boxes are unacceptable: A CDSS requires transparency so that users can understand the basis for any advice or recommendations that are offered."</p> <p>"Time is a scarce resource: A CDSS should be efficient in terms of time requirements and must blend into the workflow of the busy clinical environment."</p> <p>"Complexity and lack of usability thwart use: A CDSS should be intuitive and simple to learn and use so that major training is not required and it is easy to obtain advice or analytic results."</p> <p>"Relevance and insight are essential: A CDSS should reflect an understanding of the pertinent domain and the kinds of questions with which clinicians are likely to want assistance."</p>	<p>Knowledge</p> <p>Environmental context and resources; nature of the behavior</p> <p>Memory, attention, and decision processes; skills</p> <p>Knowledge</p>

	<p>"Delivery of knowledge and information must be respectful: A CDSS should offer advice in a way that recognizes the expertise of the user, making it clear that it is designed to inform and assist but not to re- place a clinician."</p> <p>"Scientific foundation must be strong: A CDSS should have rigorous, peer-reviewed scientific evidence establishing its safety, validity, reproducibility, usability, and reliability."</p>	<p>Social/professional role and identity</p> <p>Knowledge</p>
Stagg		
	<p>"In the context of glaucoma management, integration into clinician workflow necessitates providing the CDS to the clinician seamlessly when a specific decision is being made. For example, a CDS tool designed to help identify glaucomatous progression would need to be presented to the clinician at the moment in clinical workflow that the clinician is deciding if there has been progression. In the case of glaucoma, additional research is needed to understand the glaucoma clinical workflow and decision-making process. Integration of future CDS systems for glaucoma into the established clinical workflow will make these systems easier to access and use, which will make them more likely to improve glaucoma outcomes."</p> <p>"As CDS systems for glaucoma care are developed, it is important that user-centered design principles are followed. User-centered interface design for glaucoma CDS would involve clinicians who care for patients with glaucoma in the design and testing of the CDS interface to ensure that user needs are met and information is communicated effectively. Clinicians who care for patients with glaucoma should be actively involved in the planning, development, and testing of CDS systems designed to improve glaucoma care."</p>	<p>Nature of the behavior; environmental context and resources</p> <p>Social influences; knowledge</p>

	<p>"One key challenge of CDS is the rules developed in one context may not necessarily apply in another. For example, glaucoma CDS rules developed for an inner-city population at a large academic center may not be appropriate when applied in a private- practice, rural clinic."</p>	<p>Environmental context and resources; knowledge</p>
Tsay		
	<p>"...the black-box nature of machine learning algorithms is problematic in medical care where insight and understanding are necessary for intervention. And, although these challenges are common to the application of machine learning in general, in the authors' opinion, the slow adoption of AI applications in health care specifically is attributable in large part to 2 issues: first, an initial focus in the field on higher-order clinical cognitive tasks in clinical decision support, and second, insufficient integration of machine learning into everyday clinical operations to create a human-in-the-loop training paradigm."</p> <p>"...although having large data sets as in health care is of potential value, such data sets are not a substitute for traditional experimental rigor that goes to great lengths to ensure that data collection and analysis are valid and reliable. More simply put, electronic medical records and information technology ancillary systems in health care were never created or intended for machine learning, and thus it is much more difficult to convert these types of data into scientifically rigorous signals for actionable analysis."</p>	<p>Knowledge; environmental context and resources</p> <p>Environmental context and resources</p>
VanBiesen		

	<p>"The other three subthemes, by contrast, were related to potential drawbacks of the CDSS: creation of tunnel vision, loss of human control, alert fatigue, and the added administrative burden (so-called 'death by a thousand clicks')."</p>	<p>Emotion; memory, attention, and decision processes; social/professional role and identity</p>
Van-Cauwenberg e		
	<p>"First, the respondents mentioned some technical issues that need to be fixed in order for the CDSS to be ready for implementation: the data need to be robust; the system needs to be accurate; and the CDSS needs to be user-friendly. Second, they believed that some aspects of clinical practice are inherently unsusceptible to being automated. They argued that the CDSS is overly rigid or lacks certain clinical skills that are necessary in order to perform the physician's tasks. Third, they indicated that they simply did not want specific tasks to be automated. In general, they did not give any reasons for this."</p>	<p>Knowledge; nature of the behavior; social/professional role and identity</p>
VanGils		
	<p>"In addition, it is conceivable that patients' and their care partners' (negative) opinions regarding the tools were a possible barrier to clinicians using a tool. In this study, we showed that patients, despite their age and (potential) cognitive decline, are mainly positive regarding the use of computer tools. Most of them embrace the possibility of using a tool themselves, and their care partners share this opinion."</p>	<p>Social influences</p>

	<p>"Within the concept of EBM, clinical experience is highly essential and should not be replaced by a tool. Computer tools could support EBM by making the best available evidence more accessible to clinicians, and computer tools could clarify patient preferences. Acknowledging computer tools as a part of EBM might lead to clinicians viewing these tools as an aid complementary to their own clinical experience rather than a threat to their clinical autonomy."</p> <p>"...clinicians' confidence in the tools might be strengthened if the tools are under the jurisdiction of a regulatory body to authorize and supervise the quality. To date, there are no formal regulatory standards for tools used to support clinicians in decision-making."</p>	<p>Social/professional role and identity; knowledge</p> <p>Beliefs about consequences</p>
Varghese	<p>"Any AI-driven software or CDSS that aims to have an impact on clinical decision making and is used as such in an existing clinical workflow fulfils the definition of software as a medical device [18, 19]. As such, it needs to be approved for clinical routine. Similar to the approval of medicinal agents, for a new software system to be cleared as medical device it must be validated for secure use and effectivity regarding the intended purpose. Essentially, this approval requires initial evidence, e.g., through a literature review of similar systems, and continues with controlled – ideally multicenter – clinical trials of the actual system as the next level of evidence."</p>	<p>Beliefs about consequences; knowledge</p>



	<p>"If, however, a model with a high complexity is chosen due to the use case-specific environment and its superior performance, it is recommended to complement interpretability-increasing measures to flatten the steep fall of the interpretability of deep learning models (Fig. 2). These measures include visualization of hidden layers, permutation/sensitivity analyses and transformation to more interpretable models, and studying information gain of input features with domain experts."</p>	Knowledge
Walsh		
	<p>"DSSs can be built into the workflow strategically (multi- disciplinary tumor board level to support treatment choice, e.g., surgery or radiotherapy) and tactically (specialist level to support treatment technique, e.g., prostate spacer or not; Fig 4). Some nations already condition reimbursement (e.g., proton therapy in the Netherlands) on the use of DSSs."</p> <p>"An important factor for adoption of technologies is ensuring that stake- holders are empowered (i.e., the agency to inform, adjust, or reject the DSS) and that their concerns are addressed (e.g., for clinicians and patient advocacy groups, increased quality of care and decreased medical errors; for medical directors and insurers, reduced costs and facilitated reimbursement)."</p>	<p>Nature of the behavior; environmental context and resources; motivation and goals</p> <p>Social/professional role and identity; knowledge</p>

	<p>"Typical heuristics collected from previous implementations of AI into workflows from other industries can be used to develop a nuanced understanding of how stakeholders interact with DSSs to refine interaction patterns and data visualization techniques that work with stakeholders rather than replacing or obstructing them. In addition, the origin of information immensely influences perception. Stakeholders must have sufficient transparency."</p> <p>"To mitigate this [the black box problem], clinicians must actively engage with researchers (academic and industrial) to ensure that the solutions developed yield maximum clinical benefit."</p> <p>"Residency programs must adopt AI into curriculums."</p> <p>"Clinicians and researchers must work with policymakers on the complexities of DSSs and the consequences of errors (clinical and legal). From a regulatory perspective, despite the perplexity, approval of DSSs by the US Food and Drug Administration and notified bodies within the European Union is happening, notwithstanding the ambiguous working mechanisms."</p>	<p>Nature of the behavior; social/professional role and identity; knowledge</p> <p>Knowledge; social influences</p> <p>Knowledge</p> <p>Beliefs about consequences</p>
Watson		
	<p>"The second barrier was attitude toward the PM and ML model. Traditionally, clinicians and scientists were comfortable with performance metrics around routine statistical tests. The performance metrics used to evaluate the myriad of ML tools are less familiar to most clinicians. Also, the tools themselves are sometimes "black box" algorithms that cannot be fully dissected and deconstructed even by experts. This, according to some interviewees, has led to healthy skepticism while sometimes limiting clinical implementation."</p>	<p>Knowledge</p>

<p>"The third barrier to clinical implementation of these models was managing expectations since hype often distorted clinicians' expectations."</p>	<p>Beliefs about consequences</p>
<p>"Another factor that was identified as affecting clinical utility is the challenge of configuring alerts; striking the right balance between over-triggering and under-alerting when action is needed has proven challenging. This can have a direct impact on the clinical utility of a model. Nursing alarm fatigue, particularly with some of the most critically ill patients, is a well-characterized phenomenon."</p>	<p>Emotion; nature of the behavior</p>
<p>"The current state of technology presents a barrier to the creation of clinically useful models. The technologies themselves are relatively immature in the health care industry."</p>	<p>Environmental context and resources</p>
<p>"The variability and incompleteness in health care data quality was a barrier. One interviewee said, "the fidelity of the inputs themselves are quite incomplete" while another emphasized that, "people need to trust that the score is accurate and that really only happens when the data is complete." Further exacerbating the data challenge is the local customization of workflows and system configurations. As one interviewee pointed out, "[The data at] every EMR is different at every health system"."</p>	<p>Knowledge; environmental context and resources</p>