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REVIEW

AI and shared decision-making: a systematic review

Claudia Giorgetti[1] · Arianna Giorgetti[2] · Susi Pelotti[2] · Giuseppe Contissa[1]

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Abstract

Shared decision-making (SDM) is a collaborative process involving patients, their support networks, and the healthcare team, where patients are given a central role in making decisions about their health through effective communication. Since its introduction in the medical field, artificial intelligence (AI) has been increasingly used to support the SDM process. This systematic review is aimed at assessing the precise relationship between AI systems and the SDM process, highlighting both the potential for improvement as well as flaws. The systematic review followed the PRISMA methodology. Three databases were used to search for relevant literature: PubMed, Scopus (limited to the Medical field), and Web of Science (all fields). Two filtering rounds were performed, one on titles and abstracts, and one on the full-text of the articles. Extracted data included year, medical specialty/field, article type, AI method, developed or analyzed AI, clinical setting, use of AI, biases or limitations, funds, competing interests, ethical concerns, and algorithmic transparency/fairness. The authors also summarized the objective and contribution of each paper. The database search retrieved 927 records after duplicate removal. After the filtering rounds, 66 studies met the inclusion criteria; mostly articles published in 2024 (26.9%). Medical specialties were reported in 61.5% of studies, most frequently oncology (15.3%), orthopedics (7.7%), and cardiology (6.4%). Conceptual papers predominated (38.4%), followed by observational studies (20 reports) and reviews (18 reports). Almost half of the included articles (48.7%) did not specify an AI method. Among those that did, machine learning (28 reports) was most common, followed by others such as deep learning (9 reports) and large language models (6 reports). The objectives and contributions of the papers were distilled and discussed, including topics such as decision aids and conversation support, value consideration in recommender systems, time efficiency and aid in non-clinical tasks, black-box AI, fairness, reliability, and trust, human empathy, training and education, and design. The main risks that AI presents to the SDM process were identified in communication failures, lack of consideration for patient preferences, and absence of co-designing. Nevertheless, AI holds significant promise: it can increase clinical efficiency, contribute to chronic disease management, and enable patients to engage in self-monitoring and treatment adherence, thereby supporting sustained participation in their care. AI can also act as a decision aid and enrich patient–clinician dialog by clarifying options and aligning recommendations with individual values, ultimately fostering more collaborative decision-making. AI shall not be framed as a "negative" force for SDM, but rather should be harnessed for the opportunities it presents. Research and education should focus on overcoming the identified obstacles.

Keywords Shared decision-making · Artificial intelligence · Informed consent · Patient autonomy

1 Introduction

Artificial Intelligence (AI) systems in healthcare present novel challenges from both legal and ethical perspectives, which can hinder their widespread adoption (European Parliament 2022). Commonly explored obstacles, which are of particular concern to the healthcare system, include privacy risks, biases, lack of transparency, and accountability (Morley and Floridi 2024). Recently, these discussions have also centered on how these systems impact clinical workflows and the relationship between physicians and patients (Mittelstadt 2021).

The most popular AI applications in the healthcare field are systems designed to assist physicians in their clinical decision-making (Yu et al. 2018; Garcia-Vidal et al. 2019). So-called Clinical Decision Support Systems (CDSSs) have the potential to help physicians in diagnostic tasks, in treatment recommendations, and more (Sutton et al. 2020).

Extended author information available on the last page of the article

Broadly speaking, two main approaches may underpin these systems. Knowledge-based (or rule-based) systems rely on explicit medical rules, often using if–then logic to generate recommendations. In contrast, machine learning-based systems infer patterns from large datasets, enabling them to recognize correlations and make predictions without relying on pre-specified rules (Sutton et al. 2020). While knowledge-based systems offer transparency and interpretability, machine learning approaches promise adaptability and predictive power, but often at the cost of opacity (Sutton et al. 2020) (Amann et al. 2020). Regardless of the approach they may be based on, AI systems can insert themselves in the context of clinical decision-making by acting as co-decision makers alongside healthcare professionals (Duffourc 2023). In this sense, it seems clear that AI can acquire a crucial role in the clinical context and become part of the complex relationship between healthcare professionals and their patients.

The patient/physician relationship, in particular, has historically been the center of specific attention by ethicists and legislators (Kaba and Sooriakumaran 2007; Emanuel and Emanuel 1992; Beauchamp 2011). A paternalistic approach was characteristic of traditional medicine, where the physician has often been perceived as a "prevailing" figure over the patient, following the paradigm of "doctor knows best" (Lansdown 1994). However, not all aspects of paternalism are to be entirely discarded. Loignon and Boudreault-Fournier (2012), for example, proposed the notion of benevolent coaching, describing situations in which patients themselves may seek a more directive yet compassionate form of guidance. In this model, physicians act with empathy and commitment, offering accompaniment and support that can, under certain circumstances, empower rather than limit patients. At the same time, the broader paradigm shift that redefined the physician–patient relationship began decades earlier with the recognition of informed consent as a core medical principle in the Declaration of Helsinki (WMA. 1964). Since then, legislators have almost unanimously adopted norms that recognize informed consent as a legal obligation (Boulton and Parker 2007). Informed consent serves as a foundational element to ensure that patients receive adequate, relevant information and voluntarily agree to medical interventions. Building on this foundation, modern ethics and international scientific guidelines (NICE Guidelines 2021), emphasize that the complex patient/physician relationship should evolve toward the principles of shared decision-making (SDM) (Montori et al. 2023). As defined by Elwyn et al., SDM is: "an approach where clinicians and patients share the best available evidence when faced with the task of making decisions, and where patients are supported to consider options, to achieve informed preferences" (Elwyn et al. 2012). SDM is a collaborative process that is considered particularly appropriate for situations where two or more medically reasonable choices exist, and the purpose behind SDM is to ensure the respect of patient autonomy, not only by sharing information, but also decisional authority (Whitney et al. 2004). To be effectively protected, patients must be placed in a position to make choices that reflect their personal preferences, beliefs, and values, and be informed according to scientific evidence (Elwyn et al. 2017). Therefore, for example, while a physician might be tempted to choose an option that maximizes life expectancy, the patient might prefer an option that, while granting a lower life expectancy, allows them to achieve a greater quality of life (Kim and Kim 2023). The SDM process, while centrally focused on the patient/physician relationship, extends to a broader and complex network of figures, including other healthcare professionals, patient associations, and a variety of support persons (e.g., religious figures, relatives) (Kim and Kim 2023; Jeanne Wirpsa et al. 2019). To facilitate SDM in the discussion of options, risks, benefits, and consequences, patient decision aids or graphical presentations can also be used (NICE Guidelines 2021; O'Connor et al. 2004; Wieringa et al. 2019). SDM is considered the most effective way of protecting patient autonomy, though it is often overlooked in reality, usually due to time constraints or lack of specific training on the matter on the part of the healthcare professionals (Elwyn et al. 2023; Moleman et al. 2021; Caverly and Hayward 2020).

The involvement of AI has the potential to address some of these limitations by supporting clinicians with information processing as well as patient education and empowerment (Abbasgholizadeh Rahimi et al. 2022). There is in fact a wide variety of manners in which AI can support SDM, such as improving risk communication, recognizing patterns in specific patients' health data, recommending personalized treatment, which Rahimi et al. have summarized in ten fundamental pillars (Abbasgholizadeh Rahimi et al. 2025). On the other hand, AI could make communication, which is essential to SDM, all the more difficult (Sauerbrei et al. 2023). The relationship between AI and SDM remains insufficiently defined, both regarding its potential advantages and limitations, and in determining where future efforts should focus to ensure that SDM is respected and further strengthened.

The purpose of this systematic review is precisely that of assessing the SDM/AI relationship, for both its benefits and issues, and identifying possible solutions to the identified barriers. A similar review has already been conducted by Abbasgholizadeh Rahimi et al. 2022. This work is meant to provide a timely update, which is particularly relevant considering the increasing body of work on medical AI in the latest few years, while also employing selection criteria that allows for a more comprehensive analysis overall.

2 Methods

2.1 Search strategy

A systematic review was first conducted until February 2025, and then again in January 2026 following the PRISMA methodology. Three electronic databases were used to search for literature: PubMed, Scopus (limited to the medical field), and Web of Science (all fields). The search on PubMed and Scopus used the following keywords: ("Shared decision-making" OR "SDM" OR "informed choice") AND ("Artificial intelligence" OR "AI"). Finally, for Web of science, the search was not limited to any field, to ensure that a wider scope of studies were involved, but the keywords employed were slightly modified, by inserting two more keywords that still narrowed down the research to healthcare: ("Shared decision-making" OR "SDM" OR "informed choice") AND ("Artificial intelligence" OR "AI") AND ("health" OR "patient"). The search was limited to articles published until June 2025.

2.2 Paper selection

The selection process involved two rounds of filtering:

1. The first round was performed independently by two reviewers and was particularly inclusive as a screening procedure, so that papers were included if even one of the two reviewers considered that the inclusion criteria were met. It was only based on titles and abstracts, so the full text was not retrieved nor consulted at this stage.
2. The second round was performed independently by two reviewers and was more selective, since only manuscripts selected by both reviewers were included for the following phases. In this phase, the filtering was based on the retrieved full text. In case of disagreement between the two reviewers, a third author, an expert in legal medicine and in the field of SDM, was consulted to resolve the discrepancy and reach a consensus.

The following criteria were employed for both rounds:

- Inclusion criteria:
    a. English language;
    b. Sufficient focus on the relationship between AI and shared decision-making: the articles must highlight the benefits and/or the shortcomings of AI use in relation to SDM. Discussions that are only indirectly relevant are not covered;
    c. Studies published in a peer-reviewed journal/peer-reviewed conference proceedings.
- Exclusion criteria:
    a. Not in English language;
    b. Book chapters, interviews, unpublished works;
    c. Shared decision-making, AI, or their relationship only mentioned briefly.

2.3 Data extraction

The studies selected after the two selection rounds were used to build an Excel database and then analyzed with the extraction of the following parameters. The extraction process was performed by two authors, with a medical and law background, working collaboratively. For each of the following categories, whenever the study was not explicit, the "n/r" (not reported) tag was used.

a) Year of publication.
b) Medical specialty or field in which AI was either tested or discussed was reported, as stated by the authors of the manuscripts. If multiple medical specialties were relevant, multiple ones were mentioned.
c) Article type, classified according to the following categories: experimental study; observational study, conceptual paper, when offering theoretical, ethical, legal, or technological analysis without conducting an experiment or observational study; study protocol, when a detailed plan for a future experimental study was presented, but not yet implemented or analyzed; review article, including systematic reviews (structured, methodical, often with meta-analysis), scoping reviews (broadly map existing literature), and narrative reviews (more descriptive and less structured). Consideration was also given to whether the study fell within a clinical trial or whether clinical trials were explicitly considered as a future opportunity. Multiple category labels were considered to apply to the same article when appropriate.
d) AI method involved, comprising the labels explicitly or semi-explicitly employed by the authors of the respective studies. To minimize the risk of misattribution, no additional categorization of these labels was undertaken. Some of the identified methods include machine learning, expert systems, and large language models. The method was only recalled if it was the focus of the entire study and/or a significant part of it. Simple mentions of technologies that were not specifically analyzed and/or employed were excluded. E.g., a paper that mentions that AI advances include machine learning, but does not specifically address it or consider it as the basis of its work, would not be considered.

e) Developed or analyzed AI in the context of the study, including both products and services, even at a very early project level.
f) Clinical setting: This was meant in a comprehensive sense, including the specific subspecialty or clinical disease, or the place where the study was conducted. The place could reference a country, a city, or the specific clinic involved.
g) Use of AI, specifying the function that the AI was used for, e.g., support decision-making, generate decision aids, provide information, and perform administrative tasks. If multiple uses were mentioned, they were all reported.
h) Biases or limitations, reported as declared by the authors, in specific sections and in an explicit manner.
i) Funds, according to the authors' declarations.
j) Competing interests, as reported by the authors.
k) Ethical concerns: Authors' declarations about ethical approval/informed consent around their study were reported. Only explicit declarations, in specific dedicated sections, were covered.
l) Algorithmic transparency/fairness, indicating whether the authors referenced these types of concerns or not.

Finally, two authors independently summarized each paper's objective and contribution. The objective was understood as the study's overall aim, not necessarily as formulated by the original authors but as interpreted by the reviewers in light of the paper's broader purpose. The contribution referred specifically to how the study was judged to inform understanding of the relationship between AI and SDM. In both cases, these were interpretive assessments rather than author-declared claims, and they were not derived from predefined categories. Disagreements were solved by discussion or consultation of a third author, a physician with expertise in legal medicine and SDM.

3 Results

The literature search resulted in 467 records extracted from PubMed, 389 from Scopus, 437 from Web of Science, for a total of 1293 retrieved records, and 927 articles, after duplicates elimination.

After the first round of selection, 422 abstracts were included, 23 of which could not, unfortunately, be retrieved in full text, leaving a total of 399 articles that could undergo full-text assessment. Upon completion of the second round, 78 final studies were selected and reported on. No articles were included from the cross-reference checking. More details can be seen in the PRISMA diagram (Fig. 1).

Moving on to the selected studies, the number of identified publications by year resulted in 5 papers published in 2020, 7 in 2021, 12 in 2023, and 21 in 2024. For 2025, only 19 studies were identified by June 2025, so these data are partial (see a visualization of this data in Fig. 2, Graph A).

Relevant medical specialties were only reported in 61.5% of the articles (with some articles listing more than one specialty), of which the most common reported ones were: oncology (15.3% of all articles), orthopedics (7.7%), and cardiology (6.4%). Details are shown in Fig. 2, Graph B.

According to the article type, only two papers was relevant to multiple categories (review and a study protocol, observational study, and conceptual paper). Conceptual papers were by far the most common, comprising 38.4% of the selected studies (30 studies out of 78). Second in popularity were observational studies (20 reports), focusing mostly on physician and patient attitudes. Less frequently, reviews (18 reports, including narrative reviews and an embedded review), and finally experimental studies (6 reports) and study protocols (6 reports) were identified. Half of the experimental studies were published between 2024 and 2025 (data not shown). For details, see Fig. 3, Graph A.

No AI method was reported in 48.7% of the studies (38/66 studies). The most common label was machine learning (28 reports), followed by deep learning (9 reports), large language models (6 reports), and natural language processing (4 reports) (see Fig. 3, Graph B).

Moreover, algorithmic transparency was discussed in over half of the included articles (41 reports), while algorithmic fairness was only discussed in around one quarter of them (20 reports), of which 15 tackled both topics.

These data points, along with the remaining data related to the developed or analyzed AI, the clinical setting, the use of AI, the biases or limitations, the funds, the competing interests, and the ethical concerns, are all reported in Table A of the Supplementary material.

The summarized objective and contribution of the articles are indicated in Table 1.

4 Discussion

A first notable outcome of the present systematic review is the retrieval of a large number of records, compared to a relatively smaller set of included articles. This reflects, on the one hand, a substantial scientific production on themes related to AI and SDM, particularly concerning AI for score prediction (including risk prediction and patient-reported outcomes prediction) and AI for patient education (excluding AI-powered decision aids), which is encouraging for the field. On the other hand, 70 studies belonging to the first category and 30 belonging to the second category were not included, because, although they addressed both AI and SDM, they lacked a sufficient focus on the relationship between these two areas or specific implications and

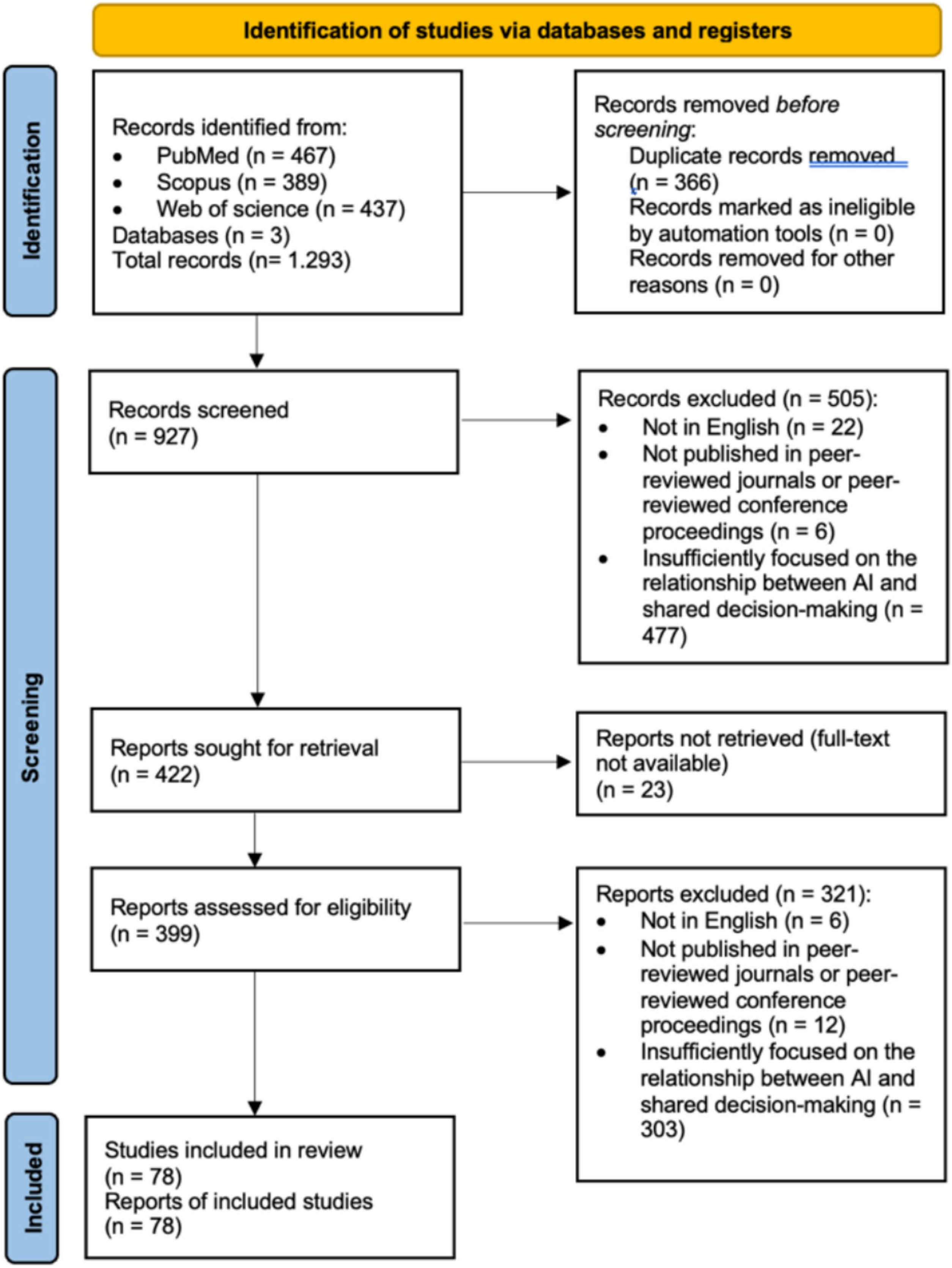

Fig. 1 PRISMA diagram

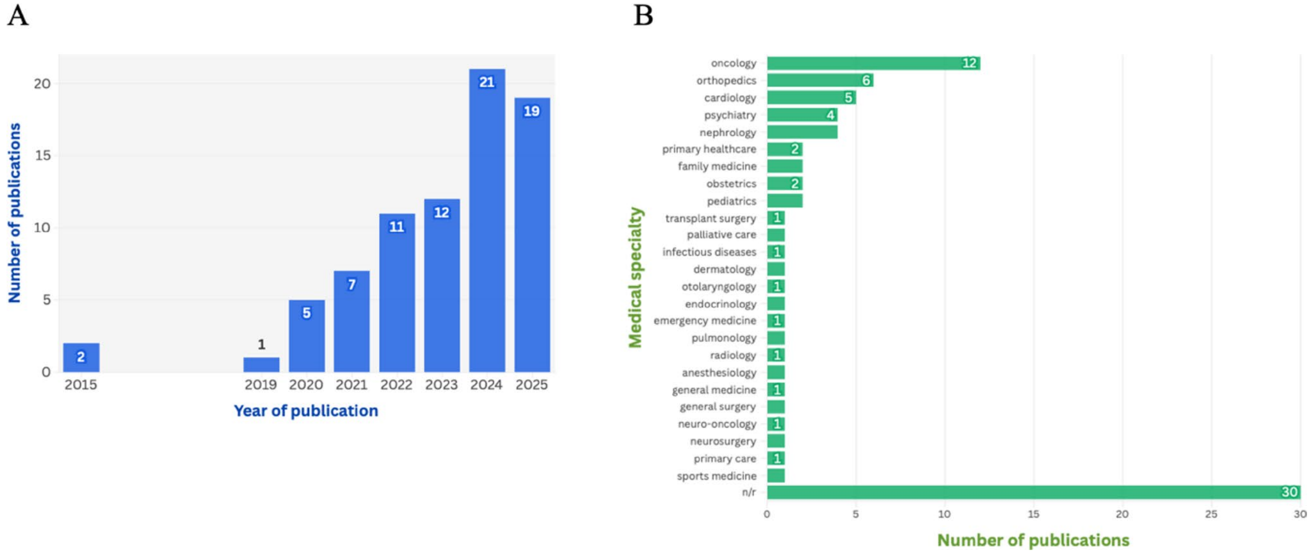

Fig. 2 Bar chart representation of the number of publications per year (graph A) and per medical specialty (graph B)

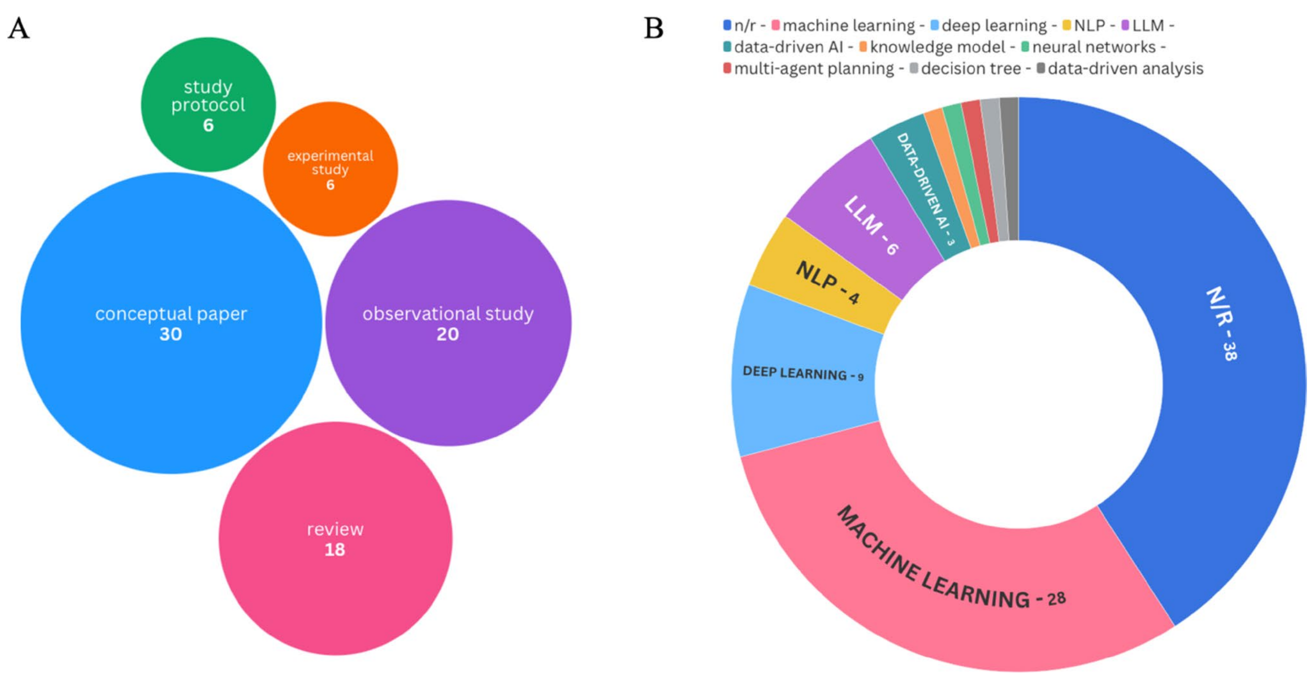

Fig. 3 Graph A: bubble chart representation of the number of publications per article type; graph B: donut chart representation of the number of publications per AI method

consequences for SDM, which were crucial to the development of this review. Additionally, no literature emerged from our review regarding patient preference predictors (PPP), though this topic was not specifically addressed by the research terms.

While these studies were not considered for the results, and consequently for the rest of the discussion, it is still important to note that AI for score prediction and patient education are very significant trends in current research.

Turning now to the included studies, an examination of publication years confirms a growing trend, as already reported in 2022 (Abbasgholizadeh Rahimi et al. 2022), which also reflects the broader rise of AI research in general (Maslej 2025). We can, thus, conclude that attention to

Table 1 Objective and contribution of each included study

Authors	Title	Objective	Contribution
Cohen IG, Ajunwa I, Parikh RB	Medical AI and Clinician Surveillance—The Risk of Becoming Quantified Workers	to discuss how medical professionals may become quantified workers	Discussed how AI-generated responses may be more empathetic compared to clinician responses, and as such that physicians may be evaluated for how empathetic their patient encounters are. This could result in prioritizing algorithmic conformity over individualized care
Ben Hmido S, Abder Rahim H, Ploem C, Haitjema S, Damman O, Kazemier G, Daams F	Patient perspectives on AI-based decision support in surgery	to investigate the views of patients who previously underwent colorectal surgery on the implementation of intra-operative predictive machine learning (IPML) by surgeons	Found that patients believe personalized care extends beyond tailored treatments to include communication that honors their unique preferences for involvement. They view the IPML as an advisor rather than a leader, trusting surgeons to make final decisions. They wish for surgeons to be able to deviate from IPML recommendations when necessary. While some participants emphasized the need for personalized explanations of how the tool works, others saw no need to be informed of its use at all
Larsson I, Svedberg P, Nygren JM, Petersson L	Healthcare leaders' perceptions of the contribution of artificial intelligence to person-centered care: An interview study	to explore healthcare leader's perceptions of the contribution of AI to person-centered care (PCC)	Found that participants believe AI supports professional competence and fosters patient trust by enabling proactivity, tailoring information, and supporting treatment recommendations. Beyond clinical care, it facilitates continuous professional development, ensures patient safety through error detection, and optimizes resources. However, AI presents some risks, particularly when used for health literacy
Ji C, Jiang T, Liu L, Zhang J, You L	Continuous glucose monitoring combined with artificial intelligence: redefining the pathway for prediabetes management	to examine the advantages of integrating CGM and AI	Argued that the use of AI can enhance patient literacy and help develop personalized intervention plans (improving treatment adherence and long-term outcomes). It also helps the shift from a prescriptive model to a collaborative model in prediabetes management
Cheetham M, Canhão H, Martin-Niedecken AL, Biller-Andorno N, Meier CA	Editorial: Digital health technologies for shared decision-making	to examine how digital health technologies can improve shared decision-making	Highlighted that AI can help integrate patient preferences into SDM consultations, personalize and encourage collaborative dialog, and translate patient's initially vague preferences into actionable insights

Table 1 (continued)

Authors	Title	Objective	Contribution
Arbelaez Ossa L, Rost M, Bont N, Lorenzini G, Shaw D, Elger BS	Exploring Patient Participation in AI-Supported Health Care: Qualitative Study	to explore how patients and medical AI professionals perceive the patient's role and the factors shaping participation in AI-supported care	Found that patients are often pushed into a passive role, leading them to delegate decisional authority to physicians to maintain a sense of security. Patients were found to base their value judgments on ideologies of life (e.g., whether they are interested in knowing more health information or being informed about health problems) instead of factual information
Bak M, Hartman L, Graafland C, Korfage IJ, Buyx A, Schermer M, 4D PICTURE Consortium	Ethical Design of Data-Driven Decision Support Tools for Improving Cancer Care: Embedded Ethics Review of the 4D PICTURE Project	to identify the key ethical challenges to be considered when developing data-driven DSTs for more personalized oncology care	Highlighted that in the 4D PICTURE project, designated points labeled as SDM moments are included to allow for discussions between health care providers and patient, though often patients may have trouble expressing their preferences
Gonzalez XT, Roubaud MS, Schaverien MV, Largo RD, Parham CS, Francis AM, Chen TA, Hoffman AS, Dickey RM, Markey MK, Reece GP	Assessment of Appearance-related Questions About Breast Reconstruction Generated by Chat Generative Pre-trained Transformer	to assess the quality of questions generated by ChatGPT for breast reconstruction patients to ask their providers	Found that experienced reconstructive surgeons rated almost all of the ChatGPT-generated questions concerning appearance-related outcomes of breast reconstruction as acceptable and likely to positively contribute to the informed consent and shared decision-making processes
Shaw F, Mccosker, A	Relational Ethics in the Administration of Healthcare Technology: AI, Automation and Proper Distance	to analyze clinical decision support system (CDSS) approvals to examine how healthcare relationships are discursively constructed within regulatory documentation, focusing on the Australian Therapeutic Goods Administration (TGA) database	Highlighted that the healthcare relationship is absent from the description of what tools do in the Australian Therapeutic Goods Administration (TGA) database. Although a degree of distance is appropriate in healthcare, this may need to be renegotiated with the advent of AI that intervenes to some degree in patient consent, practitioner responsibility and expertise, and shared decision-making
Ugar, ET	Promoting Responsible Use of AI in African Healthcare: Strengthening Patients' Moral Agency	to examine how overreliance on machine-learning–driven clinical decision support systems threatens shared decision-making and patients' moral agency, particularly within sub-Saharan African healthcare contexts	Argued that overreliance on machine learning models poses a threat to SDM. In sub-Saharan Africa, the erosion of SDM has consequences that go beyond individual autonomy, undermining the interpersonal relationships and communal practices through which moral agency and personhood are constituted

Table 1 (continued)

Authors	Title	Objective	Contribution
Zohny H, Allen JW, Wilkinson D, Savulescu J	Which AI doctor would you like to see? Emulating healthcare provider-patient communication models with GPT-4: proof-of-concept and ethical exploration	to explore the possibility of using LLMs to enable patients to choose their preferred communication style when discussing their medical case	Demonstrated how LLMs could potentially mimic different healthcare provider-patient relationship models (building on Emanuel and Emanuel's four models: paternalistic, informative, interpretive, and deliberative), offering a glimpse into how patients might be able to engage in a communication style that aligns with their individual needs and preferences
Bae SW, Laccetti A, Ozolcer M, Zhang TZ	PXAI-Coach: Designing and Evaluating a Person-Centric Explainable AI Dashboard for Athlete Health Monitoring and Coaching	to explore current health coaching strategies obtaining perceived benefits, risks, and challenges from off-the-shelf wearables that are relevant to performance and propose a person-centric health coaching dashboard design coupled with explainable AI (PXAI-Coach) to enable athletes to engage in health monitoring and coaching strategies	Showed that AI coaching tends to lack full engagement due to the absence of human interaction and the perceived irrelevance of generic insights. A semi-automated approach might enable athletes to reflect on their behaviors, though it requires manual inputs, which can be burdensome and frustrating. Identified four main themes in designing person-centric XAI (PXAI)-empowered health coaching strategies to maintain health and support performance in sports: personalizing goals, adapting to preferences, presenting explainable algorithms, and exploring behavioral patterns
Stroud AM, Curtis SH, Weir IB, Stout JJ, Barry BA, Bobo WV, Athreya AP, Sharp RR	Physician Perspectives on the Potential Benefits and Risks of Applying Artificial Intelligence in Psychiatric Medicine: Qualitative Study	to understand physician perspective on the application of AI in psychiatry	Showed that some psychiatrists believe AI could support conversations with patients, since it provides a new data point that can be discussed
Tarantini G, Fraccaro C, Porzionato A, Van Mieghem N, Treede H, Shammas N, Szerlip M, Thourani V, Gerosa G, Marchese A, Speziale G, Ludes B, Pollak S, Vanezis P, Ferrara SD	Informed Consent and Shared Decision-Making in Modern Medicine: Case-Based Approach, Current Gaps and Practical Proposal	to provide a methodological proposal for implementing SDM and enhancing consent acquisition in cardiovascular care	Highlighted the possible beneficial uses of AI in SDM (such as personalized treatment plans, tailored education, and monitoring) and described some related complexities (lack of trust and interpretability, responsibility still placed on the healthcare provider, and need to contextualize outputs)
Auf H, Svedberg P, Nygren J, Nair M, Lundgren LE	The Use of AI in Mental Health Services to Support Decision-Making: Scoping Review	to review on the use of AI in mental health services, in particular on its support in decision-making	Highlighted that none of the reviewed articles included AI systems designed explicitly for SDM, nor did they assess the role of SDM. Suggested adding AI as a third decision-maker in SDM dynamics and identifying barriers and facilitators to implementing AI in mental health care

Table 1 (continued)

Authors	Title	Objective	Contribution
Song M, Elson J, Bastola D	Digital Age Transformation in Patient-Physician Communication: 25-Year Narrative Review (1999–2023)	to identify key factors in health communication and how they've evolved over 25 years	Considered how AI is transforming patient–physician communication, as AI provides "pocket expertise" to patients to have a preliminary understanding of certain concepts (but which might also create tensions)
Shi W, Giuste FO, Zhu Y, Tamo BJ, Nnamdi MC, Hornback A, Carpenter AM, Hilton C, Iwinski HJ, Wattenbarger JM, Wang MD	Predicting pediatric patient rehabilitation outcomes after spinal deformity surgery with artificial intelligence	to propose an AI-enabled surgical planning and counseling support system for post-operative patient rehabilitation outcomes prediction in order to facilitate personalized AIS patient care	Highlighted how previously existing systems of this kind often fail to consider fairness and explainability as key factors to ensure that these tools can be used for effective shared decision-making. The proposed model addresses these issues
Schuitmaker L, Drogt J, Benders M, Jongsma K	Physicians' required competencies in AI-assisted clinical settings: a systematic review	to explore existing literature to identify required physician competencies in the context of clinical care AI	Identified the main impacts of AI in the physician/patient relationship: 1. the physician has to explain, interpret, or translate the functioning of the AI model; 2. effective and empathic communication with patients is required; 3. as information becomes even more accessible, physicians should be trained to handling this information shift; 4. black box systems may reintroduce paternalism
Alam L, Mamun TI, Mueller ST	Application of Cognitive Empathy Elements Into AI Chatbots: An Interview Study Exploring Patient–Physician Interaction	to explore the potential for cognitive empathy in healthcare AI	Developed design recommendations. AI systems should clearly state all options that patients can choose from, and further research must explore how clinicians incorporate LLM-based decision aids and how these systems may interact with patients autonomously for routine screening or triage tasks. Communication of outcomes is also very important to patients, so it is pivotal for achieving trustworthiness, though it is important to calibrate depending on user expertise
Sisk BA, Antes AL, Lin SC, Nong P, DuBois JM	Validating a novel measure for assessing patient openness and concerns about using artificial intelligence in healthcare	to assess adults' openness and concerns about the use of AI in healthcare	Analyzed openness to AI-driven healthcare technologies in US adults, finding overall moderate openness. SDM was rated highly among the 7 patient concerns
Hassan N, Slight R, Bimpong K, Bates DW, Weiand D, Vellinga A, Morgan G, Slight SP	Systematic review to understand users perspectives on AI-enabled decision aids to inform shared decision-making	to review users perspectives (both physicians and patients) on data-driven decision aids	Highlighted both the positive and negative perceptions over decision-aids of patients and clinicians. Patients found these decision aids to be generally understandable, user-friendly and empowering. Some of the issues highlighted by both patients and clinicians relate to biases, privacy, possible lack of technological skills and anxiety. This suggests future areas of work to improve AI-enabled decision aids

Table 1 (continued)

Authors	Title	Objective	Contribution
Kwon DH, Trihy L, Darvish N, Hearst E, Sumra S, Borno HT, Bose R, Chou J, de Kouchkovsky I, Desai A, Ekstrand B, Friedlander T, Kaur G, Koshkin VS, Nesheiwat S, Sepucha K, Small EJ, Aggarwal RR, Belkora J	Patients Can Administer Mobile Audio Recordings to Increase Knowledge in Advanced Prostate Cancer	to explore how consultation audio recordings may improve patient decision-making in advanced prostate cancer	Found that patient-administered audio recordings had a positive effect on decision-making and that AI can be used for transcriptions and summarizations. It is important to keep in mind possible AI inaccuracies or hallucinations. Stakeholders must also be educated, and policies must be put in place to govern AI use
Borsoi L, Listorti E, Ciani O, CINDERELLA Consortium	Artificial-Intelligence Cloud-Based Platform to Support Shared Decision-Making in the Locoregional Treatment of Breast Cancer: Protocol for a Multidimensional Evaluation Embedded in the CINDERELLA Clinical Trial	to outline a trial-based multidimensional evaluation, encompassing economic, financial, implementability, and environmental considerations associated with the CINDERELLA APProach	Highlighted the importance of PtDAS in the context of breast cancer, and that the possible aesthetic outcomes of a certain type of surgical treatment, accompanied by an objective evaluation (e.g., good/fair), can be simulated visually through AI. Stated that patient expectations will be recorded before and after intervention about the aesthetic outcome of locoregional treatment; patient usability and acceptability will also be surveyed
Sassi Z, Eickmann S, Roller R, Osmanodja B, Burchardt A, Samhammer D, Dabrock P, Möller S, Budde K, Herrmann A	Prospectively investigating the impact of AI on shared decision-making in post kidney transplant care (PRIMA-AI): protocol for a longitudinal qualitative study among patients, their support persons and treating physicians at a tertiary care center	to develop a plan for a qualitative study on SDM and AI in nephrology	Designed a mono-center longitudinal qualitative interview study employing semi-structured interviews with patients, support persons, and physicians to explore their views on the role and impact of AI-assisted SDM after kidney transplantation
Baysah Clark KS, Rudell E, Setiadi D, Agrawal T, Oliver BJ	Beyond Shared Decision-Making: Integrating Coproduction, Learning Health Systems, Artificial Intelligence, and Workforce Development for Patient-Centered Care	to explore critical factors to leverage the sustainment and advancement of SDM practice in health care (including AI)	Highlighted that AI can provide personalized treatments, help in pattern detection, be used to provide decision aids, and facilitate communication through NLP-based chatbots, thus freeing up more time for physician–patient interactions. Proposed blockchain as a possible solution to data security and privacy issues. Co-design was also proposed to help build trust
Lukkien DRM, Stolwijk NE, Ipakchian Askari S, Hofstede BM, Nap HH, Boon WPC, Peine A, Moors EHM, Minkman MMN	AI-Assisted Decision-Making in Long-Term Care: Qualitative Study on Prerequisites for Responsible Innovation	to present the results of an interview study on the prerequisites for responsible AI-assisted decision-making in nursing practice, with a focus on LTC	Highlighted that participants would support AI-DSS in this context, since it is perceived as a potential conversation tool. Some stressed that some conflicts of interests may lead to mistrust in the AI's output
Nilsen P, Sundemo D, Heintz F, Neher M, Nygren J, Svedberg P, Petersson L	Toward evidence-based practice 2.0: leveraging artificial intelligence in healthcare	to pinpoint key challenges pertaining to the three pillars of EBP and to investigate the potential of AI in surmounting these challenges and contributing to a more evidence-based healthcare practice	Highlighted that AI can save time for clinicians, potentially fostering more meaningful interactions between clinicians and patients. Presented worries around privacy, profiling (especially if used by companies for profit), and a new "computer knows best" paradigm

Table 1 (continued)

Authors	Title	Objective	Contribution
Upreti G	Advancements in Skull Base Surgery: Navigating Complex Challenges with Artificial Intelligence	to analyze the evolving landscape of AI integration in skull surgery	Highlighted useful AI uses in treatment planning alongside ethical concerns relating to opaque processes of AI, privacy issues and bias. Underlined possible patient refusal of treatment by AI tools because of distance from human care, which may be considered essential for empathy and SDM. Stated that informed consent should encompass AI use and the implications of AI-generated information
Osmanodja B, Sassi Z, Eickmann S, Hansen CM, Roller R, Burchardt A, Samhammer D, Dabrock P, Möller S, Budde K, Herrmann A	Investigating the Impact of AI on Shared Decision-Making in Post-Kidney Transplant Care (PRIMA-AI): Protocol for a Randomized Controlled Trial	to explore the impact of AI-based risk prediction for the risk of graft loss on the frequency of conversations about the treatment options after graft loss, as well as the associated SDM process	Presented a 2-year, prospective, randomized, 2-armed, parallel-group, single-center trial in a German kidney transplant center, meant to examine the influence of AI-based risk prediction on physician–patient interaction in the context of kidney transplantation
Funer F, Wiesing U	Physician's autonomy in the face of AI support: walking the ethical tightrope	to explore physician autonomy when AI is employed	Highlighted that physician autonomy is essential to SDM. AI impacts three aspects: information, competence, and voluntariness. The physician must bring knowledge together with patients' preferences, but if the physician does not know the rationale for AI support recommendations, the physician may have limited discretion in suggesting a different intervention. It is noted that to disagree with an AI recommendation, there may be a high requirement of evidence
Lawson McLean A, Wu Y, Lawson McLean AC, Hristidis V	Large language models as decision aids in neuro-oncology: a review of shared decision-making applications	to conduct a review on the involvement of LLMs in SDM in the context of neuro-oncology, exploring potential benefits and barriers	Highlighted a few benefits and challenges of AI in SDM as decision aids (e.g., no information overload, tailored literacy level through adequate prompting, but also risk of receiving non updated information). The integration of LLMs in neuro-oncology workflows was also detailed. Identified concerns include privacy, scientific rigorousness, need for ongoing evaluation, and bias. Suggested working toward seamless integration and on training healthcare professionals on these tools
Ranjbari D, Abbasgholizadeh Rahimi S	Implications of conscious AI in primary healthcare	to understand the potential impact of conscious AI in primary healthcare	Highlighted that conscious AI could enable systems to critically evaluate their outputs, thus potentially enabling better explainability, which is essential to SDM. This might also increase patient trust

Table 1 (continued)

Authors	Title	Objective	Contribution
Khosravi M, Zare Z, Mojtabaeian SM, Izadi R	Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews	to review existing reviews related to AI and decision-making in healthcare	Identified three subthemes of AI and SDM: personalized and customized information, patient self-management, and patient medication adherence
Haley LC, Boyd AK, Hebballi NB, Reynolds EW, Smith KG, Scully PT, Nguyen TL, Bernstam EV, Li LT	Attitudes on Artificial Intelligence use in Pediatric Care From Parents of Hospitalized Children	to investigate the attitudes the parents of hospitalized pediatric patients	Found that parents consider SDM very important, and that most of them found it crucial to be asked for permission for/informed about the use of AI
Rietjens JAC, Griffioen I, Sierra-Pérez J, Sroczynski G, Siebert U, Buyx A, Peric B, Svane IM, Brands JBP, Steffensen KD, Romero Piqueras C, Hedayati E, Karsten MM, Couespel N, Akoglu C, Pazo-Cid R, Rayson P, Lingsma HF, Schermer MHN, Steyerberg EW, Payne SA, Korfage IJ, Stiggelbout AM	Improving shared decision-making about cancer treatment through design-based data-driven decision-support tools and redesigning care paths: an overview of the 4D PICTURE project	to redesign patients' care paths and develop and integrate evidence-based decision-support tools to improve decision-making processes in cancer care delivery	Highlighted that currently decision-support tools often do not sufficiently address patients' preferences. Defined a methodology for the design/development of effective conversation tools
Muralidharan A, Savulescu J, Schaefer GO	AI and the need for justification (to the patient)	to identify the need for justifiability to patients in the context of healthcare AI	Highlighted that black box AI can overlook patients' values. Showed that to overcome this issue, what is required is algorithmic justifiability. Algorithmic transparency is insufficient, since it is neither necessary nor necessarily sufficient for justifiability
Karaa S	Impact of direct use of artificial intelligence algorithms on patient autonomy in dermatology	to analyze how AI algorithms in dermatology impact patient autonomy	Highlighted that the appropriate conditions for patient autonomy are not provided (information difficult to understand, and lack of background information provided by the patient). Found that AI pushes patients toward greater independence, but not autonomy: a form of neo paternalism presents itself, and patients' vulnerabilities may be exacerbated. Questioned what the doctor's role should be when AI is involved
Näher AF, Krumpal I, Antão EM, Ong E, Rojo M, Kaggwa F, Balzer F, Celi LA, Braune K, Wieler LH, Agha-Mir-Salim L	Measuring fairness preferences is important for artificial intelligence in health care	to demonstrate why measuring fairness preferences is important for healthcare AI	Highlighted that the key to shared decision-making is to balance the fairness preferences of all stakeholders. It is essential to measure differences in fairness preferences, as this allows for recognition of the autonomy of individuals or specific interest groups. It is also key to provide more transparency in the development and use of AI systems

Table 1 (continued)

Authors	Title	Objective	Contribution
Hao YX, Liu ZY, Riter RN, Kalantari S	Advancing Patient-Centered Shared Decision-Making with AI Systems for Older Adult Cancer Patients	to investigate the potential of a patient-centered SDM AI system for empowering older adult cancer patients in the cancer decision-making process	Identified key factors in treatment decision-making for both patients and clinicians. Developed an i-SDM prototype, which works through three stages: patient assessment, risk evaluation with AI, and patient end decision. Evaluated the usability of said prototype, which was considered beneficial for communication by the participants
Kim D, Vegt N, Visch V, Bos-De Vos M	How Much Decision Power Should (A) I Have?: Investigating Patients' Preferences Toward AI Autonomy in Healthcare Decision-Making	to investigate patients' preferences for the level of AI autonomy in healthcare decision-making	Highlighted that participants preferred the advisory level of AI assistance where they can actively search for risks in health decision options. They also preferred to use it with healthcare providers for further discussion. The preferred level of autonomy changes depending on a variety of factors (e.g., health history)
Lammons W, Silkens M, Hunter J, Shah S, Stavropoulou C	Centering Public Perceptions on Translating AI Into Clinical Practice: Patient and Public Involvement and Engagement Consultation Focus Group Study	to understand public perception around AI in clinical care, and to clarify how to best conduct PPIE (patient and public involvement and engagement) in projects on translating AI into clinical practice given public perceptions of AI	Showed that the public believes AI can reduce waiting time, provide better information to patients, and reduce errors and bias, but that a human touch may lack. Showed that PPIE can help reduce the development to implementation gap, and increase trust and acceptance from patients
Gould DJ, Dowsey MM, Glanville-Hearst M, Spelman T, Bailey JA, Choong PFM, Bunzli S	Patients' Views on AI for Risk Prediction in Shared Decision-Making for Knee Replacement Surgery: Qualitative Interview Study	to understand patient views on the use of AI for risk prediction in shared decision-making for knee replacement surgery	Highlighted that most study participants could see a role for AI in supporting clinical decision-making, though there were mixed views on the importance of interpretability versus performance and preference for the clinician or patient to have the final say regarding whether to use AI
Singh A, Schooley B, Floyd SB, Pill SG, Brooks JM	Patient preferences as human factors for health data recommender systems and shared decision-making in orthopedic practice	to explore patient treatment outcome preferences as significant human factors in treatment decision-making in orthopedic	Highlighted the need to collect patient treatment outcome preferences (TOPs) for health recommendation systems. Created a mobile app to collect TOPs using a direct weighting (DW) technique
Lorenzini G, Arbelaez Ossa L, Shaw DM, Elger BS	Artificial intelligence and the doctor-patient relationship expanding the paradigm of shared decision-making	to comprehend the promises and ethical issues of AI and shared decision-making	Pointed out threats to physician autonomy, which is a prerequisite to SDM to avoid "double paternalism". Pursuing a better understanding of AI's recommendation can be helpful in retaining it (in terms of usability and limitations). Highlighted that AI should only aim to assist physicians (not replace them), and that AI lacks contextual and emotional intelligence

Table 1 (continued)

Authors	Title	Objective	Contribution
Tanaka M, Matsumura S, Bito S	Roles and Competencies of Doctors in Artificial Intelligence Implementation: Qualitative Analysis Through Physician Interviews	to investigate the effect of introducing AI functions into the medical field on the role of the physician or physician–patient relationship, as well as potential concerns in the AI era	Showed that participants thought AI could help in personalization and reducing bias, but they also found it unlikely for AI to be able to take into account patient values and preferences (as they lack emotional sensing)
Sauerbrei A, Kerasidou A, Lucivero F, Hallowell N	The impact of artificial intelligence on the person-centered, doctor-patient relationship: some problems and solutions	to identify and critically discuss the main topics in the literature relating to values relevant to person-centered doctor-patient relationships (especially empathetic and compassionate care)	Highlighted that AI can be a positive force for patient autonomy, as well as a threat, as it can create a new form of paternalism. AI can also save time, which can be spent on empathetic care (though time might be spent in a different manner), but it can negatively impact trust. Identified proposed solutions in the literature including: 1. using AI only as an assistant; 2. focusing medical education on AI literacy and emotional intelligence
Badal K, Lee CM, Esserman LJ	Guiding principles for the responsible development of artificial intelligence tools for healthcare	to propose guiding principles (8) for the development of responsible AI systems in healthcare	Identified the facilitation of shared decision-making as a principle for responsible AI in healthcare. Suggested that explainability is essential to concretely understand the benefits and the risks of the AI's suggestions
Bunnell A, Rowe S	The Effect of AI-Enhanced Breast Imaging on the Caring Radiologist-Patient Relationship	to examine the effect of AI-enhanced imaging on the caring radiologist-patient relationship	Analyzed how CAD can disrupt the caring relationship between the radiologist and the patient in light of the four elements identified by Tronto: attentiveness, competence, responsiveness, and responsibility. Showed the great benefits that CAD can provide, arguing that it shall not be denied as an opportunity for patients. Highlighted that from a care ethics perspective a responsive relationships must be maintained
Turner JH	Cancer Care by Committee to be Superseded by Personal Physician–Patient Partnership Informed by Artificial Intelligence	to investigate how MTBs may be superseded by personal physician–patient partnership informed by AI	Suggested that AI may perform all current functions of MTBs, presenting data and management options which could then be considered in one-on-one discussion with the patient. Communication may also be integrated by a chatbot. AI could thus help with the lack of patient centeredness that MTBs often generate. Noted that AI still presents some lingering issues, e.g., trust, handling complex situations

Table 1 (continued)

Authors	Title	Objective	Contribution
Huang Z, George MM, Tan YR, Natarajan K, Devasagayam E, Tay E, Manesh A, Varghese GM, Abraham OC, Zachariah A, Yap P, Lall D, Chow A	Are physicians ready for precision antibiotic prescribing? A qualitative analysis of the acceptance of artificial intelligence-enabled clinical decision support systems in India and Singapore	to compare physician perceptions on the barriers and facilitators in accepting an AI-enabled CDSS for antibiotic prescribing	Found that many participants felt the non-necessity to discuss AI-based decision support with their patients as most patients would be oblivious to the decision-making mechanisms. Most patients in India still prefer physicians to make treatment decisions on their behalf, but in Singapore, there is a gradual shift to more shared decision-making. Ethical frameworks around AI use are necessary to safeguard patient interests
Shi WQ, Zhuang YC, Zhu YD, Iwinski HJ, Wattenbarger JM, Wang MD	Retrieval-Augmented Large Language Models for Adolescent Idiopathic Scoliosis Patients in Shared Decision-Making	to develop a tool for SDM for adolescent idiopathic scoliosis patients	Developed and validated an SDM tool to prepare AIS patients and families for a meaningful discussion with clinicians. The usability tests with human-in-the-loop demonstrate its effectiveness. The presented system is a chatbot, but it does not only interact with the patient, as physicians can review patient questions and responses to improve their understanding of patients, prepare for clinical visits, and improve their responses. Discussed critical considerations and potential solutions for widely adopting ChatGPT-like LLMs to facilitate clinical practice
Onitiu D	The limits of explainability & human oversight in the EU Commission's proposal for the Regulation on Al-a critical approach focusing on medical diagnostic systems	to investigate the role of transparency and accountability regarding the verification of medical diagnostic tools	Argued (regarding Art. 13 AIA) that while patients and physicians should understand the model's feature importance, turning outputs into rigid recommendations, rather than advisory insights, undermines patient autonomy. The system's instructions of use must support effective risk communication and management as part of *ex ante* transparency requirements. Highlighted that Art. 14 AIA fails to ensure patient-centered outcomes, as it neglects how technical specifications should help healthcare providers explain risks and uncertainties to patients
Samhammer D, Roller R, Hummel P, Osmanodja B, Burchardt A, Mayrdorfer M, Duettmann W, Dabrock P	"Nothing works without the doctor:" Physicians' perception of clinical decision-making and artificial intelligence	to shed light on the needs and challenges arising from the use of AI-DSS from physicians' perspectives	Highlighted that physicians believe AI-DSS do not relieve them from the task of communicating the results to patients in a way they can understand. AI-DSS in SDM should also not constrain the physician–patient relationship, but rather provide relief to intensify said relationship. Explainability is considered essential to a meaningful interaction with the patient

Table 1 (continued)

Authors	Title	Objective	Contribution
Abbasgholizadeh Rahimi S, Cwintal M, Huang Y, Ghadiri P, Grad R, Poenaru D, Gore G, Zomahoun HTV, Légaré F, Pluye P	Application of Artificial Intelligence in Shared Decision-making: Scoping Review	to identify and evaluate published studies that have tested or implemented AI to facilitate SDM	Compiled literature indicating how AI can be used for tasks such as personalization and risk communication, but that patients still expect the healthcare provider to have final discretion and to adapt recommendations to their unique situation. AI is also expected to potentially free up more time for physician/patient interaction, though the lack of explainability and interpretability of AI is a major obstacle. The design of AI systems should involve the stakeholders to implement SDM. The review highlighted that AI to support SDM is still in its infancy, considering the lack of relevant research
Ankolekar A, van der Heijden B, Dekker A, Roumen C, De Ruysscher D, Reymen B, Berlanga A, Oberije C, Fijten R	Clinician perspectives on clinical decision support systems in lung cancer: Implications for shared decision-making	to examine treatment decisions in lung cancer both quantitatively in terms of patient deviations and qualitatively by exploring clinician insights, with the aim to determine how CDSSs combined with SDM can support this complex decision-making process	Highlighted that clinicians believed they (and patients) might benefit from CDSS presenting information on the relevant treatment options, though they felt that there is often a clinically superior treatment that they would still recommend. Identified some more barriers to CDSS implementation according to physicians, including: difficulty for patients to interpret predictions, lack of trust (due to lack validation), and need for additional time and effort
Gundersen T, Bærøe K	The Future Ethics of Artificial Intelligence in Medicine: Making Sense of Collaborative Models	to examine the role of medical doctors, AI designers, and other stakeholders in making applied AI and machine learning ethically acceptable on the premises of shared decision-making in medicine	Articulating and examining a "collaborative model" AI system focused on the inclusion of medical doctors and bioethicists in algorithmic design and improving their AI literacy in the context of application
Holm S	Handle with care: Assessing performance measures of medical AI for shared clinical decision-making	to define how to interpret and assess the significance of different performance measures for clinical decision-making. to analyze the professional obligations that practitioners have to communicate information about the quality of an algorithm's output to patients in light of the principles of autonomy, beneficence, and justice	Highlighted that communicating the CDSS' output, to protect patients' autonomy, might at times conflict with the principle of beneficence. Similarly, communicating certain information to the patient may conflict with a wider societal interest. In this sense it is important for the physician to be educated on AI and to try to balance these interests, as no precise delimitation can be drawn

Table 1 (continued)

Authors	Title	Objective	Contribution
Pierce R, Sterckx S, Van Biesen W	A riddle, wrapped in a mystery, inside an enigma: How semantic black boxes and opaque artificial intelligence confuse medical decision-making	to explore the issue of the "semantic" black box and opaque AI, on the basis of cases from intensive care nephrology	Suggested that a solution to the semantic box is that a more transparent translation of KDIGO (Kidney Disease Improving Global Outcome) criteria is put into the model, along with adequate regulation/governance, and ensuring adequate personnel and processes. A combination of these elements should be sought. Highlighted that accuracy of the outcome is not sufficient, as effective communication requires more than that
Greco F, Picozzi M	Understanding the impact of Artificial Intelligence on physician–patient relationship: A revisitation of conventional relationship models in the light of new technological frontiers	to understand how conventional models of doctor-patient relationships are changing when considering the impact AI has on medical practice	Described how Emanuel's conventional models are modified through the implementation of AI. Listed actions that need to be taken to ensure SDM, including: physician education and training on AI and communication skills, more research on patient autonomy/values/education, and more active involvement of patients, maintaining the centrality of the physician/patient relationship (especially when trade-offs need to be considered)
Westerbeek L, de Bruijn GJ, van Weert HC, Abu-Hanna A, Medlock S, van Weert JCM	General Practitioners' needs and wishes for clinical decision support Systems: A focus group study	to learn general practitioners' (GPs) needs and wishes for a CDSS focused on diminishing medication-related fall risk	Showed that GPs considered a question prompt list (QPL) to be useful for the preparation of patients, which facilitates SDM (though they may lack capability or preparedness). Also highlighted GPs preferences on how risk information should be presented to patients (visual displays are preferred). GPs expressed that they did not want to receive SDM-related advice from the CDSS
Chua IS, Ritchie CS, Bates DW	Enhancing serious illness communication using artificial intelligence	to identify different ways in which AI can enhance serious illness communication	Noted that AI could help through conversational agents to be used by patients before visits (maximizing face-to-face time in in-person visits). It may also be used to streamline documentation, and to provide speech analysis and personalized feedback to clinicians (who may use this information to improve their communication skills)

Table 1 (continued)

Authors	Title	Objective	Contribution
Bonneux C, Mahmood DY, Scherrenberg M, Falter M, Ruiz GR, Kindermans H, Hansen D, Laaksonen R, Dendale P, Coninx K	The CoroPrevention-SDM Approach: A Technology-supported Shared Decision-making Approach for a Comprehensive Secondary Prevention Program for Cardiac Patients	to identify and evaluate eHealth solutions to support secondary prevention after a cardiac event	Designed: 1) an extended ePRO (electronic patient-reported outcomes) application that collects patient-reported outcomes and patient preferences; 2) a caregiver dashboard with a decision support system, and with a heavy focus on SDM support; 3) a patient mobile app that support patients in behavioral changes. These are meant to cover the three stages of SDM: before, during, and after the encounter. Highlighted that both patients and caregivers are willing to use this Tool Suite
Tanguay-Sela M, Benrimoh D, Popescu C, Perez T, Rollins C, Snook E, Lundrigan E, Armstrong C, Perlman K, Fratila R, Mehltretter J, Israel S, Champagne M, Williams J, Simard J, Parikh SV, Karp JF, Heller K, Linnaranta O, Cardona LG, Turecki G, Margolese HC	Evaluating the perceived utility of an artificial intelligence-powered clinical decision support system for depression treatment using a simulation center	to evaluate the perceived utility and impact of a previously developed AI-powered CDSS	Highlighted that physicians found the system to be useful and beneficial for SDM. In particular, the tool is considered to be more useful with repeated use. Noted that trust may grow alongside interpretability, and that clinical trials are required to assess effectiveness
Heyen NB, Salloch S	The ethics of machine learning-based clinical decision support: an analysis through the lens of professionalization theory	to analyze the ethics of machine learning-based CDSS (ML_CDSS) through professionalization theory	Argued that when using ML_CDSS particular attention must be given to "soft" facts of the individual case that cannot be comprehensively considered by ML_CDSS. Physicians shall focus on empowering patient autonomy, and the implications arising from the use of ML_CDSS need to be thoroughly reflected on by both institutions and individual physicians. Better physicians' education shall also be pursued, along with further interdisciplinary research on ML_CDSS
Clement J, Maldonado AQ	Augmenting the Transplant Team With Artificial Intelligence: Toward Meaningful AI Use in Solid Organ Transplant	to provide an update about the state of challenges to implementing AI in transplant	Noted that literature considered the lack of interpretability as a significant obstacle to the incorporation of AI recommendations. Discussing the use of AI with patients is particularly sensitive, as they may react differently when learning that AI influenced the decision. In some cases, revealing AI involvement could lower trust in the physician

Table 1 (continued)

Authors	Title	Objective	Contribution
Begley K, Begley C, Smith V	Shared decision-making and maternity care in the deep learning age: Acknowledging and overcoming inherited defeaters	to draw upon and extend a recent framework for shared decision-making (SDM) that identified a duty of care to the client's knowledge as a necessary condition for SDM	Highlighted that future AI shall assess women individually, taking into account a wide range of factors (such as: smoker, diet, life-style, as well as the usual clinical factors of parity, gestation, medical and obstetric history) and combine these with client preferences or at least input, to provide a holistic picture when making clinical decisions
Jayakumar P, Moore MG, Furlough KA, Uhler LM, Andrawis JP, Koenig KM, Aksan N, Rathouz PJ, Bozic KJ	Comparison of an Artificial Intelligence-Enabled Patient Decision Aid vs Educational Material on Decision Quality, Shared Decision-Making, Patient Experience, and Functional Outcomes in Adults With Knee Osteoarthritis: A Randomized Clinical Trial	to assess the effect of an AI-enabled patient decision aid that includes education, preference assessment, and personalized outcome estimations	Found that decision aids integrating patient education, preference assessment, and AI-enabled analytics built with PROM data can provide a personalized data-driven approach to SDM for patients with advanced knee OA considering TKR. Patients may feel more involved and in control of the decision-making process by being able to express preferences through a scales system and quantified variability in outcomes
Wu C, Xiao L	Evidence based on patient's experience data and clinical guidelines-for patient-oriented clinical decision support	to integrate patients' subjective references in clinical decision-making AI tools	Proposed a side-effect knowledge model (based on patient experience data and clinical guidelines) and a comprehensive decision-making system architecture that can consider clinical symptoms and subjective preferences
Kudina O	Regulating AI in Health Care: The Challenges of Informed User Engagement	to question the regulatory challenges of informed user engagement in healthcare AI	Noted that physicians have an elevated responsibility to check for factors not suggested by the AI, but that patients must also be vocal. AI regulations shall clarify the scope of human-AI collaboration. Choosing how to communicate the algorithm's role to patients is crucial to ensure their autonomy; staff education may be helpful in this sense. Found that the (at the time proposed) AI Act underestimates responsibilities placed on individual users to handle the implementation of AI
Michalowski M, Rao M, Wilk S, Michalowski W, Carrier M	MitPlan 2.0: Enhanced Support for Multi-morbid Patient Management Using Planning	to develop a mitigation framework for disease management planning for multi-morbid patients	Developed MitPlan 2.0, which identifies a treatment plan optimized according to a weighted multivariate objective function. This allows the combination of clinical dimensions with different treatment aspects like: financial cost, patient's burden, patient's perceived adherence to treatment, or cost of clinical resources required for treating a patient

Table 1 (continued)

Authors	Title	Objective	Contribution
Kazmierska J, Hope A, Spezi E, Beddar S, Nailon WH, Osong B, Ankolekar A, Choudhury A, Dekker A, Redalen KR, Traverso A	From multisource data to clinical decision aids in radiation oncology: The need for a clinical data science community	to analyze and articulate the need to create a clinical data science community in radiation oncology	Identified a patient-centered learning health care system as a key milestone: AI analytics shall include patient perspective data, expandability of AI analytics shall be improved, and decision aids shall be combined with shared decision-making. Lack of explainability is recalled as a major issue for this last achievement
Sisk BA, Antes AL, Burrous S, DuBois JM	Parental Attitudes toward Artificial Intelligence-Driven Precision Medicine Technologies in Pediatric Healthcare	to measure of parental openness and concerns with AI-driven technologies in their child's healthcare	Showed that parents who rated shared decision-making highly were less likely to be open to AI-driven healthcare. Some parents worry these technologies might decrease their role in making decisions on behalf of their child. Suggested that further research should focus on ensuring that new technologies engage parents in the decision-making process, to enhance their openness
Jayakumar P, Bozic KJ	Advanced decision-making using patient-reported outcome measures in total joint replacement	to present a protocol for a randomized clinical trial for OM1 Shared Decision Maker v1.0, Boston (an SDM tool) and to discuss current concepts in the field	Showed an SDM tool which works through a combination of patient-focused data collection tools (PROMs) and point-of-care concepts supporting patient–professional interactions (SDM), augmented by AI. For example, patients must select ratings on a "values module" where they select a desired level of pain relief, level of commitment to taking time off for recovery, and level of surgical risk they are willing to accept
Triberti S, Durosini I, Pravettoni G	A "Third Wheel" Effect in Health Decision-making Involving Artificial Entities: A Psychological Perspective	to identify possible dysfunctional effects of AI's inclusion in medical practice and consultation	Identified three possible forms of "third wheel" effect in medical consultation: organizational, communicational, and socio-relational aspects. The risks include: decision paralysis, "confusion of the tongues", and role ambiguity. Suggested that future research focuses on these topics
Arambula AM, Bur AM	Ethical Considerations in the Advent of Artificial Intelligence in Otolaryngology	to present ethical considerations around AI in the field of otolaryngology	Pointed out that personal patient factors (e.g., socioeconomic and cultural background) are not taken into consideration in AI programs. Patients may also refuse AI care to avoid separation from human providers

Table 1 (continued)

Authors	Title	Objective	Contribution
McDougall RJ	Computer knows best? The need for value-flexibility in medical AI	to explore the relationship between the ethical ideal of shared decision-making and AI systems that generate treatment recommendations, using the example of IBM's Watson for Oncology	Highlighted the risk of a computer knows best scenario. Suggested the development of value-flexible designs. Usually, ranked recommendations are not driven by patients' values: they should instead allow for diversity among the values of individual users and incorporate different values into decision-making based on the specific user
Sacchi L, Rubrichi S, Rognoni C, Panzarasa S, Parimbelli E, Mazzanti A, Napolitano C, Priori SG, Quaglini S	From decision to shared-decision: Introducing patients' preferences into clinical decision analysis	to propose a framework to promote a more patient-oriented SDM clinical decision process	Presented a framework that combines decision models and instruments to elicit patients' preferences into a single tool, which is integrated in the patient health record. It allows physicians to utilize electronic data management, evidence-based medicine, and SDM in the same encounter. This unified framework to elicit patients' preferences, and consequently run personalized decision trees, can help cut down on the time needed to perform these kind of analyses during an encounter. Showed that this tool can help overcome some barriers perceived by physicians in SDM
Parimbelli E, Quaglini S, Bellazzi R, Holmes JH	Collaborative Filtering for Estimating Health Related Utilities in Decision Support Systems	to propose a decision theory methodological framework to integrate the MobiGuide project	Proposed decision theory as a methodological framework to tailor pre-defined generic decision models to individual patients, where the patient is involved in the customization of the model parameters. The methodology could help cope with situations where traditional elicitation methods may fail. Highlighted that not all patients are suitable for this approach (nor SDM in general)

the topic is spreading and that in the future, we may expect even more works covering the topic. While fewer studies are recorded for 2025 than for 2024, 2025 data were limited to articles published until June, so the final total will likely exceed that of 2024.

The high percentage of articles with "not reported" medical specialty points toward a more comprehensive discussion of the topic, rather than in specific clinical contexts. The reported specialties align with fields traditionally associated with shared decision-making the most (Shinkunas et al. 2020; Stacey et al. 2024), where patient preferences and values matter the most, due to the variety of treatment options and impact on personal life, e.g., oncology.

A broad "big picture" discussion of the topic of AI-SDM also emerges from the analysis of the reported types of AI methods, which were not specified by the majority of articles. The cited methods are mainly to do with the macro-category of data-driven AI (e.g., machine learning and deep learning). Rule-based systems, meaning systems where knowledge was symbolically represented,[1] are only very rarely mentioned. This reflects general research trends in the field of AI (Russell and Norvig 2021; Maslej et al. 2025).

Despite a growing and comprehensive discussion on the topic, it seems that experimental studies are lacking, which is coherent with the low number of medical specialty-focused articles. On the other hand, experimental studies (and study protocols) seem to be growing in popularity over the last couple of years, so it could be expected that they will further grow in popularity. While ethics/policy-focused studies are certainly necessary, it is time to also develop some more concrete applications to see how feasible and effective the suggested solutions are in practice.

The identified articles shed light on relevant recurring themes at the intersection of SDM and AI, underscoring SDM as a crucial guiding principle for responsible AI in healthcare. In the following sections, these themes will be explored in detail.

4.1 Decision aids and conversation support

The most significant application of AI in ensuring SDM is in the form of decision aids (Baysah Clark et al. 2024), which could be used to empower patients' autonomy. AI can serve as a decision aid itself, as in the case of chatbots, or generate them (Lawson McLean et al. 2024). Given their interactive nature, chatbots can be particularly effective in answering patients' questions and responding to their expressed preferences. The advantage of these AI-powered decision aids over traditional ones is that they can be tailored to the individual patient (Khosravi et al. 2024). However, these tools should undergo rigorous validation to avoid misleading or incomplete information, which may ultimately lead to more harm (Song et al. 2025).

Decision aids, particularly chatbots, could also be intended to interact with physicians, that could use it to review patients' questions, in preparation for their in-person interaction, thus improving their responses (Shi et al. 2023). Some "conversation tools" are also designed to involve other individuals (e.g., patients' significant others), and are trained using patient experience data (Rietjens et al. 2024). Jayakumar et al. found that, for patients with advanced knee osteoarthritis, decision aids incorporating preference scales and personalized outcome estimates increased feelings of being informed, involved, and in control of the decision-making process (Jayakumar et al. 2021).

AI applications can also provide a data point that can be discussed during patient/physician communication (Stroud et al. 2025; Lukkien et al. 2024; Cheetham et al. 2025) or can act as "pocket expertise" for patients, enabling them to fill in some gaps in knowledge and to prepare questions, and thus laying the groundwork for a more collaborative process and reducing asymmetries in the relationship (Song et al. 2025; Ji et al. 2025; Gonzalez et al. 2025). AI can be used as a "conversational agent" even prior to visits, to maximize the utility of the in-person consultation (Chua et al. 2022). In oncology, for instance, Turner (2023) suggested that AI could replace the functions of multidisciplinary tumor boards (MTBs), providing tailored data and management options that support personalized, one-on-one clinical discussions between clinicians and patients. More generally, it has been suggested that AI systems could be used alongside chatbots to answer patients' questions, recreating a more intimate personal setting where spiritual and cultural values could be better explored (Turner 2023). It is important to consider, though, that while AI-supported care may promote a collaborative environment, it may also push patients into a more passive role, delegating authority to physicians (Arbelaez Ossa et al. 2025).

4.2 Value consideration in recommender systems

AI recommender systems, meaning algorithmic tools that retrieve, predict, and suggest personalized health options (Tran et al. 2021; Sun et al. 2023), particularly those providing ranked suggestions, tend not to take patient preferences and values into account (Arambula and Bur 2020), but focus on lifespan (McDougall 2019). However, patients may consider other factors to be more important, e.g., prioritizing the preservation of their looks over a more effective treatment. The AI's lack of consideration for patients' priorities risks

[1] Rule-based systems are computational approaches in which knowledge is expressed explicitly as a set of "if–then" rules (symbolic representations). Reasoning is achieved by applying these rules to known facts, in contrast to machine learning methods, which infer patterns directly from data. (Russel & Norvig, 2021).

enforcing a "computer knows best" scenario (McDougall 2019), in which the machine relegates patient preferences to an afterthought, or bypasses them completely, leading to a new form of digital paternalism (Sauerbrei et al. 2023), or to a situation of "double paternalism" (Lorenzini et al. 2023). To address the "computer knows best" scenario, McDougall has suggested value-flexible AI designs, that incorporate individual patient values, thereby ensuring that treatment recommendations are shaped by personal preferences rather than generic criteria (McDougall 2019). Attention must also be given to "soft facts" such as the patient's personality, life situation, or cultural background, which are essential for safeguarding patient autonomy (Heyen and Salloch 2021).

Although machine learning-based CDSS cannot currently comprehensively integrate these nuanced factors (Heyen and Salloch 2021), there is emerging potential for patient preferences to be incorporated in these tools (Rietjens et al. 2024). Such tools can be used alongside recommendation systems to foster dialogue with physicians, with the aim of adapting outputs to patient preferences. For instance, Hao et al. developed a prototype called "i-SDM" to support SDM by assessing patient preferences and integrating them into a visual, interactive interface that facilitates dialog (Hao et al. 2024). Similarly, the CoroPrevention approach includes an application to collect patient-reported outcomes and preferences, a caregiver dashboard that integrates a decision support system alongside SDM support, and finally a patient mobile app to support patients in their required behavioral changes journey (Bonneux et al. 2022). Other authors have also suggested assigning specific weights to patient treatment outcome preferences, influencing the AI-generated recommendations (Singh et al. 2023).Wu and Xiao (2021) proposed a comprehensive decision-making system architecture that integrates clinical symptoms with subjective patient preferences by matching structured side-effect profiles with patient-entered values and concerns. This rule-based approach, which produces recommendations by drawing on structured, symbolic knowledge representations rather than opaque machine learning models, is inherently highly interpretable (Wu and Xiao 2021). Another technical framework proposal is that of "MitPlan 2.0", designed to identify an optimized treatment plan based on a weighted multivariate objective function, considering financial cost, patient's burden, and patient's perceived adherence to the treatment (Michalowski et al. 2021). Other authors have introduced an SDM tool in which patients complete a "values module," where they rate their desired level of pain relief, willingness to take time off for recovery, and acceptable level of surgical risk, generating personalized risk–benefit profiles (Jayakumar and Bozic 2020). Preference elicitation tools could also be embedded within the patient health record (Sacchi et al. 2015). Some frameworks also explicitly incorporate designated 'SDM moments' to facilitate clinician–patient dialog (Bak et al. 2025). When direct elicitation is not feasible, approaches based on collaborative filtering and natural language processing could allow to estimate patient-specific utility values, inferring preferences from similar patients and patient-reported experiences (Parimbelli et al. 2015). However, not all patients may be suitable for this approach. Moreover, when AI is used in clinical care, physicians may bear greater responsibility to identify relevant factors overlooked by the system and to encourage patient input (Kudina 2021). This is especially important in maternity care, which requires the reconstruction of a holistic picture to make sound clinical decisions (Begley et al. 2021).

Nevertheless, these proposals demonstrate how AI could enhance SDM by systematically ensuring that patient preferences are by design integrated in the clinical decision, thereby addressing the limitations sometimes observed in the traditional processes.

4.3 Time efficiency and aid in non-clinical tasks

The use of AI systems in clinical care could free up more time for physician/patient interaction, allowing them to focus more on engaging with patients emotionally and evaluating their values closely (Nilsen et al. 2024; Sauerbrei et al. 2023). However, it is crucial for this scope to ensure that physicians are sufficiently educated; otherwise, the opposite effect could be achieved (Sauerbrei et al. 2023).

AI can also be used for non-clinical task, that may still impact on SDM. For instance, AI can be used to record, transcribe, and summarize consultations, making patient preferences and values available over time (Kwon et al. 2024). In the setting of surgical treatments, AI-simulated reconstructions of aesthetic outcomes after surgery can help patients form their opinions by visualizing the expected results (Borsoi et al. 2024). Other applications also include AI to streamline documentation and to analyze patient speech, to provide feedback for clinicians, so that they may coherently improve their communication (Chua et al. 2022).

4.4 Black-box AI

The most commonly cited downside of AI impacting SDM is the possibility of incurring in communication failures. This concerns "black-box" AI, especially, since their lack of interpretability and/or explainability was found to be a major obstacle to proper communication (Tarantini et al. 2025; Schuitmaker et al. 2025; Samhammer et al. 2022; Ranjbari and Abbasgholizadeh Rahimi 2024), as well as to time efficiency (Abbasgholizadeh Rahimi et al. 2022).

The black-box phenomenon may challenge physicians when relaying system outputs to patients and aligning them with patient values, as evaluating their reliability and generalizability requires understanding the system's inputs, excluded variables, and training data, as highlighted in discussions of KDIGO (Kidney Disease Improving Global Outcome) automation (Pierce et al. 2022).

Lacks of understanding of the AI's output poses the risk over-reliance on the AI that in turn, endangers physician autonomy (Funer and Wiesing 2024; Lorenzini et al. 2023).

Opacity may also force physicians to mediate between the patient and AI, which becomes an ambiguous third party, delaying or paralyzing decision-making and reducing mutual understanding—the so-called "third wheel" effect (Triberti et al. 2020).

AI systems interacting directly with patients might prove even more burdensome, due to combined lack of understanding of AI outputs compounds and the traditional medical knowledge asymmetry (Karaa 2024). While AI could theoretically lead to "full independence" of the patient, it may instead leave them with "relative ignorance", forcing them to accept or reject a decision that is based on not easily understandable data (Karaa 2024).

Explainable AI (XAI) could present a solution to this matter (Bae et al. 2025; Shi et al. 2025; Badal et al. 2023), generating post hoc explanations for the outputs of otherwise opaque 'black-box' models (Babic et al. 2021). At the same time, though, what may be needed is not explainability nor transparency, but rather justifiability: showing why a recommendation is appropriate for a patient's values ("value-based reasons"), providing a "*justification accessible to the patient (i.e., which they can evaluate in light of their values, priorities, and the facts of their situation) for the AI's recommendation*" (Muralidharan et al. 2024). Justifiable AI differs from value-flexible AI (McDougall 2019) in that it does not match an individual's values in advance, but provides justifications based on general value assumptions, which patients can then accept or reject.

4.5 Fairness, reliability, and trust

Biases and unreliability, including those introduced by false, misleading, or outdated information—especially if not contextualized—may undermine the SDM process, particularly in patient-facing AI (Shi et al. 2025), (Hassan et al. 2024), (Lawson McLean et al. 2024; Song et al. 2025).

Some authors emphasize incorporating diverse "fairness preferences", such as prioritizing the "sickest first" or societal benefit, into SDM, though AI's lack of transparency can hinder the ability to balance these preferences effectively, thereby challenging trust and stakeholder involvement in healthcare decisions (Näher et al. 2024).

A lack of fairness and reliability contributes to a broader lack of trust in the use of AI (Tarantini et al. 2025; Tanguay-Sela et al. 2022), compounded by privacy and ethical concerns (Upreti 2024; Hassan et al. 2024; Sassi et al. 2024; Osmanodja et al. 2024).

Observational studies show that patients, physicians, and healthcare leaders are open to using AI in SDM (Sisk et al. 2025; Gould et al. 2023; Larsson et al. 2025)—provided that physicians remain involved (Ben Hmido et al. 2025). Clear information on the tools advantages and limitations along with patient permission is essential for trust (Haley et al. 2024; Badal et al. 2023). Revealing the involvement of AI could, however, lower trust in the physician (Clement and Maldonado 2021) or introduce role ambiguity, as patients struggle to understand whether the physician or the AI holds decision-making authority (Triberti et al. 2020). Presenting information about AI in the care process in an understandable manner for the patients (Samhammer et al. 2022) seems to represent now a core task for physicians, essential to maintaining trust.

Patients were shown to prefer for AI to have an "assistive" role (Sauerbrei et al. 2023), with the healthcare provider having final discretion, and to adapt the choice according to their own unique situation (Abbasgholizadeh Rahimi et al. 2022). The preferred level of autonomy, though, could change depending on various factors, such as health history, nationality (Kim et al. 2024; Huang et al. 2023) or setting, e.g., in pediatric care, parents expressed concern that AI could reduce their decision-making role on behalf of their children (Sisk et al. 2020).

Physicians' lack of trust stems from a lack of emotional sensing for patient preferences and values (Tanaka et al. 2023), combined with perceived need for additional time and effort, poor interpretability, alongside the belief they would still recommend a "clinically superior" treatment (Ankolekar et al. 2022). General practitioners prefer risk information to be presented to patients through visual displays rather than as percentages or color codes alone (Westerbeek et al. 2022) and typically do not trust CDSS to offer advice about SDM (Westerbeek et al. 2022).

Greater trust in AI in healthcare may result from meaningful patient and public involvement and engagement (PPIE)—early, inclusive, and empowering collaboration that supports co-design, which can help align systems with patient needs and values (Lammons et al. 2023).

4.6 Human empathy

Connected with the lack of trust is the potential reduction of the "human touch" (Upreti 2024; Lammons et al. 2023). Indeed, the *ars medica* goes beyond simply performing accurate predictions of treatment efficacy, including a component of empathy and emotional intelligence, a feature that does not belong to AI (Lorenzini et al. 2023). While recent advances in affective computing suggest that AI systems are beginning to detect and respond to certain emotional cues (Guo et al. 2024; Hadjar et al. 2025), this remains distinct from the relational depth of human empathy. Health decisions are often taken in "emotionally fraught" circumstances and this could represent a reason why physician autonomy over the AI must still be retained, with AI only used in an assistive role (Lorenzini et al. 2023; Onitiu 2023). As AI-generated responses are increasingly perceived as more empathetic than those of clinicians, there is a growing risk that physicians may be surveilled and evaluated against algorithmic benchmarks; this could incentivize algorithmic conformity over truly individualized care (Cohen et al. 2025). This also connects to the concept of a responsive clinical relationship, where physicians actively interpret and adapt that care in response to patients' emotional states, cultural values, and variable preferences (Bunnell and Rowe 2023; Ugar 2026). Responsiveness is central to maintaining ethical relationships when AI tools are involved, particularly when patients may react with confusion or anxiety to AI-generated outputs (Bunnell and Rowe 2023). Emotional dissonance and patient demoralization may stem from a "confusion of the tongues" phenomenon, in which human-centered, narrative experience of illness is inadequately translated into the data-centric classifications used by AI leading patients to feel reduced to mere statistics (Triberti et al. 2020). These issue could be addressed through the design of AI tools that display all options and their associated consequences for patients to consider (Alam et al. 2025). At the same time, empathy entails recognizing that some patients may prefer to delegate the final choice to their physician, an attitude captured by the idea of benevolent coaching, where guidance is offered in a compassionate and supportive way (Loignon and Boudreault-Fournier 2012). To support this, AI systems could emulate different communication models (Zohny et al. 2025). A need to renegotiate the "proper distance" between patient and practitioner also emerges as automation becomes part of the shared decision-making (Shaw and McCosker 2025).

4.7 Training and education

The lack of specific training on AI for healthcare professionals has also been suggested as an obstacle for SDM-compliant AI. Education could help to rebalance the lack of explainability, preventing that the use of AI becomes counterintuitively more time-consuming, and avoiding spending less time with patients due to increased workload (Abbasgholizadeh Rahimi et al. 2022). Training was also considered crucial to learn how to embody this new intermediation role between AI and patients, how to handle the information shift, as well as how to maintain effective empathetic communication (Schuitmaker et al. 2025; Baysah Clark et al. 2024; Greco and Picozzi 2022; Heyen and Salloch 2021; Kudina 2021). Physicians are advised to acknowledge that they may encounter multiple, and at times conflicting, interests (Greco and Picozzi 2022), including those of individual patients, institutional policies, and broader societal goals such as cost-efficiency and fairness, the balancing of which in the context of shared clinical decision-making requires proper training to ensure that the use of decision-support systems aligns with ethical principles, such as autonomy, beneficence, and justice (Holm 2022).

4.8 Design

Authors found that usually AI systems are not designed to explicitly give consideration to SDM, and even more rarely are they developed while keeping SDM in mind as an end goal (Auf et al. 2025), with a few virtuous exceptions.

A significant concern remains that several AI systems are not co-designed (Baysah Clark et al. 2024), including the inputs from physicians, patients, and other relevant stakeholders (Abbasgholizadeh Rahimi et al. 2022), such as bioethicists (Gundersen and Bærøe 2022). It is increasingly recognized that involving these groups is essential to embedding core SDM elements by design, and enhancing AI literacy among clinicians and bioethicists can further promote effective collaboration between developers and users (Gundersen and Bærøe 2022). This is in line with the study conducted by Kazmierska et al. (2020), who advocate for a clinical data science community in oncology including also patients, where multidisciplinary collaboration is foundational to the development of decision aids based on multisource data.

4.9 Limitations

This study has several limitations. First, the search strategy was restricted to three databases, which means that relevant contributions not indexed in these sources may have been inadvertently excluded. Second, the keywords employed were limited in scope and may have led to the unintentional omission of pertinent studies. For example, no retrieved studies tackled the topic of Patient Preference Predictors (PPP). Third, only two reviewers conducted the screening and data extraction processes; although a third researcher was consulted to resolve disagreements, the possibility of reviewer bias cannot be entirely ruled out. Fourth, many studies identified during the search were only indirectly related to the research question and were excluded on the basis of the predefined eligibility criteria, which may have further narrowed the scope of the evidence considered. Fifth, most of included work predates the current wave of gen-AI and LLM-mediated SDM tools, which have mainly emerged from 2024 onwards. Sixth, neither inter-rater agreement reporting nor formal quality and bias assessment were performed, which may limit the robustness and objectivity of the review. Finally, no meta-analysis was performed, limiting the ability to provide a quantitative synthesis of findings across studies.

5 Conclusions

Our results highlight that AI is not an overall "negative force" for the shared decision-making (SDM) process. While some issues remain barriers to its use in healthcare, the potential benefits are significant. Particularly, AI has emerged as a tool that can enhance clinical efficiency, support chronic illness management, and assist patients in self-monitoring and treatment adherence, reinforcing long-term engagement with care. It can also function as a decision aid and support conversations between patients and physicians, bridging knowledge gaps and fostering collaborative decision-making. Future research should address communication failures, especially by ensuring the justifiability of outputs. In parallel, recommender systems should incorporate patient preferences and values to avoid digital paternalism and promote patient empowerment. Efforts should also focus on co-design in system development and on providing physicians with the necessary education. Given AI's current limitations in emotional intelligence, preserving the physician's presence in SDM is crucial to guarantee that empathy and human sensitivity remain at the heart of the patient experience, with AI serving as supportive input.

All in all, if developed and implemented responsibly, AI can become a powerful enabler of SDM, embedding patient-centered care as a standard rather than an aspiration.

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Declarations

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Authors and Affiliations

Claudia Giorgetti[1] · **Arianna Giorgetti**[2] · **Susi Pelotti**[2] · **Giuseppe Contissa**[1]

✉ Arianna Giorgetti
arianna.giorgetti@unibo.it

Claudia Giorgetti
claudia.giorgetti6@unibo.it

Susi Pelotti
susi.pelotti@unibo.it

Giuseppe Contissa
giuseppe.contissa@unibo.it

[1] Department of Legal Studies, ALMA-AI, University of Bologna, Bologna, Italy

[2] Department of Medical and Surgical Sciences, Unit of Legal Medicine, University of Bologna, Bologna, Italy