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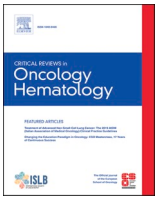

Clinical decision support systems for multidisciplinary team decision-making in patients with solid cancer: Composition of an implementation model based on a scoping review☆

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ABSTRACT

Generating guideline-based recommendations during multidisciplinary team (MDT) meetings in solid cancers is getting more complex due to increasing amount of information needed to follow the guidelines. Usage of clinical decision support systems (CDSSs) can simplify and optimize decision-making. However, CDSS implementation is lagging behind. Therefore, we aim to compose a CDSS implementation model. By performing a scoping review of the currently reported CDSSs for MDT decision-making we determined 102 barriers and 86 facilitators for CDSS implementation out of 44 papers describing 20 different CDSSs. The most frequently reported barriers and facilitators for CDSS implementation supporting MDT decision-making concerned CDSS maintenance (e.g. incorporating guideline updates), validity of recommendations and interoperability with electronic health records. Based on the identified barriers and facilitators, we composed a CDSS implementation model describing clinical utility, analytic validity and clinical validity to guide CDSS integration more successfully in the clinical workflow to support MDTs in the future.

1. Introduction

A personalized clinical advice for cancer patients prepared by an oncological multidisciplinary team (MDT) improves patient outcomes and patient satisfaction (Prades et al., 2015). However, clinical decision-making by MDTs to reach a treatment advice for each unique patient is getting more complex since the amount of scientific knowledge on tumor characteristics and treatment options increase rapidly. Moreover, patients undergo more diagnostic testing and subsequent more patient and disease characteristics (data-items) have to be taken into account to generate a personalized guideline-based recommendation during the MDT for each unique patient. This complexity and the availability of all relevant information during MDT meetings is challenging. Relevant data-items are often suboptimal extracted from the patient files and reported during MDT meetings, which impedes MDTs to keep an overview of all relevant information and make optimal decisions (Lamb et al., 2011; Ebben et al., 2020).

To support MDTs in reaching the challenging goal of evidence based informed decision-making, information technology and data science can be helpful to manage, register and re-use all relevant data and generate treatment recommendations. Many studies have shown that clinical decision support systems (CDSSs) can be effective tools to increase physician concordance with clinical practice guidelines (Garg et al., 2005; Roshanov et al., 2013). Furthermore, CDSS usage is associated

Abbreviations: CDSS, clinical decision support system; MDT, multidisciplinary team; WFO, Watson for Oncology.

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with positive clinical outcomes in two systematic reviews (Pawloski et al., 2019; Klarenbeek et al., 2020). One systematic review evaluating clinically relevant outcomes related to CDSS usage for the diagnosis, treatment and supportive care revealed that 23 out of 24 included studies suggested a positive impact on the quality of care by the use of CDSSs for clinical decision making (Pawloski et al., 2019). Another systematic review focusing on CDSSs impact on process outcomes (e.g. percentage change MDT treatment decision after using CDSS), guideline adherence and clinical outcomes included nine studies and found that CDSS implementation did significantly improve process outcomes and guideline adherence but no improvement in clinical outcomes (Klarenbeek et al., 2020). Importantly, these two reviews did not focus on implementation of CDSS in MDT settings and both included only two articles that focused on CDSS for decision-making in the MDT. Moreover, implementation of CDSSs in the clinical workflow is challenging, which makes the implementation of CDSS in clinical practice lag behind (Chua et al., 2021). A recent systematic review and meta-analysis described the usage and accuracy of CDSSs for multiple tumor types, but did not focus on MDT decision support (Oehring et al., 2023).

Overcoming the challenges as mentioned above implies the need for a scoping review focusing on the currently reported CDSSs for MDT decision-making in solid cancer and to identify the reported barriers and facilitators for implementation of these CDSSs. Based on these barriers and facilitators, a CDSS implementation model will be composed to support future development and implementation of CDSSs in clinical practice.

2. Methods

2.1. Search strategy and selection criteria

Based on the aims of our study, a scoping review was chosen as study design (Munn et al., 2018; Peters et al., 2015). To provide an overview of the currently existing CDSSs for multidisciplinary decision-making in solid cancer, a search strategy was determined with the support of two health information specialists. The conducted search syntax is reported in supplemental table A. The syntax combined synonyms for 'multidisciplinary', 'decision support', 'cancer' and 'human'. The Cochrane Library (https://www.cochranelibrary.com/cdsr/reviews/topics, MEDLINE (accessed through PubMed) and Scopus were systematically searched up to November 20th, 2023.

A CDSS is defined as a system intended to improve healthcare delivery by enhancing medical decisions with targeted clinical knowledge, patient information, and other health information (Osheroff et al., 2012). A CDSS can be any software in which individual patient characteristics (data-items) are matched to a computerized knowledge data-base (e.g. rule-based, using IF-THEN statements) or a data-base leveraging artificial intelligence, machine learning or statistical pattern recognition. Based on this match patient-specific recommendations are generated (Sutton et al., 2020). Studies concerning CDSSs for multidisciplinary decision-making in solid cancer were included if they met the following inclusion criteria. The CDSS should:

1) be data-driven, making usage of information technology and/or data science. Preferably, a description of the CDSS explaining the CDSS methodology should be available; 2) the CDSS should go beyond fixed decision rules (i.e. the system should be able to support decision-making for multiple possible combinations of patient and/or tumor characteristics by using a computerized knowledge data-base or a data-base leveraging artificial intelligence, machine learning or statistical pattern recognition); 3) support multidisciplinary decision-making by MDTs. CDSSs focusing on only one discipline were not eligible; 4) focus on medical professionals, not patients; 5) focus on solid cancer; 6) should be reported in a peer-reviewed journal in English. Articles reporting on the design and implementation of CDSSs for MDT in solid cancer were also eligible for inclusion.

2.2. Screening, data abstraction & statistics

Two reviewers (MH & KE) independently screened the title and abstract of all identified articles for compatibility with the research topic. In case of non-uniform assessment, discrepancies were resolved by discussions between the two reviewers. The references listed in studies that were selected for full-text review were screened for potentially useful studies. EndNote X9 was used for reference management. The result of the selection process was visualized according to the PRISMA 2009 flow diagram (http://www.prisma-statement.org/documents/PRISMA%202009%20flow%20diagram.pdf).

To summarize the reported CDSSs and to identify barriers and facilitators for implementation of CDSSs in daily clinical practice, the following data were extracted for each included study: study aim (including reporting main findings of the most frequent aims), study design, CDSS characteristics, CDSS knowledge base, main study outcome, barriers and facilitators for implementation of the CDSS. For descriptive statistics, Microsoft Excel was used. Data were presented by CDSS, in order of frequency. Numbers were indicated as absolute numbers with or without percentages, or as a median with range. The scoping review included, by design, no meta-analysis of the included studies (Munn et al., 2018). The identified CDSSs were not scored for risk of bias, as there is no available tool for systematically assessment, such as QUADAS-2 for assessment of diagnostic test accuracy or the prediction model risk of bias assessment tool (PROBAST) (Whiting et al., 2011; Wolff et al., 2019).

2.3. Composition of a CDSS implementation model

The basic principle of a CDSS is that the appropriate clinical data is processed in such way that these data can be adequately matched to the database of the CDSS in order to reach a valid recommendation. Subsequently, this recommendation should be applicable to decision-making at the point of care. All identified barriers and facilitators were categorized and ranked in order of reported frequency. The five most frequently reported categories of both barriers and facilitators qualified for a detailed report. Based on the identified categories, a model was composed highlighting all important aspects that need to be covered by the CDSS for implementation in daily practice. This imposes requirements on the validity of a CDSS respectively. The model had to cover both the input level of the CDSS with accurate clinical data (i.e. analytic validity) and the output level with valid recommendations (i.e. clinical validity), resulting in a balanced weighing favoring clinical utility of the CDSS.

3. Results

3.1. Study selection

The search strategy in the following database Cochrane Database, MEDLINE (accessed through PubMed) and Scopus resulted in 27, 881 and 326 hits respectively. After removal of duplicates, 1083 abstracts were screened based on title and abstract. Of these, 81 studies fulfilled the inclusion criteria and were considered eligible for full text review. After reading the full text, 44 articles describing twenty CDSS were included in this scoping review (Fig. 1) (Aikemu et al., 2021; Alcorn et al., 2022; Bouaud et al., 2014, 2012; Bouaud and Séroussi, 2011; Bouaud et al., 2015; Choi et al., 2019; Cypko et al., 2017; Ebben et al., 2022; Eccher et al., 2014; Epstein et al., 2006; Gaudioso and Elkin, 2017; Griewing et al., 2023; Heiden et al., 2015; Hendriks et al., 2020, 2019; Keikes et al., 2021; Kim et al., 2019, 2020; Lee and Lee, 2020; Lee et al., 2018; Lin et al., 2016; Liu et al., 2018; Lukac et al., 2023; Macchia et al., 2022; Ng et al., 2023; Chaudhari et al., 2008; Prebet et al., 2018; Redjdal et al., 2020, 2021; Rossille et al., 2005; Séroussi et al., 2007, 2017, 2013a, 2012, 2013b; Sesen et al., 2014; Shekarriz et al., 2020; Somashekhar et al., 2018; Thavanesan et al., 2023; Tian et al., 2020; Zhao

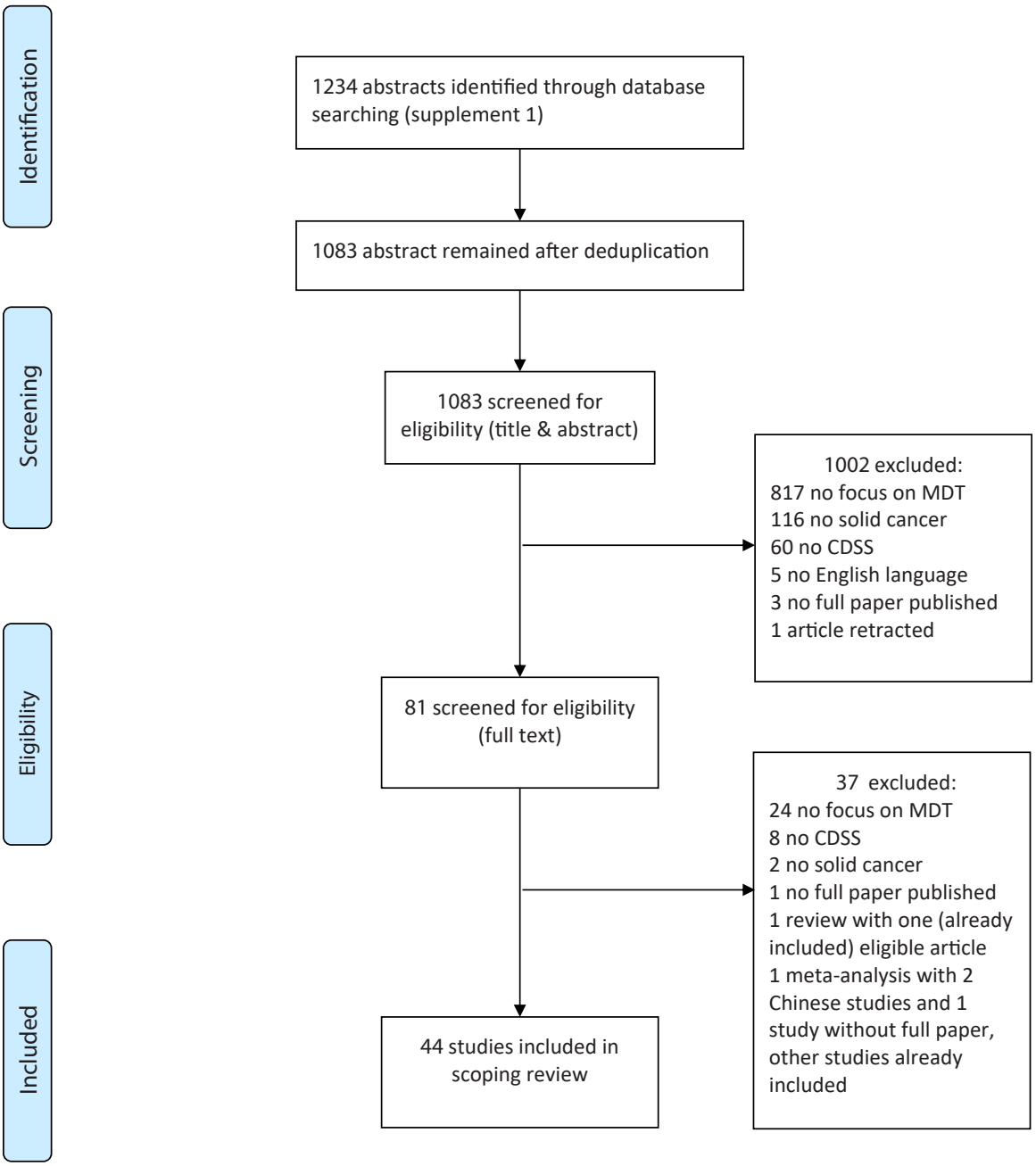

Fig. 1. Flow diagram.

et al., 2020; Zhou et al., 2019; Zou et al., 2020). A meta-analysis of Watson for Oncology's (WFO) clinical performance was excluded because two of the included studies were in Chinese, for one study there was no full paper available and all other studies were already included in our scoping review (Jie et al., 2021).

3.2. *Existing CDSSs for multidisciplinary decision-making in solid cancer*

Table 1 depicts a detailed summary of all included articles. Most articles originated from European (n = 26) and Asian study groups (n = 12). Twenty-three papers (52%) focused on breast cancer exclusively. Most articles were single center studies (n = 28) and had a retrospective design (n = 22). Decision support was investigated in the non-metastatic setting in 22 studies (50%), the metastatic setting in two studies (5%), and 19 studies (43%) in both settings. One study did not report the disease setting.

In the 44 included articles, twenty unique CDSSs were described. The most frequently described CDSSs were WFO (n = 12), OncoDoc 2 (n = 8), the guideline-based decision support system (GL-DSS) (n = 3), and Oncoguide (n = 4). WFO used a cognitive computing system (which refers to the use of reasoning, language processing, machine learning and human capabilities that help regular computing better solve problems and analyze data) as knowledgebase. OncoDoc2, GL-DSS and Oncoguide used decision trees as knowledgebase. Of all included studies, 27 studies (61%) reported reference guideline(s) or databases (in case of survival prediction CDSSs) used as knowledgebase for the studied CDSS. In all included studies, a median of 250 (range 10 – 420) patients were described and a median of 512 (range 158 – 1861)

Table 1
Characteristics of all 44 included articles in this scoping review.

Paper	Study period	Cancer type	Country	Setting	Study design	CDSS	Knowledge base	Reference guideline	Decisions (n)	Patients (n)
Aikemu, 2021	2017 - 2018	colorectal cancer	China	M- & M+	prospective, single center, observational study	WFO	cognitive computing system	NA $		250
Choi, 2019	2017 - 2017	gastric cancer	Korea	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		65
Kim, 2019	2016 - 2017	colorectal cancer	Korea	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		69
Kim, 2020	2018	lung cancer	Korea	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		405
Lee, 2020	2018	breast, colorectal, gastric, gynecological, liver, lung, thyroid cancer	Korea	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		285
Lee, 2018	2009 - 2016	colon cancer	Korea	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		656
Liu, 2018	2017	lung cancer	China	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		149
Somashekhar, 2018	2014 - 2016	breast cancer	India, USA, UK	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		638
Tian, 2020	2016 - 2018	gastric cancer	China	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		235
Zhao, 2020	2016 - 2018	breast cancer	China	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		302
Zhou, 2019	2017	lung, breast, gastrointestinal, gynecological cancer	China	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		362
Zou, 2020	2016 - 2018	cervical cancer	China	M- & M+	retrospective, single center, observational study	WFO	cognitive computing system	NA $		246
Bouaud, 2014	2009 - 2010	breast cancer	France	M-	prospective, multicenter cluster RCT	OncoDoc2	decision tree	local CancerEst CPG	557	
Bouaud, 2012	2007 - 2009	breast cancer	France	M-	prospective, multicenter cluster RCT, subanalysis	OncoDoc2	decision tree	local CancerEst CPG	199	
Bouaud, 2011	2007 - 2009	breast cancer	France	M-	prospective, multicenter cluster RCT, subanalysis	OncoDoc2	decision tree	local CancerEst CPG	169	
Bouaud, 2015	2009 - 2010	breast cancer	France	M-	prospective, multicenter cluster RCT, subanalysis	OncoDoc2	decision tree	local CancerEst CPG	394	
Séroussi, 2007	2005 - 2006	breast cancer	France	M-	prospective, single center, uncontrolled before/after intervention study	OncoDoc2	decision tree	local CancerEst CPG	467	316

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Table 1 (*continued*)

Paper	Study period	Cancer type	Country	Setting	Study design	CDSS	Knowledge base	Reference guideline	Decisions (n)	Patients (n)
Séroussi, 2013	2007 - 2009	breast cancer	France	M-	prospective, single center, observational cohort	OncoDoc2	decision tree	local CancerEst CPG	1624	
Séroussi, 2012	2007 - 2009	breast cancer	France	M-	prospective, single center, observational cohort	OncoDoc2	decision tree	local CancerEst CPG	1624	
Séroussi, 2013	2009 - 2010	breast cancer	France	M-	prospective, multicenter cluster RCT, subanalysis	OncoDoc2	decision tree	local CancerEst CPG	825	
Redjdal, 2020	NA	breast cancer	France	M-	retrospective study	GL-DSS; OncoDoc	rule-based & subsumption-based; decision tree	local CancerEst CPG	1861	
Redjdal, 2021	NA	breast cancer	France	M-	retrospective study	GL-DSS; OncoDoc	rule-based & subsumption-based; decision tree	local CancerEst CPG	1861	
Séroussi, 2017	NA	breast cancer	France	M-	original report with a case study	GL-DSS	rule-based & subsumption-based	eight (inter) national CPGs		
Ebben. 2022	2019	breast, colorectal, prostate cancer	Netherlands	M- & M+	prospective, multicenter, observational study	Oncoguide	decision tree	Dutch guideline for breast, colo-rectal and prostate cancer	296	
Hendriks, 2019	NA	breast cancer	Netherlands	M-	original report	Oncoguide	decision tree	Dutch guideline for breast cancer		
Hendriks, 2020	2012 - 2015	breast cancer	Netherlands	M-	retrospective, single center, observational study	Oncoguide	decision tree	Dutch guideline for breast cancer		394
Keikes, 2021	2016 - 2017	colorectal cancer	Netherlands	M- & M+	original report	Oncoguide	decision tree	Dutch guideline for colorectal cancer	158	
Alcorn, 2022	2007 - 2013	lung, breast, prostate cancer, other	USA	M+	retrospective, single center, observational study	BMETS-DSP	machine-learning model	institutional database		397
Cypko, 2017	not reported	laryngeal cancer	Germany, Poland, USA	M- & M+	retrospective, validation workflow	Kernal for Workflow, Knowledge, and Decision Management	Bayesian network model	not reported		
Eccher, 2014	2009 and 2012	breast cancer	Italy	M-	prospective, single center, observational cohort	OncoCure	Asbru-based	(inter) national guidelines		61
Epstein, 2006	not reported	breast cancer	Hong Kong	M-	prospective, single center, observational cohort	Adjuvant!	Bayesian network model	SEER database		102
Gaudioso, 2017	NA	breast cancer	USA	not reported	prospective, single center, observational	not reported	not reported	not reported		
Griewing	2023	breast cancer	Germany	M- & M+	prospective, single center, observational	ChatGPT 3.5	AI-based large language model	German breast cancer guideline		20
Heiden, 2015	NA	breast, colon, prostate cancer	Germany	M- & M+	original report	Health Care Management Platform	meta-model	existing clinical practice guidelines		
Lin, 2016	2007-2015	breast cancer	Australia	M-	retrospective, single center, original report		supervised machine learning	ESMO & NCCN		1065
Lukac, 2023	2023	breast cancer	Germany	M-	retrospective, single center, observational study	ChatGPT 3.5	AI-based large language model	German breast cancer guideline		10

(*continued on next page*)

Table 1 (*continued*)

Paper	Study period	Cancer type	Country	Setting	Study design	CDSS	Knowledge base	Reference guideline	Decisions (n)	Patients (n)
Macchia, 2022	2015 - 2018	cervical cancr	Italy	M-	retrospective, single center, observational study	MTB virtual assistant	natural language processing & supervised learning technique	medical guidelines and machine learning		96
Ng, 2023	NA	liver cancer	Germany	M- & M+	prospective, single center RCT	ADBoard	natural language processing & machine learning	current guidelines		
O'Reilly, 2008	2004	colorectal cancer	UK	M+	retrospective, single center, external validation study	Oncosurge	RAND/UCLA Appropriateness Method (RAM)	NA		98
Prebet, 2018	NA	breast cancer	France	M-	original report		decision tree	ESMO & NCCN		
Rossille, 2005	NA	breast cancer	France, Canada	M-	original report		multi-model reasoning (rule-based & case-based)	SOR guidelines & case series		
Sesen, 2014	2006 - 2010	lung cancer	UK	M- & M+	original report	Lung Cancer Assistant	rule-based & probalistic interference	four (inter) national CPGs		4020
Shekarriz, 2020	2008 - 2017	pancreatic cancer	Germany	M-	retrospective, single center, observational study	MEBDAS®	quantitative calculation	NA		126
Thavanesan, 2023	2010 - 2020	esophageal cancer	UK	M-	retrospective, single center, observational study	not reported	machine-learning model	NA		399

Abbreviations: BMETS-DSP, bone metastases ensemble trees for survival decision support platform; CDSS, clinical decision support system; CPG, clinical practice guideline; EHR, electronic health record; EP, emerging pattern; ISPM, IntelliSpace Precision Medicine; Multidisciplinary Team Orchestrator; MSM, multidisciplinary staff meeting; MDT, multidisciplinary team; MTB, multidisciplinary Tumor Board; RCT, randomized clinical trial; WFO, Watson for Oncology.

$ Watson for Oncology is based on relevant studies, expert recommendations by doctors of Memorial Sloan-Kettering Cancer Center and American guidelines

decisions were reported.

3.3. Study aims of the 44 included studies

There were differences in main aims per study (supplemental table B). Most studies (n = 25) investigated the concordance rate between the CDSS and MDT generated recommendations and searched patient patterns associated with disconcordance. Nine studies focused on the development or methods to design a CDSS. Two studies described the development of a machine learning model to predict MDT decisions. Two studies investigated the integration of complementarity of different guidelines in the CDSS. Two studies evaluated the impact of CDSS based survival prediction on MDT decision-making. The remaining four studies all had different goals (supplemental table B).

3.4. The main findings of the defined aims of 44 included studies

Of the 25 studies that focused on concordance rate between the CDSS and MDT generated recommendations, four studies compared concordance rates in both situations, where the CDSS was used and was not used (control arm): three studies with OncoDoc2 and one study with WFO. These four studies considered a MDT recommendation concordant if the recommendation corresponded to the 'to be recommended' or 'for consideration' category of the CDSS. The studies concluded that CDSS usage improved the concordance rate (Bouaud et al., 2014; Séroussi et al., 2007, 2013b; Somashekhar et al., 2018). In the other 21 studies, there was no control arm. Five studies focused on reasons for non-concordance between CDSS and MDT recommendations (Bouaud et al., 2012; Bouaud and Séroussi, 2011; Séroussi et al., 2013a, 2012, 2013b). The study of Bouaud et al. proposed four reasons for non-concordance: (1) practice evolution; (2) particular cases not covered by current guideline; (3) MDT judgment that an alternative treatment is better suited for the patient than the CDSS recommendation; (4) specific patient preference (Bouaud and Séroussi, 2011).

Nine studies described the development and/or validation of a CDSS (Cypko et al., 2017; Gaudioso and Elkin, 2017; Hendriks et al., 2019; Keikes et al., 2021; Macchia et al., 2022; Sesen et al., 2014) or method to design a CDSS (Heiden et al., 2015; Redjdal et al., 2021; Rossille et al., 2005) to support treatment decisions. Two studies developed machine learning models to predict MDT decisions. In a breast cancer study, machine learning did more accurately predict adjuvant chemotherapy recommendation by the MDT compared to simple application of guidelines. The authors concluded that some non-clinicopathologic variables such as patient preference and resource availability are weighted by the MDT, but these factors are not captured by guidelines (Lin et al., 2016). Another study showed that machine learning-based models trained on pretreatment clinicopathological variables of patients with esophageal cancer can predict curative MDT treatment decisions with good accuracy (Thavanesan et al., 2023). Two studies demonstrated that CDSSs can use multiple reference guidelines as knowledgebase to generate recommendations and this complementarity improves and enriches coverage of more specific clinical situations (Prebet et al., 2018; Séroussi et al., 2017).

One study with survival prediction model Adjuvant! found that MDT initial treatment recommendations for breast cancer were modified after showing the impact of adjuvant systemic therapy on survival in 12.7% of cases (Epstein et al., 2006). A pilot study with BMETS-DSP, a CDSS for multidisciplinary management of bone metastases, showed significantly improvement of survival estimation accuracy by physicians and selection of prognosis-appropriate palliative radiotherapy regimens (Alcorn et al., 2022). A study investigating MDT attitude towards CDSS usage found that a guideline-based CDSS, when wrongly used, could deliver

non guideline-based recommendations (automation bias) (Bouaud et al., 2015). Lee and Lee found that WFO usage during MDT meetings positively changed patient satisfaction and leads to a positive patient perception after treatment (Lee and Lee, 2020). Redjdal et al. investigated the interoperability between two CDSSs for breast cancer. The authors of that study had to solve semantic and structural interoperability issues to make OncoDoc data reusable by the GL-DSS of DESIREE 2 (Redjdal et al., 2020). And finally, one retrospective study found a low data availability in patient records for adequate application of a CDSS in breast cancer (Hendriks et al., 2020).

3.5. Barriers for CDSS implementation

Specific information on barriers for CDSS implementation was reported in 35 studies (supplemental table C & Fig. 2). All mentioned barriers (n = 102, supplemental table C) were categorized in groups and reported in order of frequency (Fig. 2). Definitions of all categories are included in supplemental table E.

The first most frequently reported barrier concerns CDSS maintenance. For example, guideline-outdated recommendations should be updated (Bouaud et al., 2012; Bouaud and Séroussi, 2011; Choi et al., 2019; Hendriks et al., 2020; Tian et al., 2020; Zhao et al., 2020; Zhou et al., 2019; Zou et al., 2020). Another example: some patient cases are not supported by CDSSs due to recommendation gaps in the guideline (Eccher et al., 2014; Keikes et al., 2021; Redjdal et al., 2021; Séroussi et al., 2007). Further, identified discrepancies between different guidelines (NCCN & ESMO) should be addressed by guideline working parties to update the CDSS (Prebet et al., 2018).

A second largest barrier is the lack of internal and external validation of CDSSs. A potential risk of converting text-based guideline recommendations and considerations into computer interpretable decision trees is losing nuance (Keikes et al., 2021). This is an example of potential loss of internal validity. Most CDSSs have been tested by the developers of the CDSS, without sufficient external validation.

The third most often mentioned barrier reflects loco-regional feasibility of the recommendations, pinpointing the importance of CDSSs to deal with context specific requirements or limitations: e.g. CDSSs can recommend certain treatments that are not available (or tolerated) locally or lack reimbursement (Choi et al., 2019; Kim et al., 2019, 2020; Lee et al., 2018; Liu et al., 2018; Somashekhar et al., 2018; Tian et al., 2020; Zhao et al., 2020; Zhou et al., 2019; Zou et al., 2020).

Fourth, CDSS do not include clinicians' and patients' preferences in their recommendations. This means that that CDSS include not all factors that are relevant to the clinician and/or patient in their recommendation (Bouaud and Séroussi, 2011; Choi et al., 2019; Lukac et al., 2023; Thavanesan et al., 2023). Clinicians' treatment decisions can be influenced by additional covariables that are not included in the guideline (and therefore not in de CDSS) (Epstein et al., 2006). Two studies reported that clinicians have a holistic view on the disease which can alter parameter thresholds in patient subpopulations based on comorbidity, patient preferences and level of social support systems, which is not supported by the CDSS (Eccher et al., 2014; Somashekhar et al., 2018).

Another barrier reflects data accuracy. Manual input of patient data in the CDSS is sensitive to errors (Keikes et al., 2021). Moreover, the lack of interoperability between CDSSs and other sources like electronic health records is challenging and threatening the availability of accurate data (Eccher et al., 2014; Macchia et al., 2022).

Other barriers that were identified more frequently were: the fact that certain subpopulations are treated differently based on age and/or

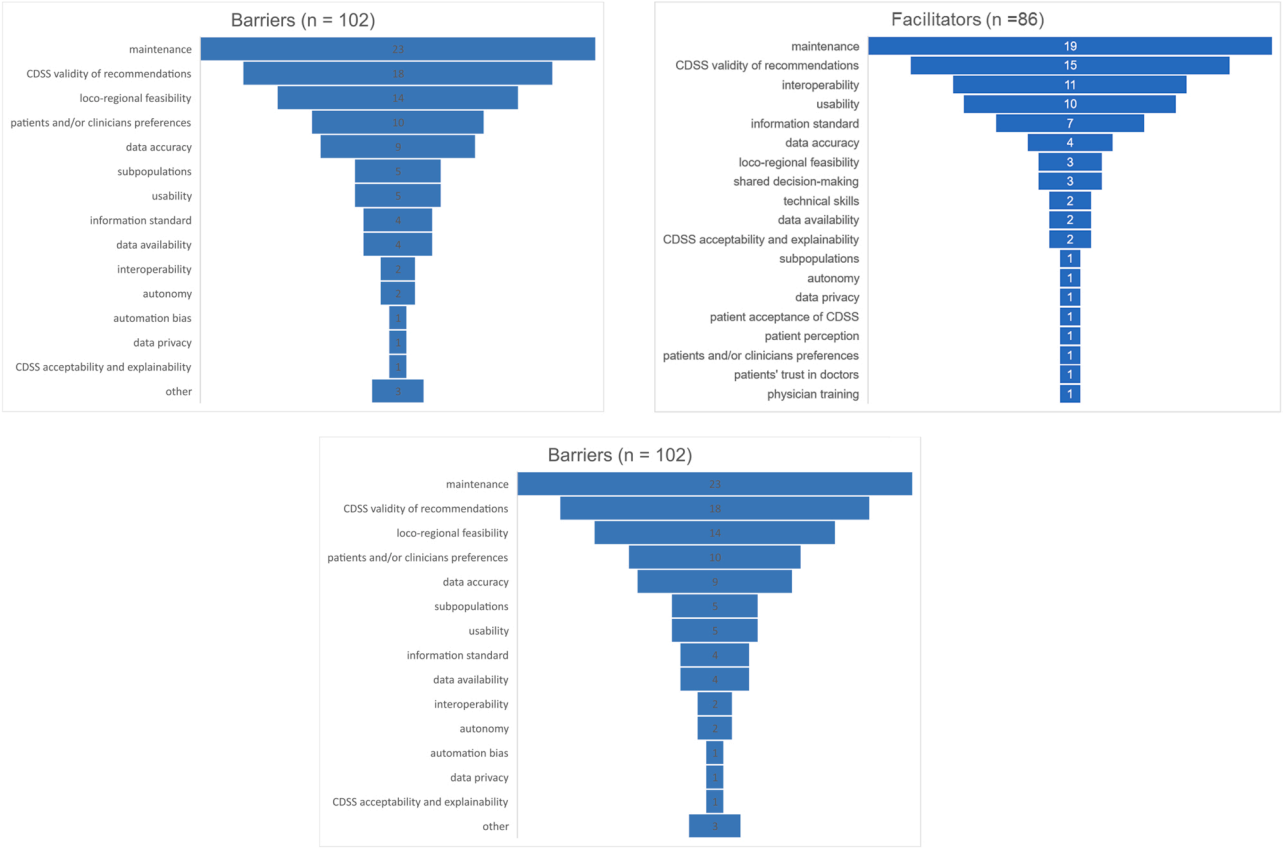

Fig. 2. Barriers and facilitators mentioned in the 44 included studies. For details, see supplementary tables C, D & E. For each included study the number of reported barriers (B) and facilitators (F) are scored for each category. Note: in total there were 188 barriers and facilitators, however this table only reflects the 15 most common categories, reflecting 98 barriers and 82 facilitators.

Table 2
Overview of the most frequently reported categories of barriers and facilitators. For each included study the number of reported barriers (B) and facilitators (F) are scored for each category. Note: in total there were 188 barriers and facilitators, however this table only reflects the 15 most common categories, reflecting 98 barriers and 82 facilitators.

			maintenance		CDSS validity		loco-regional feasibility		usability		data accuracy		interoperability		information standard	
CDSS	first author		B	F	B	F	B	F	B	F	B	F	B	F	B	F
WFO	Aikemu	2021	1	1	1	1	1	1								
WFO	Choi	2019	1		1		1	2								
WFO	Kim	2019		1	2		1									
WFO	Kim	2020			1		1									
WFO	Lee	2020			1											
WFO	Lee	2018			2		1									
WFO	Liu	2018	4	1			1									
WFO	Somashekhar	2018					1									
WFO	Tian	2020	1	1		1	1									
WFO	Zhao	2020	1				2									
WFO	Zhou	2019	2	1		1	2									
WFO	Zou	2020	2	1			2									
OncoDoc2	Bouaud	2014							1	1	1	1				
OncoDoc2	Bouaud	2012	1	1												
OncoDoc2	Bouaud	2011	1	1												
OncoDoc2	Bouaud	2015							1	1	1	1				
OncoDoc2	Séroussi	2007	1	1						1						
OncoDoc2	Séroussi	2013		1												
OncoDoc2	Séroussi	2012														
OncoDoc2	Séroussi	2013														
GL-DSS	Redjdal	2020											1			
GL-DSS	Redjdal	2021	1	1												
GL-DSS	Séroussi	2017		2										1		1
Oncoguide	Ebben	2022								1				1		1
Oncoguide	Hendriks	2019		1		1			1					1	1	1
Oncoguide	Hendriks	2020	1	1										2	1	1
Oncoguide	Keikes	2021	1	1	2	2			1	1	1	1		2		1
BMETS-DSP	Alcorn	2022			1	1										
Kernal for Workflow, Know-ledge & Decision Management	Cypko	2017			2	1					2					
OncoCure	Eccher	2014	1							1	1		1			
Adjuvant!	Epstein	2006														
NR	Gaudioso	2017								2						
ChatGPT 3.5	Griewing	2023	1		2											
Health Care Management Platform	Heiden	2015														
NR	Lin	2016	2	1		2									1	
ChatGPT 3.5	Lukac	2023				2				1						
MTB virtual assistant	Macchia	2022			1						1			1		1
ADBoard	Ng	2023			1					1	1					
Oncosurge	O'Reilly	2008				1										
NR	Prebet	2018	1	1												
NR	Rossille	2005				1								1		
Lung Cancer Assistant	Sesen	2014		1	1				1		1			1	1	1
MEBDAS®	Shekarriz	2020				1										
NR	Thavanesan	2023										1		1		
Barriers (n)		98	23		18		14		5		9		2		4	
Facilitators (n)		82		19		15		3		10		4		11		7

medical history (Bouaud and Séroussi, 2011; Choi et al., 2019; Epstein et al., 2006); ambiguous guideline terminology usage for guideline rule-based CDSSs reflecting the need for an information standard (Hendriks et al., 2019; Sesen et al., 2014), and the usability of the CDSS in daily practice. Manual input of data in a CDSS is time consuming (Bouaud et al., 2014; Hendriks et al., 2019; Keikes et al., 2021; Ng et al., 2023; Sesen et al., 2014). If a CDSS is being used, it is important to use it well. A study with OncoDoc2 found that MDT compliance with clinical practice guidelines was better when the CDSS was not used than navigating through the system improperly (Bouaud et al., 2014, 2015).

3.6. Facilitators for CDSS implementation

Facilitators for CDSS implementation were reported in 37 studies (supplemental table D + Fig. 2). All mentioned facilitators (n = 86, supplemental table D) were categorized in groups and reported in order of frequency (Fig. 2).

The first most frequently reported facilitator concerns CDSS maintenance. This included the usage of up-to-date guidelines (Bouaud and Séroussi, 2011; Kim et al., 2019), taking into account the loco-regional characteristics of patients (Choi et al., 2019; Liu et al., 2018), the possibility for modular updating of the CDSS (Hendriks et al., 2020, 2019), enlarging the coverage of CDSSs and enriching recommendations by making use of complementarity of clinical practice guidelines (Prebet et al., 2018; Séroussi et al., 2017).

Secondly, evaluating CDSS validity can facilitate CDSS implementation. CDSSs can by their systematically design elucidate information gaps, inconclusive treatment recommendations and guideline

patient & clinician preferences		patient sub-populations		data availability		CDSS acceptability and explainability		autonomy		shared decision-making		techniqual skills		data privacy	
B	F	B	F	B	F	B	F	B	F	B	F	B	F	B	F
		1		1											
1		1													
1															
1															
								1							1
1															
		1		1											
1		1				1									
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				1											
1															
												1			
1						1		1							
10		5		4		1		2		0		0		1	
	1		1		2			2		1		3		2	1

considerations which should be described in the CDSS and can be addressed in guideline updates (Hendriks et al., 2019; Keikes et al., 2021). Further, it is recommended to check the validity of non-concordance between MDT decisions and CDSS recommendations by (guideline updating) experts (Bouaud et al., 2012; Cypko et al., 2017; Keikes et al., 2021; Lin et al., 2016; Chaudhari et al., 2008; Séroussi et al., 2007, 2013a; Shekarriz et al., 2020; Tian et al., 2020).

A third facilitator involves CDSS interoperability. Important other conditions for implementing decision tree-based knowledge bases in CDSSs and interoperability with electronic health records are usage of unequivocal and unambiguous definitions of data (i.e. patient and tumor characteristics) on the basis of internationally acknowledged classification and coding system. Reaching consensus internationally on these data definitions is recommended by three included studies, it can pave the way for reconciliation of guidelines, covering and enriching more clinical patient situations with CDSSs by complementarity (Hendriks et al., 2019; Prebet et al., 2018; Séroussi et al., 2017).

The fourth most mentioned facilitator concerns CDSS usability. Gaudioso reported two important factors when starting to use a CDSS: (1) users prefer relevant clinical information to be displayed on a single screen as human cognitive load is limited and (2) users need to trust the system. However, one article states that medical oncologists want to read pathology reports fully, as they do not trust somebody else's interpretation (Gaudioso and Elkin, 2017).

The fifth most reported facilitator concerns the importance of using an information standard. One study reports the importance of

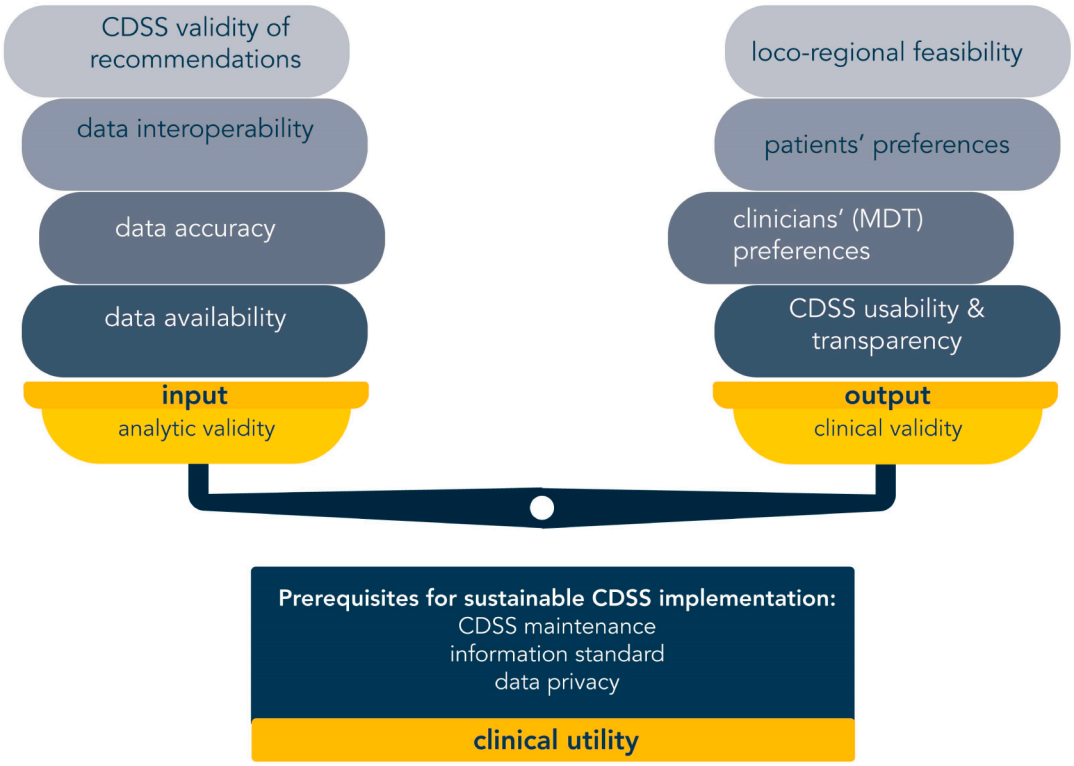

Fig. 3. A CDSS implementation model. The left side of the scale reflects the analytic validity of the input of the CDSS: necessary data for the CDSS need to be available, accurate and interoperable between data sources (e.g. electronic health records) and the CDSS. The generated recommendations by the CDSS need to be valid (e.g. they should adequately adhere to the reference database of the CDSS such as a guideline). The right part of the scale represents the clinical validity of the CDSS: is the CDSS usable and transparent? Can preferences of the MDT and the patient be integrated? Are the generated recommendations of CDSS locally feasible in the clinic? The bottom of the scale shows the prerequisites for sustainable CDSS implementation: the maintenance (i.e. governance, regular updating the CDSS), an information standard (to preserve that the right data are processed at the input level of the CDSS) and data privacy (to comply with international standards like the General Data Protection Regulation). And "clinical utility" at the very bottom reflects the validity of the CDSS as a whole.

addressing vagueness and uncertainty in rule eligibility criteria by explicating the implicit expert knowledge (Sesen et al., 2014). Further, usage of information standards can solve the problem of limited interchangeability of data between various CDSSs and the electronic health record (Bouaud et al., 2014; Ebben et al., 2022; Eccher et al., 2014; Hendriks et al., 2019; Keikes et al., 2021; Macchia et al., 2022; Redjdal et al., 2020; Rossille et al., 2005; Sesen et al., 2014).

3.7. Barriers and facilitators per CDSS

Based on the most frequently reported categories of barriers and facilitators for CDSS implementation, we evaluated for each CDSS which of those categories have been explicitly addressed or not by the authors (Table 2). WFO is not addressing the categories usability, information standard and interoperability. Further, WFO is not solely based on guidelines, but also on expert opinion of one tertiary hospital in the USA, impeding localized use of WFO in other countries. OncoDoc2 has been extensively studied but has never been validated outside the hospital group of Paris. Oncoguide is a more recent developed CDSS requiring manual data entry and interoperability of the system with the electronic health record to facilitate implementation. For all CDSSs, patient privacy is an issue that needs to be addressed. This point was mentioned both as a barrier and a facilitator (Redjdal et al., 2020; Zhou et al., 2019).

3.8. A CDSS implementation model

Based on all barriers and facilitators identified (Fig. 2; supplemental tables C and D), we composed an implementation model that captures the balance of most important factors to consider for implementing a CDSS for real-time MDT decision support (Fig. 3 and Table 2). Although some factors were mentioned more often than other ones in the included studies, all of them are important and need to be addressed.

The input of a CDSS (i.e. analytic validity) is clinical data (patient and tumor characteristics), that need to be real-time available and accurate. These data (originating from radiology reports, pathology reports, standardized / synoptic reporting in electronic health records) should be interoperable with the CDSS and lead to a valid recommendation. On the output level (i.e. clinical validity), CDSS usability and transparency is essential key for clinicians to use the system and trust the generated recommendations. As CDSSs cannot take into account clinicians' and patients' preferences, it is important that the theoretical treatment options generated by the CDSS can be explainable tailored to each specific patient during MDT meetings. The CDSS should generate recommendations that are locally available and feasible. Ultimately, the MDT must determine which recommendations are in the best interest of the patient and, if applicable justify when deliberate guideline deviations are made.

To warrant a balance between CDSS input and output, three factors are important: (1) CDSS maintenance (e.g. timely updating the CDSS when new guidelines / evidence becomes available); (2) using an information standard to prevent vagueness and to facilitate usage of the complementarity of guidelines; (3) to secure data privacy (CDSSs are medical devices for which CE certification is mandatory).

4. Discussion

This is the first review focusing explicitly on CDSSs for multidisciplinary team decision-making in solid cancer. In the 44 included studies in our scoping review, only four CDDSs have been studied more

intensely with three or more publications on the same CDSS: WFO, OncoDoc2, GL-DSS and Oncoguide. Importantly, these CDSSs are not implemented yet in a broad sense in the clinical workflow. Based on the many barriers and facilitators for CDSS implementation identified in this review, a compact theoretical model has been composed aiming to promote and support CDSS implementation. This model visualizes the balance between analytic and clinical validity with a solid basis of utility and may guide further development and implementation of CDSSs in the clinical workflow at the MDT level. Further studies are warranted to evaluate the usability of this CDSS implementation model.

Factors undermining implementation of CDSS use during MDT meetings are missing data, not easily reusable data (lack of interoperability of a CDSS and the electronic health record) and data of which a standardized definition (information standard) is lacking. Many CDSSs use manual data-entry which is error prone. Moreover, data collection should not be time consuming, trustworthy and the CDSS should be able to deliver real-time support (Janssen et al., 2018). Software solutions are needed for incorporation of real-time decision support in clinical workflow (Nabhan and Feinberg, 2017). Ideally, a CDSS should import relevant (standardized) data from the electronic health record automatically and uses these error-free copied source data for decision-support. This also contributes to the transparency of a CDSS, which is important for clinicians to trust the system. In this context, rule-based CDSSs are more intuitive for clinicians to understand compared to systems using machine learning techniques (Bradley et al., 2019). For each CDSS counts that the system should be safe to use in terms of patient privacy and data security (Zhou et al., 2019).

Besides the more technical issues, a major concern is the maintenance process of a CDSS to ensure the CDSS uses the most recent guideline update. Most CDSSs refer to local and/or (inter)national clinical practice guidelines regarding the generated recommendations. Guideline committees can validate a CDSS when a system is referring to their (updated) guideline. The rule-based CDSS Oncoguide is an example of this (Hendriks et al., 2019). More challenging are CDSSs that use more knowledge bases, like WFO. The latter is based on database training with patients treated in a tertiary hospital in the USA and WFO does for instance recommend systemic therapy options that are not reimbursed or available in other countries or recommend treatment options that are not feasible locally (Choi et al., 2019; Kim et al., 2019, 2020; Lee et al., 2018; Lin et al., 2016; Somashekhar et al., 2018; Tian et al., 2020; Zhao et al., 2020; Zhou et al., 2019; Zou et al., 2020). Further, it is important to assess the clinical utility of a CDSS, preferably by adequate multicenter validation studies and using both an intervention arm where the CDSS is used and a control arm where the CDSS is not used. Importantly, development of internationally accepted criteria is needed to assess the analytic and clinical validity, the clinical utility and the risk of bias of a CDSS.

The chosen focus on CDSSs for multidisciplinary team decision-making in solid cancer is clinically relevant and reviews on this particular topic were lacking. A limitation of our review is that included studies were not systematically scored for methodological quality because internationally accepted criteria to assess the risk of bias for CDSSs are lacking. Regarding the design of included studies in this review, many suffered from drawbacks such as a retrospective and/or single center design and the lack of a control arm. Furthermore, most studies evaluating a CDSS were led by the developers of the particular CDSS. It turns out that CDSSs were more likely to improve practitioner performance in studies where the authors also developed the CDSS compared to studies in which the authors were not the developers (Garg et al., 2005). Of all included studies in our review, only WFO has been studied by authors that were not the developers of the CDSS.

4.1. Practice implications and recommendations on the model

To improve CDSS implementation in the clinical workflow to support MDT clinical decision-making in daily clinical practice, more guidance in CDSS development, implementation and evaluation is needed. Based on the identified barriers and facilitators for implementation of CDSSs to guide MDTs in solid cancer we recommend clinicians of MDTs, CDSS developers, guideline working party members and electronic health record suppliers to collaborate and focus on the essential prerequisites of a CDSS as shown in the proposed CDSS implementation model. The usability of this theoretical model should be explored in future studies.

With a joint effort, it should be possible to successfully overcome the most important outstanding challenges: 1) to make necessary data-items for guideline-based decision making available during MDT meeting; 2) to promote data accuracy by reusing data from source documents which prerequisites; 3) data-interoperability with the electronic health record; 4) to assess the CDSS validity of recommendations; 5) to improve CDSS usability and transparency in such a way that the CDSS is easily real-time usable during MDT meetings; 6) to include clinicians' and 7) patients' preferences in the MDT decision reporting; 8) to include the loco-regional feasibility in the MDT decision reporting; 9) to warrant CDSS maintenance procedures; 10) to reach an internationally accepted information standard that supports unambiguously guideline development; 11) to comply with data privacy regulations; 12) to assess the clinical utility of the CDSS. Once these challenges are overcome, the data-driven CDSSs can potentially boost electronic health records into learning health systems, and potentially leading to growth of real-world population-based "big data" that can be analyzed systematically using both regular techniques and more modern data analysis techniques such as machine-learning. A huge opportunity to bring personalized medicine a step further (Walsh et al., 2019).

The next step involves performing multicenter studies to evaluate the effectiveness of CDSS application in daily practice patient care (Oehring et al., 2023). As MDT workload is expanding due to increasing number of patients and more recommendations in the guideline related to more treatment options, implementation of CDSS can help to structure, reuse, organize and present data in MDTs to support decision-making and to make this process more efficiently (Ebben et al., 2022; Winters et al., 2021). MDTs are also challenged to apply increasing knowledge regarding treatment data to their patients, and artificial intelligence is ideally suitable to deal with large amounts of data (Griewing et al., 2023; Lukac et al., 2023). With a view to broader implementation of CDSS in the clinical workflow, it is important that the CDSS to be investigated have sufficient clinical utility, analytic validity and clinical validity. Future research will elucidate whether such CDSS meet the outlined expectations in terms of optimizing recommendation quality, alleviating MDT burden, and eventually enhancing care.

5. Conclusion

We have shown that only a few CDSSs have been externally validated and implemented in daily care. CDSS maintenance, validity of recommendations and interoperability are important facilitators for CDSS implementation. Internationally accepted criteria are needed to assess the analytic and clinical validity, the clinical utility and the risk of bias of a CDSS. Our novel implementation model for CDSS development and implementation in the clinical workflow can hopefully fulfill the challenging aim of supporting oncological MDTs, providing an overview of the increasing amount of available knowledge to further generate personalized state-of-the-art recommendations for our patients.

Ethics approval

Not required.

CRediT author contributions statement

Conceptualization (MH, AJ, SS), data curation (MH, KE), formal analysis (MH, AJ, KE, SS), investigation (all), methodology (MH, AJ, JT, MH), project administration (MH), resources (SS), supervision (AJ, SS),

validation (MH, KE, SS), visualization (MH, AJ, SS), writing – original draft (MH), writing – review & editing (all). All authors declare that they have no conflict of interest.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.critrevonc.2024.104267.

References

Aikemu, B., Xue, P., Hong, H., et al., 2021. Artificial intelligence in decision-making for colorectal cancer treatment strategy: an observational study of implementing Watson for oncology in a 250-case cohort. Front. Oncol. 10.
Alcorn, S.R., LaVigne, A.W., Elledge, C.R., et al., 2022. Evaluation of the clinical utility of the bone metastases ensemble trees for survival decision support platform (BMETS-DSP): a case-based pilot assessment. JCO Clin. Cancer Inf. 6, e2200082.
Bouaud, J., Séroussi, B., 2011. Revisiting the EBM decision model to formalize non-compliance with computerized CPGs: results in the management of breast cancer with OncoDoc2. AMIA Annu Symp. Proc. 2011, 125–134.
Bouaud, J., Messai, N., Laouénan, C., et al., 2012. Elicitating patient patterns of physician non-compliance with breast cancer guidelines using formal concept analysis. Stud. Health Technol. Inf. 180, 477–481.
Bouaud, J., Blaszka-Jaulerry, B., Zelek, L., et al., 2014. Health information technology: use it well, or don't! Findings from the use of a decision support system for breast cancer management. AMIA Annu Symp. Proc. 2014, 315–324.
Bouaud, J., Spano, J.P., Lefranc, J.P., et al., 2015. Physicians' attitudes towards the advice of a guideline-based decision support system: a case study with OncoDoc2 in the management of breast cancer patients. Stud. Health Technol. Inf. 216, 264–269.
Bradley, A., van der Meer, R., McKay, C., 2019. Personalized pancreatic cancer management: a systematic review of how machine learning is supporting decision-making. Pancreas 48, 598–604.
Choi, Y.I., Chung, J.W., Kim, K.O., et al., 2019. Concordance rate between clinicians and watson for oncology among patients with advanced gastric cancer: early, real-world experience in Korea. Can. J. Gastroenterol. Hepatol. 2019, 8072928.
Chua, I.S., Gaziel-Yablowitz, M., Korach, Z.T., et al., 2021. Artificial intelligence in oncology: path to implementation. Cancer Med. 10, 4138–4149.
Cypko, M.A., Stoehr, M., Kozniewski, M., et al., 2017. Validation workflow for a clinical Bayesian network model in multidisciplinary decision making in head and neck oncology treatment. Int J. Comput. Assist Radio. Surg. 12, 1959–1970.
Ebben, K., Sieswerda, M.S., Luiten, E.J.T., et al., 2020. Impact on quality of documentation and workload of the introduction of a national information standard for tumor board reporting. JCO Clin. Cancer Inf. 4, 346–356.
Ebben, K., Hendriks, M.P., Markus, L., et al., 2022. Using guideline-based clinical decision support in oncological multidisciplinary team meetings: a prospective, multicenter concordance study. Int J. Qual. Health Care 34.
Eccher, C., Seyfang, A., Ferro, A., 2014. Implementation and evaluation of an Asbru-based decision support system for adjuvant treatment in breast cancer. Comput. Methods Prog. Biomed. 117, 308–321.
Epstein, R.J., Leung, T.W., Mak, J., et al., 2006. Utility of a web-based breast cancer predictive algorithm for adjuvant chemotherapeutic decision making in a multidisciplinary oncology center. Cancer Invest 24, 367–373.
Garg, A.X., Adhikari, N.K., McDonald, H., et al., 2005. Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: a systematic review. JAMA 293, 1223–1238.
Gaudioso, C., Elkin, P., 2017. Considerations of human factors in the design and implementation of clinical decision support systems for tumor boards. Stud. Health Technol. Inf. 245, 1324.
Griewing, S., Gremke, N., Wagner, U., et al., 2023. Challenging ChatGPT 3.5 in senology—an assessment of concordance with breast cancer tumor board decision making. J. Pers. Med. 13.
Heiden, K., Sinha, M., Böckmann, B., 2015. Virtual oncological networks–IT support for an evidence-based, oncological health care management. Stud. Health Technol. Inf. 216, 953.
Hendriks, M.P., Verbeek, X., van Vegchel, T., et al., 2019. Transformation of the national breast cancer guideline into data-driven clinical decision trees. JCO Clin. Cancer Inf. 3, 1–14.
Hendriks, M.P., Verbeek, X., van Manen, J.G., et al., 2020. Clinical decision trees support systematic evaluation of multidisciplinary team recommendations. Breast Cancer Res Treat. 183, 355–363.
Janssen, A., Robinson, T., Brunner, M., et al., 2018. Multidisciplinary teams and ICT: a qualitative study exploring the use of technology and its impact on multidisciplinary team meetings. BMC Health Serv. Res. 18, 444.
Jie, Z., Zhiying, Z., Li, L., 2021. A meta-analysis of Watson for oncology in clinical application. Sci. Rep. 11, 5792.
Keikes, L., Kos, M., Verbeek, X., et al., 2021. Conversion of a colorectal cancer guideline into clinical decision trees with assessment of validity. Int J. Qual. Health Care 33.
Kim, E.J., Woo, H.S., Cho, J.H., et al., 2019. Early experience with Watson for oncology in Korean patients with colorectal cancer. PLoS One 14, e0213640.
Kim, M.S., Park, H.Y., Kho, B.G., et al., 2020. Artificial intelligence and lung cancer treatment decision: agreement with recommendation of multidisciplinary tumor board. Transl. Lung Cancer Res. 9, 507–514.
Klarenbeek, S.E., Weekenstroo, H.H.A., Sedelaar, J.P.M., et al., 2020. The effect of higher level computerized clinical decision support systems on oncology care: a systematic review. Cancers 12.
Lamb, B.W., Brown, K.F., Nagpal, K., et al., 2011. Quality of care management decisions by multidisciplinary cancer teams: a systematic review. Ann. Surg. Oncol. 18, 2116–2125.
Lee, K., Lee, S.H., 2020. Artificial intelligence-driven oncology clinical decision support system for multidisciplinary teams. Sensors 20.
Lee, W.S., Ahn, S.M., Chung, J.W., et al., 2018. Assessing concordance with watson for oncology, a cognitive computing decision support system for colon cancer treatment in Korea. JCO Clin. Cancer Inf. 2, 1–8.
Lin, F.P., Pokorny, A., Teng, C., et al., 2016. Computational prediction of multidisciplinary team decision-making for adjuvant breast cancer drug therapies: a machine learning approach. BMC Cancer 16, 929.
Liu, C., Liu, X., Wu, F., et al., 2018. Using artificial intelligence (Watson for Oncology) for treatment recommendations amongst chinese patients with lung cancer: feasibility study. J. Med Internet Res. 20, e11087.
Lukac, S., Dayan, D., Fink, V., et al., 2023. Evaluating ChatGPT as an adjunct for the multidisciplinary tumor board decision-making in primary breast cancer cases. Arch. Gynecol. Obstet. 308, 1831–1844.
Macchia, G., Ferrandina, G., Patarnello, S., et al., 2022. Multidisciplinary tumor board smart virtual assistant in locally advanced cervical cancer: a proof of concept. Front. Oncol. 11.
Munn, Z., Peters, M.D.J., Stern, C., et al., 2018. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. BMC Med. Res. Method. 18, 143.
Nabhan, C., Feinberg, B.A., 2017. Clinical pathways in oncology: software solutions. JCO Clin. Cancer Inf. 1, 1–5.
Ng, S.S.T., Oehring, R., Ramasetti, N., et al., 2023. Concordance of a decision algorithm and multidisciplinary team meetings for patients with liver cancer-a study protocol for a randomized controlled trial. Trials 24, 577.
Oehring, R., Ramasetti, N., Ng, S., et al., 2023. Use and accuracy of decision support systems using artificial intelligence for tumor diseases: a systematic review and meta-analysis. Front. Oncol. 13.
O'Reilly, D.A., Chaudhari, M., Ballal, M., et al., 2008. The Oncosurge strategy for the management of colorectal liver metastases - an external validation study. Eur. J. Surg. Oncol. 34, 538–540.
Osheroff, J.A., Teich, J.M., Levick, D., et al., 2012. Improving outcomes with clinical decision support: an implementer's guide. Himss Publishing.
Pawloski, P.A., Brooks, G.A., Nielsen, M.E., et al., 2019. A systematic review of clinical decision support systems for clinical oncology practice. J. Natl. Compr. Canc Netw. 17, 331–338.
Peters, M.D., Godfrey, C.M., Khalil, H., et al., 2015. Guidance for conducting systematic scoping reviews. Int J. Evid. Based Health 13, 141–146.
Prades, J., Remue, E., van Hoof, E., et al., 2015. Is it worth reorganising cancer services on the basis of multidisciplinary teams (MDTs)? A systematic review of the objectives and organisation of MDTs and their impact on patient outcomes. Health Policy 119, 464–474.
Prebet, C., Bouaud, J., Guézennec, G., et al., 2018. Taking into account the complementarity of contemporary breast cancer guidelines to leverage decision support in the DESIREE project. Stud. Health Technol. Inf. 247, 755–759.
Redjdal, A., Bouaud, J., Guézennec, G., et al., 2020. Creating synthetic patients to address interoperability issues: a case study with the management of breast cancer patients. Stud. Health Technol. Inf. 275, 177–181.
Redjdal, A., Bouaud, J., Guézennec, G., et al., 2021. Reusing decisions made with one decision support system to assess a second decision support system: introducing the notion of complex cases. Stud. Health Technol. Inf. 281, 649–653.

Roshanov, P.S., Fernandes, N., Wilczynski, J.M., et al., 2013. Features of effective computerised clinical decision support systems: meta-regression of 162 randomised trials. BMJ 346, f657.
Rossille, D., Laurent, J.F., Burgun, A., 2005. Modelling a decision-support system for oncology using rule-based and case-based reasoning methodologies. Int J. Med. Inf. 74, 299–306.
Séroussi, B., Bouaud, J., Gligorov, J., et al., 2007. Supporting multidisciplinary staff meetings for guideline-based breast cancer management: a study with OncoDoc2. AMIA Annu Symp. Proc. 2007, 656–660.
Séroussi, B., Soulet, A., Messai, N., et al., 2012. Patient clinical profiles associated with physician non-compliance despite the use of a guideline-based decision support system: a case study with OncoDoc2 using data mining techniques. AMIA Annu Symp. Proc. 2012, 828–837.
Séroussi, B., Laouénan, C., Gligorov, J., et al., 2013a. Which breast cancer decisions remain non-compliant with guidelines despite the use of computerised decision support? Br. J. Cancer 109, 1147–1156.
Séroussi, B., Soulet, A., Spano, J.P., et al., 2013b. Which patients may benefit from the use of a decision support system to improve compliance of physician decisions with clinical practice guidelines: a case study with breast cancer involving data mining. Stud. Health Technol. Inf. 192, 534–538.
Séroussi, B., Guézennec, G., Lamy, J.B., et al., 2017. Reconciliation of multiple guidelines for decision support: a case study on the multidisciplinary management of breast cancer within the DESIREE project. AMIA Annu Symp. Proc. 2017, 1527–1536.
Sesen, M.B., Peake, M.D., Banares-Alcantara, R., et al., 2014. Lung cancer assistant: a hybrid clinical decision support application for lung cancer care. J. R. Soc. Interface 11, 20140534.
Shekarriz, J., Keck, T., Shekarriz, H., 2020. Computerized medical evidence-based decision assistance system "MEBDAS®" improves in-hospital outcome after pancreatoduodenectomy for pancreatic cancer. Pancreatology 20, 746–750.
Somashekhar, S.P., Sepúlveda, M.J., Puglielli, S., et al., 2018. Watson for oncology and breast cancer treatment recommendations: agreement with an expert multidisciplinary tumor board. Ann. Oncol. 29, 418–423.
Sutton, R.T., Pincock, D., Baumgart, D.C., et al., 2020. An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ Digit Med. 3, 17.
Thavanesan, N., Bodala, I., Walters, Z., et al., 2023. Machine learning to predict curative multidisciplinary team treatment decisions in oesophageal cancer. Eur. J. Surg. Oncol. 49, 106986.
Tian, Y., Liu, X., Wang, Z., et al., 2020. Concordance between Watson for oncology and a multidisciplinary clinical decision-making team for gastric cancer and the prognostic implications: retrospective study. J. Med. Internet Res. 22, e14122.
Walsh, S., de Jong, E.E.C., van Timmeren, J.E., et al., 2019. Decision support systems in oncology. JCO Clin. Cancer Inf. 3, 1–9.
Whiting, P.F., Rutjes, A.W., Westwood, M.E., et al., 2011. QUADAS-2: a revised tool for the quality assessment of diagnostic accuracy studies. Ann. Intern Med. 155, 529–536.
Winters, D.A., Soukup, T., Sevdalis, N., et al., 2021. The cancer multidisciplinary team meeting: in need of change? History, challenges and future perspectives. BJU Int. 128, 271–279.
Wolff, R.F., Moons, K.G.M., Riley, R.D., et al., 2019. PROBAST: a tool to assess the risk of bias and applicability of prediction model studies. Ann. Intern. Med. 170, 51–58.
Zhao, X., Zhang, Y., Ma, X., et al., 2020. Concordance between treatment recommendations provided by IBM Watson for oncology and a multidisciplinary tumor board for breast cancer in China. Jpn J. Clin. Oncol. 50, 852–858.
Zhou, N., Zhang, C.T., Lv, H.Y., et al., 2019. Concordance study between IBM Watson for oncology and clinical practice for patients with cancer in China. Oncologist 24, 812–819.
Zou, F.W., Tang, Y.F., Liu, C.Y., et al., 2020. Concordance study between IBM Watson for oncology and real clinical practice for cervical cancer patients in China: a retrospective analysis. Front. Genet. 11.

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