Advancing Patient-Centered Shared Decision-Making with AI Systems for Older Adult Cancer Patients

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ABSTRACT

Shared decision making (SDM) plays a vital role in clinical practice guidelines, fostering enduring therapeutic communication and patient-clinician relationships. Previous research indicates that active patient participation in decision-making improves satisfaction and treatment outcomes. However, medical decision-making can be intricate and multifaceted. To help make SDM more accessible, we designed a patient-centered Artificial Intelligence (AI) SDM system for older adult cancer patients who lack high health literacy to become more involved in the clinical decision-making process and to improve comprehension toward treatment outcomes. We conducted a pilot feasibility study through 12 preliminary interviews followed by 25 usability testing interviews after the system development, with older adult cancer survivors and clinicians. Results indicated promise in the AI system's ability to enhance SDM, providing personalized healthcare experiences and education for cancer patients. Clinician responses also provided useful suggestions for SDM's new design and research opportunities in mitigating medical errors and improving clinical efficiency.

CCS CONCEPTS

• **Human-centered computing** → *Accessibility systems and tools*; *Visualization toolkits*; • **Social and professional topics** → **Seniors**; • **Information systems** → **Personalization**; **Presentation of retrieval results**; • **Applied computing** → **Health care information systems**.

KEYWORDS

Shared Decision Making; Clinical Decision Making; Older Adults; Cancer Care; Risk Communication

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1 INTRODUCTION

Patients with limited medical knowledge often have difficulty accessing healthcare and understanding their treatment plans. The recent COVID-19 pandemic, along with other stresses on the healthcare system, have further contributed to resource constraints, increased patient load, and heightened anxiety among patients and clinicians. These circumstances hinder the provision of comprehensive healthcare information and support, especially for older adult patients with low health literacy [46]. The inability to communicate fully and at length with clinicians and to understand the impact of various treatment options can present a barrier to older adult patients' involvement and reduce their feelings of dignity and agency, while making it harder to reach effective decisions that meet patients' particular needs and circumstances [91].

Shared decision-making (SDM) is a valuable approach in healthcare that promotes active collaboration between clinicians and patients to help overcome these barriers [41]. However, complex medical decisions, time constraints, patient obstacles, and resource limitations can hinder effective SDM. The time sensitivity of some decisions can create imperatives that reduce patients' opportunities for learning and reflection. Many clinicians today are extremely pressed for time, partly due to the staff shortages that remain in the wake of the pandemic and the worsening clinician-to-patient ratios in many healthcare settings [76]. As a result of these time pressures and limited communications training, many clinicians are unable to pursue effective SDM practices. Patients also sometimes confront obstacles that may limit their ability to rationally evaluate potential benefits and risks, and strained healthcare providers may not have adequate funding, staffing, or communications training to engage in detailed SDM processes [22]. In recent years, there has been a growing recognition of the need to shift toward patient-centered decision-making models [7, 59, 64, 73], which indicates that when patients actively participate in the decision-making process it leads to higher satisfaction levels and improved treatment outcomes [53]. The SDM approach is a part of this conceptual shift.

New technologies provide intriguing modalities for stepping into this gap to help promote SDM, particularly when it comes to enhancing communication between highly specialized professional healthcare providers and their patients [31]. While not a substitute for patient–clinician interactions, SDM-based technological platforms can be suitable in some cases to help patients learn about their options in more detail and better understand the potential consequences of treatment choices, while easing pressure on clinicians' communication skills [4, 43]. Artificial Intelligence (AI) has the potential to be implemented during SDM as a means of better tailoring information and treatment plans to specific patient circumstances [8, 16, 55, 85]. This is in alignment with the goal of a more transparent and evidence-based healthcare system that takes into account personal factors in the process of finalizing clinical treatment decisions. The role of AI in this process is to serve as an assistive technology for patients, as well as their family members or guardians, to deliver tailored presentations of concepts specifically relevant to the patient's case, and to help clarify complex medical terminology [72].

In the current paper, we present two studies that were conducted to evaluate the effectiveness of an SDM AI system system prototype. In Study 1, we conducted 12 one-on-one interviews with older adult patients and clinicians, to better understand their needs as related to the clinical SDM process. In Study 2, we designed a prototype SDM AI system focused on treatment decisions for older adult cancer patients. We then engaged in 25 one-on-one usability interviews with older adult cancer survivors and cancer-related clinicians or healthcare providers. This evaluation sought to assess the ease of use of the prototype system and its potential effectiveness in facilitating the SDM process within the context of cancer care.

Through these two studies, we aimed to comprehensively understand the needs and perspectives of older adult cancer patients and cancer-related clinical providers. By combining qualitative interviews and usability evaluations, we addressed three main research questions:

RQ1: How can the clinical SDM process become more effective in improving communications and relationships between older adult cancer patients and clinicians?

RQ2: Will older adult cancer patients and clinicians accept the SDM AI System as readily usable within the context of their shared decision-making processes for cancer treatment?

RQ3: How do older adult cancer patients and clinicians perceive the SDM AI system as augmenting clinical effectiveness?

Exploring the answers to understand the specific needs and challenges faced by older adult cancer patients and clinicians during the difficult decision-making process, we grounded the system's development in an aging patient-centered design approach. The primary contribution of the paper shows that the SDM process is feasible to *optimize older adult cancer patients and clinicians' therapeutic communication and relationship* by contributing to well-tailored treatment plans and promoting patient engagement and compliance. A secondary contribution is that the SDM patient-centered AI system could *elevate cancer healthcare experience*, helping older adult cancer patients to feel more empowered and knowledgeable with their treatment plans. Furthermore, our work contributes to the field of SDM to *enhance resource allocation*, by alleviating time pressures on clinicians and fostering better therapeutic patient-clinician relationships.

2 BACKGROUND AND RELATED WORK

2.1 The Effectiveness of SDM in Clinical Practice

The clinical decision-making process has historically placed greater emphasis on the role of healthcare providers in determining the course of action, often overlooking the vital roles and perceptions of patients themselves. This oversight is particularly striking considering that patients are the ultimate recipients of the decisions made during their healthcare journeys [11, 14, 38]. By relegating patients to being passive recipients of care, healthcare systems risk undermining the principles of autonomy, empowerment, and respect, as well as potentially overlooking important aspects of patients' lives that may contribute to treatment adherence and to healthcare outcomes [61, 88].

To facilitate effective SDM, various systems and strategies have been developed and implemented. These may include broad clinical decision support systems (CDSSs), which often assist in forming diagnoses as well as in treatment comparisons; and specific patient decision aids (PDAs), which provide up-to-date information about risks, benefits, and potential outcomes associated with different treatment options [5, 27, 51, 69, 71, 79, 94]. Such decision support systems can be in the form of paper-based materials, online resources, or interactive applications, all aimed at enhancing patient engagement, information sharing, and collaborative decision-making [16, 21, 95–97]. Various criteria and evaluation metrics are developed to elevate the quality and efficacy of patient decision aids, such as International Patient Decision Aids Standards (IPDAS), Interprofessional Shared Decision Making Model (IP-SDM), which help establish a shared, evidence-informed framework, complete with a set of criteria for enhancing their content, development, implementation, and assessment [1, 50, 89].

Previous studies have highlighted areas for improvement in the implementation of SDM. Of particular concern is research indicating that patients sometimes fail to fully understand the risks and potential benefits of various treatment options. This indicates troubling communication failures and a need for more comprehensive, well-paced, and open conversations, including room for patient reflection and questions. Researchers have also found a lack of assessment regarding the patient's level of understanding, which may result in misperceptions going unaddressed [12, 75].

2.2 Engagement of Older Adult Cancer Patients in Cancer Decision Making

Patients aged 70 years and older constitute 42% of the total cancer patient population [82]. Older adult cancer patients have a complex decision-making process, with a higher likelihood of comorbid conditions and declines in health status associated with aging [29, 52, 65]. The older adult cancer patients' decision-making is influenced by several factors, including the clinician's recommendation, trust in the clinician, communication with the clinician, expectations regarding potential side effects, and the treatment experiences of close contacts [52, 78]. Additionally, decision-making for older adult cancer patients is situated within a social context, wherein other individuals, particularly family members, caregivers, and healthcare providers, contribute insights and perspectives on behalf of the patients [30].

There are age differences in patients' preferences for participation in cancer treatment decision-making [29]. In a 2004 systematic review, 81% of the older patients want to receive relevant information regarding their illness and treatment, but in a language they understand, free of medical jargon, and at a speed that allows them to process this material [77]. Multiple research studies have shown that clinical SDM practices can enhance patients' healthcare experiences, improve health outcomes, and contribute to better relationships between patients and clinicians [32, 40, 74, 83]. Some of the noted benefits include "improvement in knowledge, increased risk perception, decreased decisional conflict, and an enhancement in participation" [69]. These benefits are particularly significant for patients with chronic disease, who may face complex treatment decisions and require additional support to make informed choices [42, 68].

2.3 Potential Uses of AI in SDM

Integrating AI into the SDM process holds tremendous potential for improving SDM's effectiveness [80]. The potential benefits are mostly related to leveraging AI's data processing capabilities for the purpose of personalized recommendations and tailored patient education [71, 72, 92]. Previous research showed AI systems' ability to assist patient-centered clinical decision-making [18, 37]. The AI systems with feature selection offer clinicians summarization of quantitative analysis, including predicted decision-making and explanations based on salient features, supporting consistent decision-making [54, 67].

Based on patient-specific characteristics, AI can generate personalized treatment recommendations, leveraging machine learning algorithms to consider a patient's medical history, family history, genomic profile, comorbidities, and treatment preferences, among other factors [15, 17, 19, 63]. While these outputs need to be carefully reviewed by clinicians, they can incorporate the most up-to-date healthcare information, ensuring that discussions are based on the most current and relevant evidence [98]. They can also account for detailed individual patient factors that harried clinicians may sometimes overlook. This empowers patients and healthcare providers to consider a wider range of treatment options and make choices that align with the best available evidence [39]. In addition to its potential role in helping create personalized treatment plans, AI can also be used to develop information presentations tailored to a patient's specific medical needs and knowledge level, which may be more effective than generalized informational literature [45].

AI is used commonly in lots of clinical settings and spaces [3, 18, 66, 90]; however, there are significant challenges for applying AI in SDM contexts [20, 34, 56]. Especially when working with older adult patients, there is a concern about difficulty in using or feeling comfortable with the new technology [44, 60]. This could be a particular concern if future widespread use of AI-based technologies leads other information modalities to become rarer and more difficult to access. The anticipation of sophisticated AI systems has also raised concerns about when clinicians might choose not to use them or make decisions contrary to the system's recommendations, potentially placing the burden of proof on the clinician deviating from AI guidance [13, 70]. Multiple concerns also exist about transparency, accountability, responsibility, and liability in relation to these new technologies when they are applied to high-uncertainty and high-stakes clinical decision-making [26, 86].

3 METHODS

The project was divided into two studies. In Study 1, we conducted preliminary interviews to evaluate the perspectives of older adult cancer patients and clinicians regarding the SDM process and ways in which technology might improve it. In Study 2, we developed a prototype SDM AI system, which we called "i-SDM," and then conducted usability interviews with older adult cancer patients and clinicians to evaluate its perceived utility. The interviews for both studies were conducted remotely via Zoom. In both studies, the primary outcome variable that we considered was impacts on patient satisfaction, with a secondary outcome variable of perceived likely impact on clinical decision quality.

The study procedures were approved by the university's Institutional Review Board (IRB) prior to any research activities. Following IRB approval, a targeted recruitment approach was used to reach out to potential participants who were older adult cancer patients/survivors ($\geq$ 60 years of age) or clinicians working in cancer-related care. Invitations to participate in the study were distributed via e-mail lists and through university's social media platforms. This included the lists of local senior centers, cancer care centers, senior housing groups, and the university's medical school. Each participant received a $10 gift card as compensation for their time. A demographic snapshot of the study participants based on their self-reported data is provided in Tables 1-2 and 4-5.

All of the interview questions were open-ended. We video-recorded and later transcribed the interviews in both studies, and used thematic analysis to identify central topics of interest shared by the participants. This involved individual coding by multiple researchers, iterative comparisons of the individual coding results, and identifying the common themes that emerged during coding. The coders met multiple times to compare their evolving codes and definitions, ultimately creating a consensus coding schema. The first author then applied this finalized schema during the focused coding of the transcripts. Regular discussions with the other authors took place to clarify the emerging themes. Excerpts associated with these themes were reviewed, and descriptions were written for each theme, forming the basis for this paper's findings.

4 STUDY 1: INVESTIGATING THE SDM NEEDS OF OLDER ADULT PATIENTS

To answer **RQ1: SDM's role in enhancing therapeutic communications and relations**, we conducted twelve semi-structured, one-on-one interviews were conducted with 7 older adult patients with chronic diseases (4 women, 3 man, mean age 72.14, SD = 2.29) and 5 clinicians (mean years of practice 12, SD = 10.20), to understand their needs in the clinical decision-making process.

Our participant sample for Study 1 included both cancer and non-cancer chronic illness patients, and clinicians from varied medical specialties. This was an intentional choice to help broaden representation in the collected perspectives. We wanted to ensure that factors relevant to medical decision-making for diverse patients

Study 1 Patient Participant ID	Age	Gender	Education Level	Race/Ethnicity	Cancer Type
P1	72	F	M.S.	Caucasian	Non-Cancer Chronic Illness
P2	71	F	M.S.	Caucasian	I stage Breast Cancer
P3	80	M	M.S.	Caucasian	II stage Prostate Cancer
P4	67	M	Ph.D.	Caucasian	I stage Prostate Cancer
P5	71	F	M.S.	Caucasian	Non-Cancer Chronic Illness
P6	76	F	Ph.D.	Caucasian	Non-Cancer Chronic Illness
P7	68	M	Ph.D.	Caucasian	III stage Thyroid Cancer

Table 1: Study 1 patient participant profiles, including age, gender, education level, race/ethnicity group, and cancer type.

Study 1 Clinician Participant ID	Clinical Domain	Experience	SDM in Current Practice (%)
C1	Psychiatry	6 yrs	80
C2	Cancer	4 yrs	60
C3	Nursing	8 yrs	50
C4	Psychiatry	32 yrs	50
C5	Nursing	10 yrs	60

Table 2: Study 1 clinician participant profiles, including practice domain, years of clinical experience, and self-report SDM rate in the current practice.

would be included in the i-SDM system, so that it could potentially expand beyond cancer-specific applications. The inclusion of clinician participants specializing in nursing and psychiatry also brings valuable perspectives on managing the daily life and mental health of patients, enhancing the overall breadth and depth of insights. The interviews with older adult patients were divided into 5 question categories, including demographics and basic health information, previous SDM experiences, health literacy, perspectives on health outcomes, and design recommendations for SDM systems. The questions for clinician participants were divided into three categories, including clinical domains and experience, previous SDM experiences, and design recommendations for SDM systems.

By asking the participants to suggest useful features for an SDM system, we initiated a "co-design" approach, which involves the active engagement and feedback of individuals who are likely to use the designed technology [62]. For the patient participants, if any difficulties in understanding clinical decisions were mentioned, we specifically asked them to elaborate on the systems they used (if any) to interpret and better understand the decision. This allowed us to gain valuable insights into how the patients preferred to navigate medical knowledge barriers, as well as the specific factors they considered important to learn in understanding clinical decisions. At the end of the interviews, we also asked the patients directly for suggestions about technological systems that might be useful during dialogues with their clinicians.

For the clinician participants, we first invited each of them to share how they delivered one recent clinical decision to older adult patients who lacked extensive medical knowledge, including what information they provided and any educational systems or materials they used. We then asked the clinicians to describe a typical SDM experience and discuss the difficulties or barriers they had encountered when engaging in dialogue with patients about medical conditions and treatments. Finally, we also asked the clinicians for their suggestions for technological systems to enhance the SDM process.

One of the major goals of these preliminary interviews was to elicit the open expression of opinions, experiences, and innovative ideas regarding SDM technologies, so that the insights would not be limited to a simple evaluation of predetermined features. Many of the emerging ideas were used in our current prototype system development (Study 2), but the open-ended interviews also yielded some broader insights about barriers and techniques for optimizing SDM, as presented in the Results section below.

5 STUDY 1 FINDINGS

A central finding in Study 1 was that the older adult patients faced significant challenges in understanding their diagnoses and treatment options. These patients expressed frustration and difficulty in comprehending technical terminology associated with their medical conditions, leading to confusion and hampering their ability to actively participate in collaborative decision-making. To address this issue, both patients and clinicians highlighted the importance of simplifying the technical language and providing comprehensive explanations. Another factor that was frequently mentioned in the clinician interviews was a lack of available time for engaging with patients in adequate detail. In regard to specific technologies, a majority (5 out of 7) of the patients volunteered that incorporating visual aids, such as graphs and illustrations, into a technological platform would greatly assist them in processing the information communicated by their clinicians. In the clinician interviews the strongest concern that emerged about the technology was its usefulness in communicating high-quality, accurate information.

5.1 Treatment Management for Older Adult Patients

The patients who participated in the study indicated that they had already employed various technologies to manage their health, including phones, computers, and other smart devices. All of the patient participants reported using telehealth services as one of the means through which they contacted their healthcare providers. A representative quotation in this area was: "*I spend a lot of time on my computer, though I'm not an expert. But I don't have any problems [using the information technologies]*" (P3, stage 2 prostate cancer patient).

Six out of the seven patient participants reported that they generally adhered to their health professionals' advice. However, the majority also stated that they had strong opinions about their healthcare and wanted to make their own decisions. For example: "*I try to stay away from surgery as much as possible, and so I research alternative approaches to things. When I found a reasonable alternative approach, I always attempted it first*" (P1, stage 3 thyroid cancer patient). Our participant sample was well-educated, and in the interviews they expressed a good understanding of what constituted high-quality medical information. One stated: "*I read the New York Times every day, and they have a wellness section. There's a lot of good information in there. Or if I have a question about something like my health or treatment, I know how to look things up and do research*" (P5, chronic illness patient). Another patient mentioned being "*leery of a lot of information on the Internet*" (P1, stage 3 thyroid cancer patient) and thus valuing the guidance and assistance of trained clinicians.

Despite this relatively high level of information competence, many of the patient participants felt that they had knowledge gaps about their treatment plans or what alternatives were available for managing their diseases. This was particularly true regarding potential harms and adverse effects of treatments, potential drug interactions, and other safety issues. Five out of the seven participants said they felt that their health literacy was relatively weak (P1-3, P5-6), and one patient participant said they were uncertain about the effectiveness of the medications they were taking (P3, stage 2 prostate cancer patient).

5.2 Clinician Views on SDM

The majority of the clinicians interviewed confirmed that they viewed SDM as a valuable means of enhancing the management of chronic illnesses among older adult patients. For example: "*I think the shared decision-making era is coming and like, in some ways, we [clinicians] need to be involved to make sure that it is used appropriately*" (C2, cancer). The one clinician participant who did not support the use of SDM cited time pressures as the reason for not involving patients in the decision process: "*there is a time pressure on each patient visit that really makes it very difficult*" (C5, nursing).

For cancer clinicians' decision-making process, clinicians generally follow a three-step process to identify and synthesize the list of imperfect evidence to conclude a care decision: Clinicians first go through patients' cancer cases (e.g. examination results, electronic health records (EHR), and previous medication history). Then they "*guesstimate*"(C2, Cancer) the likely treatment outcome of a patient population that shares some characteristics with their patient and if necessary, seek out external research or other clinicians to affirm the potential treatments. Thirdly, the follow-up visits with patients to discuss and finalize the treatment options.

Despite their generally positive evaluation of SDM, the other clinicians expressed some concerns, mostly related to patients' abilities to assess medical information objectively and analytically. This included the potential for patients to fixate on treatments that offered potentially transformative solutions while ignoring their low chances of success and potential risks. Several of the clinicians also expressed concern that miscommunications during the SDM process might lead to inaccurate patient expectations, or to clinicians not accurately understanding their patients' goals. Finally, clinicians expressed concerns that patients might rely on poor-quality or overgeneralized information resources when understanding their conditions, and would not be able to evaluate the best evidence-based approach for addressing their particular circumstances in a treatment plan.

The clinicians indicated that the most useful form of SDM technology would be systems that could mitigate these issues by helping patients to understand their suggested treatment options more clearly: "*Obviously, the communication . . . is where the technology might be able to make a difference*" (C3, nursing). The majority of the clinicians felt that technology could potentially play a useful role in SDM by reducing the workload involved in dialogue and the struggle to explain medical concepts (it could "*take load off*" clinicians, according to participant C2). Clinicians also affirmed that such technology-enhanced SDM would likely help to improve patient adherence to treatment plans.

5.3 Design Strategies for the Prototype SDM AI System

Combining the interview results from the patients and the clinicians, we identified ten factors that the participants believed were important to include when engaging in SDM communication processes. The clinicians gravitated strongly to four of the factors: potential medical benefits or effects of treatment, potential risks, detailed information about alternative options, and patient ages at which the treatment was most valuable. Notably, some of the other factors that multiple patients mentioned as significant for their lives, including the cost of the treatment and the travel distance required to access the treatment, were not mentioned by any of the clinicians (Table 3).

These ten factors provided the basis for our initial design of the prototype i-SDM tool. In addition, based primarily on the clinician interviews, we established the following working principles for issues that the tool is intended to address:

- **Variability in patient situations and disease characteristics.** Many cancers are variable diseases, with different stages and grades that require different treatment options. They may also be interconnected with other diseases and other aspects of a patient's life. For a technological platform

Ten Important Factors for SDM (From High to Low)	Clinician Participant (C1-C5)	Patient Participant (P1-P7)	Total Participants' Approved Factors (Out of 12)
Survival Rates in Five Years	5 approved	7 approved	12
Potential Risk	5 approved	7 approved	12
Alternative Treatment Options	5 approved	6 approved, 1 unimportant	11
Average Patient Age for the Treatment	5 approved	5 approved, 2 unimportant	10
Distance (Treatment Location)	5 unimportant	7 approved	7
Detailed Treatment Understanding	1 approved, 4 unimportant	2 approved, 5 unimportant	7
Treatment Duration	1 approved, 4 unimportant	5 approved, 2 unimportant	6
Pain Degree	1 approved, 4 unimportant	5 approved, 2 unimportant	6
Nursing Service	5 unimportant	4 approved, 3 unimportant	4
Treatment Fee	5 unimportant	3 approved, 4 unimportant	3

Clinician Participants Approved   Clinician Participants Saw as Unimportant   Patient Participants Approved   Patient Participants Saw as Unimportant

Table 3: Ten Important Factors in SDM Discussions of Medical Treatments.

to be useful in clinical SDM practice, it will need to incorporate a great deal of nuance in regard to specific information pages that can be brought up for an individual patient, so as to effectively address that patient's situation without confusion.

- **Variability in desired patient engagement.** Receptivity to SDM and the desired depth of medical discussions may vary widely for different patients. The technology will need to be situated as one potential tool in the physicians' arsenal, to be judiciously used in situations where patients find it to be desirable and helpful. It should also be able to provide multiple "*depth*" levels, so that patients can receive either basic information or more in-depth information depending on their individual preferences.
- **Time limitations in clinical care.** The time constraints that current healthcare systems place on clinical decisions reduce the possibility of discussing treatment options with patients in depth, even when demonstrably best medical practices and clinician preferences would point toward the greater use of SDM [9, 76]. Our platform may assist with reducing communication burdens during SDM, but it should be understood and designed as an enhancement, not a substitute, for clinician–patient relationships.

6 STUDY 2: DESIGN AND USABILITY EVALUATION OF THE PROTOTYPE SDM AI SYSTEM

6.1 Features of the i-SDM Prototype

The findings from Study 1, along with established design principles for AI-based clinical decision support systems and core SDM elements, established a strong foundation for the development of our i-SDM prototype. To design the SDM AI platform [24], we first developed a conceptual schema using a double-diamond design diagram (Figure 1)[23], showing optimal patient involvement [33, 48, 57, 61, 87]. In the first diamond (Figure 1, red arrows), clinicians are in charge of discovering the patients' cancer diseases, defining the health outcomes/goals, and identifying treatment options. Patients start to be involved in the decision-making after the first diamond. In the second diamond, patients (Figure 1, green arrows) are tasked with learning more about each clinical treatment option and voicing their outlooks and preferences. After completing the two stages, clinicians and patients together finalize the optimized clinical decision. During this SDM process, patients and clinicians engage in in-depth discussions about the best available evidence pertaining to the patient's condition and/or treatment options [81]. The primary objective is to incorporate their values, preferences, and goals into the decision-making.

Based on the number of participants' approved factors among the ten important factors in Study 1 (Figure 3), we divided the factors into three groups: a) survival rates, potential risks, and alternate treatment options; b) average patient age for the treatment and detailed treatment understanding; and c) pain degree, distance to the treatment location, nursing service, and treatment fee. Then we summarized the three groups into three main steps of the SDM process: survival rates, side effects, and other factors. We began with three active treatment options (surgery, radiation, and active surveillance) and a an unrecommended base option of no treatment. The i-SDM prototype focused on central usability features such as the treatment-comparison format, the clear presentation of risks and potential benefits, and a multi-stage design with increasing levels of detailed information that enhances easy comparisons between different treatment plans across central metrics.

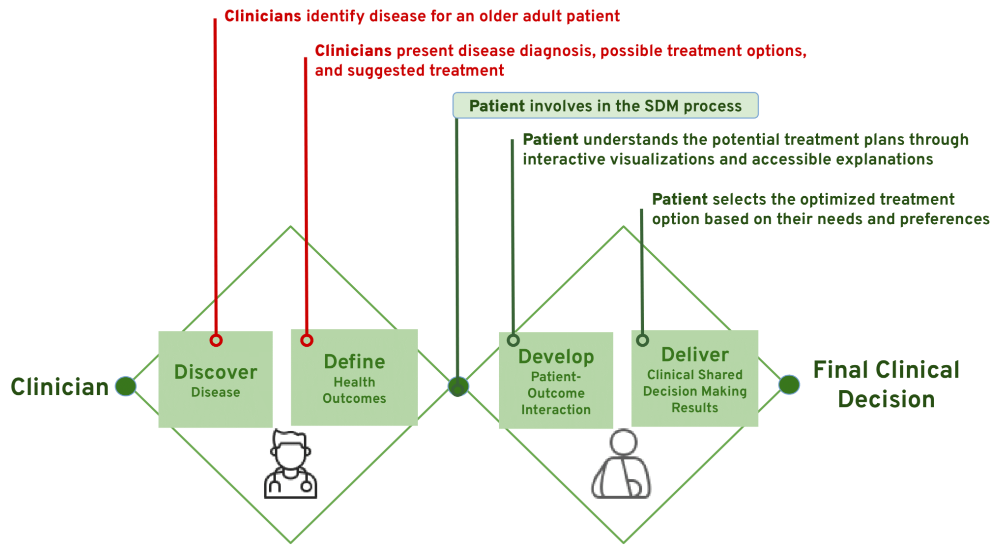

Figure 1: Double-diamond visualization of optimal patient involvement in the clinical decision-making process

6.2 Development and Deployment of the i-SDM System

Our i-SDM system was specifically designed to assist in the second diamond of the double-diamond decision-making process (Figure 1) by targeting the effective consideration of treatment options and the presentation of those options to the patient. We applied multiple operational ML models for this purpose, as discussed in the following paragraphs. We also exclusively employed the "Wizard of Oz" (WoZ) method for quality control in AI predictions for older adult cancer patients, which helped to focus on refining system design and optimizing the presentation of information to users. For the purposes of usability evaluation in Study 2, the i-SDM prototype's interface was then populated with information for a hypothetical prostate cancer case [2, 6]. We worked with two prostate cancer clinicians who were not participating in the study to clarify the hypothetical clinical case information.

Essential medical information that clinicians view as significant for treatment plan evaluation was added to the tool for patient education, as well as factors such as cost, duration, and pain levels that the patients prioritized in Study 1. This presentation of relevant information is in the service of the system's primary function of prompting dialogue and understanding between clinicians and patients. Such mutual engagement can assist both parties in developing a well-rounded perspective on the potential benefits, drawbacks, and implications associated with each treatment option [28, 47, 58]. In addition, i-SDM was designed to empower patients by offering direct links to high-quality online support resources. Given that all of our patient participants discussed turning to online resources for better understanding, the integration of such links into the system will help direct them to applicable and high-quality sources of information, including educational materials, emotional support networks, and practical guidance to navigate their medical journey more effectively.

We ultimately developed a **six-step** presentation format, in which various comparison factors are presented to the patient and clinician in sequence before reaching a concluding summary page. The six steps are categorized into three stages: patient assessment, risk evaluation with AI, and patient end decision. The multi-stage evaluation process allows the SDM dialogue to step through each important factor sequentially so that none are overlooked (Figure 2). In Step 1, patients begin by indicating the factors that they are most concerned about, out of the ten overall metrics that we developed from the interviews. In Step 2 they are asked to confirm basic information about the patient's diagnosis and personal demographic factors. In Step 3, they can start to compare the treatment options by looking at associated survival rates. Step 4 presents potential side effects and risks, and Step 5 presents other factors as selected by the user out of the ten possible factors. Finally, Step 6 presents a summary overview of the treatment option factors and links to more in-depth information. All of these screens can be printed out for further discussion or to share with friends and family members.

ML models are integrated in Steps 2, 3, 4, and 5 of this process. Step 2 generates a patient's full clinical case description as well as a short summary based on the patient's existing clinical profile, by leveraging the extractive summarization feature of GPT-4, a pre-trained large language model (LLM). In Step 3, i-SDM employs the ML algorithm - Light Gradient Boosting Machine (LightGBM) - to provide personalized ranges of predicted survival rates from the potential treatments suggested by the clinicians. This model generates the survival rates based on historical demographic data in the Medical Information Mart for Intensive Care (MIMIC-IV) [49] database, tailoring it to the patient's individual circumstances. Participants can set the prediction length to three months, six months, one year, or five years. Then, in Step 4, participants proceed to compare the specific side effects and risks of treatments. The ML model displays the predicted range of possibilities that specific participants may experience specific side effects, based on their

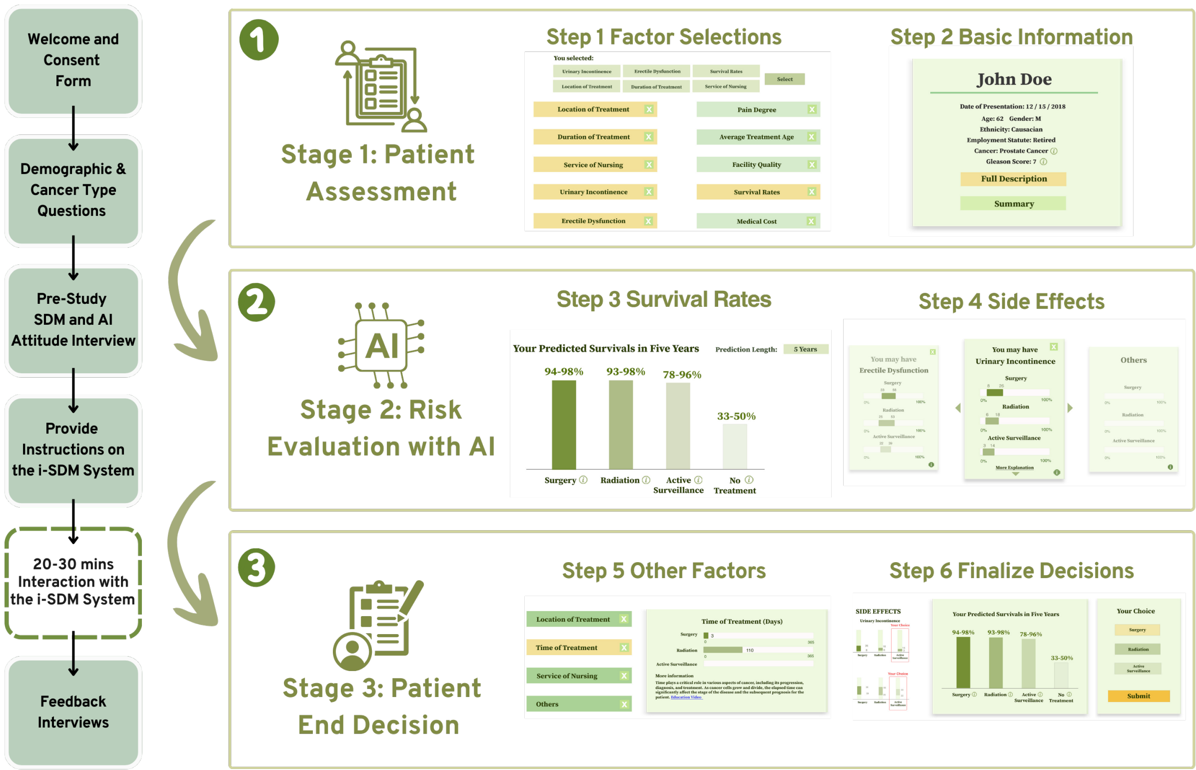

Figure 2: i-SDM prototype's multi-stage evaluation process and Study 2 testing process. (The interactive presentation of this process is available in the supplementary material video.)

demographic information. The LLM was also used to formulate accessible explanatory information for describing the side effects. Step 5 contains the LLM-generated explanations about pain degree, nursing service, treatment fee, and other specific factors that are tied to the specific types of cancer. As "wizards," we manually rectified a few errors in the machine learning-curated results. It's important to note that the primary focus of this study is not to assess the predictive or summarization capabilities of these LLM or ML models.

6.3 Usability Evaluation of the Prototype SDM System

To evaluate the i-SDM tool's usability, we conducted testing interviews with 18 older adult cancer survivors (11 women, 7 men, mean age 69.22, SD = 7.33) and 7 cancer-related clinicians (mean years of practice 13.6, SD = 9.42). The usability study addresses **RQ2: SDM AI usability acceptance in older adult cancer patients** and **RQ3: patient and clinician perceptions of SDM AI effectiveness**.

The Study 2 interviews with patients are divided into 4 main question categories: demographics, clinical decision-making processes, i-SDM prototype usability testing (adapting evaluation metrics from International Patient Decision Aids Standards (IPDAS), the Interprofessional Shared Decision Making Model (IP-SDM), and Patient Education Materials Assessment Tool (PEMAT) [84]), and recommendations for i-SDM's future improvements. In each interview, we first asked about the patient's experiences with the clinical process and the extent of their perceived knowledge and engagement. Without showing them our prototype, we then explained the concept of SDM and asked how they felt about it. Finally, we introduced them to our i-SDM system and asked for feedback about the interface and for suggestions to improve it.

The interviews with clinicians were divided into three main sections: recent SDM experiences, i-SDM prototype usability testing, and recommendations for i-SDM's future improvements. Similar to the patient interviews, we first discussed the clinicians' general view of SDM without showing them our system, and then subsequently introduced i-SDM for feedback. In addition to asking the clinicians to evaluate the system's interface and usability, we also sought their perspective on the likelihood of i-SDM reducing medical errors and enhancing the quality of healthcare outcomes.

7 STUDY 2 FINDINGS

7.1 Participant Evaluations of the SDM AI System

We used the recorded video and audio data to evaluate the i-SDM system, employing a combination of Visual-Verbal Video Analysis (VVVA) [35], semantic analysis, axial coding [10], and affinity diagrams [25]. Participants in the experiment were prompted to

Study 2 Patient Participant ID	Age	Gender	Education Level	Race/Ethnicity	Cancer Type
P8	82	F	High School	Caucasian	III stage Ovarian Cancer
P9	60	F	B.S.	Caucasian	IV stage Breast Cancer, Lyme Disease
P10	66	M	High School	African American	Prostate Cancer
P11	70	M	B.S.	African American	II Stage Prostate Cancer
P12	71	M	Ph.D.	Caucasian	II stage Prostate Cancer
P13	64	F	M.S.	Caucasian	II stage Thyroid Cancer
P14	63	F	High School	Asian	I stage Urinary Cancer
P15	75	M	Ph.D.	Caucasian	II stage Prostate Cancer
P16	63	F	N/A	Caucasian	Breast Cancer
P17	63	M	High School	Caucasian	II stage Prostate Cancer, Skin Cancer
P18	72	F	M.S.	Caucasian	I stage Urinary Cancer
P19	62	F	B.S.	Caucasian	III stage Rectal Cancer
P20	68	F	B.S.	Caucasian	Thyroid Cancer, Triple-Negative Breast Cancer
P21	68	F	J.D.	Caucasian	Thyroid Cancer
P22	85	M	M.S.	Caucasian	Prostate Cancer
P23	62	F	M.S.	Caucasian	Blood Cancer (Myeloma)
P24	70	M	J.D.	Caucasian	Blood Cancer (Multiple Myeloma), Skin Cancer
P25	82	F	High School	Caucasian	I stage Breast Cancer, Sepsis

Table 4: Study 2 patient participant profiles, including age, gender, education level, ethnicity, specific cancer stages, and estimated family income level.

Study 2 Clinician Participant ID	Clinical Domain	Experience	SDM in Current Practice (%)
C6	Cancer	33 yrs	80
C7	Breast Cancer	15 yrs	60
C8	Cancer	5 yrs	70
C9	Oncology	11 yrs	20
C10	Pharmacy	3 yrs	50
C11	Cancer	9 yrs	60
C12	Nursing	19 yrs	70

Table 5: Study 2 clinician participant profiles, including practice domain, years of clinical experience, and self-report SDM rate in the current practice.

vocalize their thoughts while engaging with all six steps of the prototype (Fig 2). We parsed this data to examine: (a) the type of information that the participants sought at each step, (b) their process of synthesizing and interpreting information from i-SDM, and (c) their approach to prioritizing the clinical information within a limited timeframe.

Next, we performed axial coding to synchronize participants' verbal, visual, and/or gestural cues, and assigned corresponding labels as illustrated in Table 6, Negative cues were represented by the color red, positive cues by green, and neutral cues by yellow. These color codes were used to create a heatmap of the i-SDM interface, with more highly saturated colors indicate more extensive interactions with the prototype. An example heatmap for Step 6 of the i-SDM process is shown in Figure 3. Through the use of color, this heatmap shows the outcomes for participants' verbal and behavioral responses to the SDM AI system's interface.

In this usability study, older adult cancer patient participants spent an average of 23.3 minutes interacting with the i-SDM prototype, while clinician participants spent an average of 19.6 minutes. A total of 316 labels were collected, comprising 145 positive cues labels (45.89%), 73 neutral cues labels (23.10%), and 98 negative cues labels (31.01%).

Coding Labels	Sample Labels
Negative Cues	• **Verbal Cues** "*I may not want to rely solely on this information [on step 5] for my decision since there are various factors involved, including personal beliefs and cultural practices, that influence my choices. If I do choose to see the data, I'll likely delve into its sources and context to understand its validity and relevance better.*" (P25, I stage Breast Cancer patient) • **Gesture Cues** [In Step 3, the participant expressed disagreement by shaking their head upon observing the predicted survival numbers.] (P22, Prostate Cancer patient)
Positive Cues	• **Verbal Cues** "*I think this shared decision-making printout takeaway [step 6] for patient-clinician communication is integral to our entire process... It's the most important thing, really.*" (C7, Breast Cancer) • **Verbal Cues** "*I like the visuals [in step 3] because I think graphs are the best way to display information. It seems very organized.*" (P15, II stage Prostate Cancer patient)
Neutral Cues	• **Verbal Cues** "*I have asked for those numbers [step 4], but in my experience, they kept changing depending on which physician I spoke to. Each person seemed to have their own perspective, with some giving more leeway to make it sound positive, while others were more straightforward and maybe accurate.*" (P8, III stage Ovarian Cancer patient) • **Visual Cues** [In Step 4, the participant remained in the "Urinary Incontinence" window, alternating between clicking on the two treatment options—surgery and radiation—three times.] (P10, Prostate Cancer patient)

Table 6: i-SDM prototype's sample coding label for usability testing analysis.

Figure 3: i-SDM prototype's heatmap for evaluating users' acceptance for step six: Finalize Decisions. The other five steps heatmap are presented in the appendix (Section A.1: Figure 4).

7.2 AI Usability Acceptance in Older Adult Cancer SDM

7.2.1 Information Accessibility. The study participants had overall positive reactions to how i-SDM presented information. One notable theme emerging from the interviews is that the system's graphical presentations effectively communicate treatment comparisons. This is commensurate with the Study 1 findings, in which participants also desired clear graphical comparisons. P8 from Study 2 commented:

> "*I think it's fabulous that the patient can see this SDM prototype if they're talking to the clinician in the office. I know the clinicians would say, "Well, surgery and radiation, both are 98% and active surveillance is 96%." Unless you're going to sit there and take lots of notes, that information isn't going to stick, especially to older cancer patients like me. But it is wonderful that you can actually see predictive survival. There's only a 2% difference in survival, and it's still really good*" (P8, stage 3 ovarian cancer patient).

The clinician participants also reiterated the importance of using accessible language to explain the treatment plans, an approach that can enhance patient confidence and empower them to play a more active role in decision-making:

> "*The [clinical decision-making] process can be quite daunting, as making a decision without access to highly reliable information can be emotionally overwhelming.*

> *The fear that arises stems from the uncertainty of not having concrete, trustworthy details, leaving patients unsure about the most suitable treatment to follow*" (C11, Cancer).

7.2.2 Trust. The interview participants emphasized that trust is key to building patient-clinician therapeutic relationships. However, distrust of the healthcare system as a whole is well-established and currently rising in the U.S. The i-SDM prototype confronts the task of winning patients' trust and respect as effectively as possible. Patients directed to a technological information source may sometimes feel shunted or question their clinician's knowledgeability. The goal of any such system should be to help patients to feel more knowledgeable and active in the process. Some of the interview responses appeared to indicate that i-SDM was successful in this task:

> "*Spending time to understand what specific treatment is hard for us to process because they just don't know anything about this. It's scary because making this clinical decision could be emotional without highly reliable pieces of information*" (P10, prostate cancer patient).

The participants also felt that using i-SDM could encourage more open dialogue, particularly by providing openings for patients to express their concerns, invoke their preferences, and seek clarification about their treatment options. Such enhanced communication is intrinsically valuable, and it may provide clinicians with information that would otherwise be overlooked or withheld:

> *"Through this step-by-step SDM [process], cancer patients like me have the opportunity to learn each treatment option's survival rates and risks, acknowledge various cancer research or resources, and I can calm myself down even [cancer] has so much uncertainty and is very complex*" (P18, stage 1 urinary cancer patient).

7.2.3 Assistive Role. Clinicians envisioned i-SDM to serve as an assistant system to support in-person visits. i-SDM helps clinicians with explanations in lay languages and interactive visualizations. "*...[clinicians'] preference may lean toward verbal communication, delivering essentially the same information verbally as the i-SDM system presents visually. However, I do see a valuable role for this in the clinic that we could display it briefly, maybe for 2 or 3 minutes, while explaining things [to cancer patients]*" (C9, Oncology).

A clinician worried about i-SDM which may diminish clinician skills and partially undermine their authority in clinical decision-making. "*[i-SDM] is a tool for the clinician to use together with cancer patients… It's important that [i-SDM] will not replace the clinicians or caring staff. This is a tool to help cancer patients in their decisions, just like a telephone, or a fax machine which helps them communicate efficiently with their doctor*" (C7, Breast Cancer).

7.3 Perceptions of SDM AI Effectiveness

7.3.1 Patient Education. Several interview participants affirmed the view that i-SDM has the potential to improve patients' health literacy. For example, one stated that:

> "*For me, the first step is [go to] the primary care provider. Next, I need to know and learn more. And I think most patients would love to learn more about their cancer . . . because it is quite serious and it is about my life. I need to collect as much information as I possibly can. So I think this i-SDM platform is a good approach to educate us*" (P24, blood and skin cancer patient).

Such improved knowledge and engagement could potentially lead to better health outcomes, as some patients acknowledged: "*When you feel confident and optimistic about a clinical decision and staff, your medical or health outcome will be better*" (P20, thyroid and triple-negative breast cancer patient). One likely outcome is improved treatment adherence, as patients may better comply with the chosen treatment plan if they feel that they understand it and have an active role in the decision-making process.

However, three clinicians (C6, C9, C11) suggested a concern about i-SDM which may require to allocate extra time and energy to explain to patients. "*SDM is like an investment because it takes time, it takes education, sometimes it takes negotiating, and so on*" (C6, Cancer). Implementing shared decision-making in cancer care requires dedicating time, resources, patient education, and occasionally negotiation to achieve the best treatment outcomes. Using the i-SDM system might raise patients' expectations to receive full explanations of all aspects of clinician's evidence-based processes and diagnoses, which are often extremely technical and would be onerous and/or overwhelming to explain to non-specialist patients. "*It's very difficult for the patients to hop on board and identify with their process or with their treatment and collaborate if they are not familiar with the [cancer] field*" (C9, Cancer).

7.3.2 Resource Limitations. The patient participants also mentioned that the system could likely help overcome some of the limitations imposed by time constraints in clinical practice. Although larger systemic changes beyond the scope of our project will be needed to ensure that clinicians have adequate time to spend with patients and that effective SDM practices become more common, the efficiency provided by the system can assist in reducing communication burdens. One patient noted that: "*Spending time to understand what specific treatment is hard for us to process because they just don't know anything about this. It's scary because making this clinical decision could be emotional without highly reliable pieces of information*" (P12, stage 2 prostate cancer patient).

8 DISCUSSION

The findings from the interviews in both Study 1 and Study 2 revealed that the clinicians and older adult patients expressed agreement with the SDM approach. They also affirmed that using information technologies such as i-SDM has a valuable role in enhancing clinician–patient dialogues. The primary value attributed to the use of such technologies was their ability to improve communication by providing ready-made, lay-language descriptions of medical treatments and their benefits and risks, and visualizing related information through graphs and illustrations.

8.1 Participants' Concerns about the SDM AI System

Three cancer patients and two clinicians from Study 2 expressed concerns with AI prediction accuracy regarding topics such as five years' survival rate. While one of the potential advantages of AI is greater personalization and detailed inputs, some participants also believed that AI would be unable to address complex medical cases:

> "*A lot of cancer patients need personalized care because their scenarios are pretty complex. That's why AI could only cover some common basic diseases but not complex diseases like cancer. For example, I had knee surgery, and got sepsis three months before being diagnosed with breast cancer. AI can predict each singular disease, but the combination would be very complex and need senior doctors' inputs*" (P25, I stage Breast Cancer patient).

Since the diagnosis-to-treatment process is a complicated evidence-based practice, and if patients without sufficient clinical background use it, it may become a huge burden for healthcare professionals to break down the evidence-based process and explain the detailed reasons for forming the treatment options [70]. Without clear explanations and details, both cancer patients and healthcare professionals have doubts about the i-SDM system. The participants' concerns about AI predictions may undermine the accountability and trustworthiness of the i-SDM prototype. Our Study 2 findings regarding users' trust of AI (Section 7.2.2) were also grounded in a perception that it would not be able to accurately predict specific numerical values for intricate cancer treatment outcomes. This lack of trust in AI predictions is also linked to the working principle identified in Study 1, which highlighted the diverse nature of patient situations and disease characteristics. In the context of the older adult cancer patient population, limited existing data points and clinical trials contribute to participants' concerns regarding the effectiveness of the AI-based system.

Finally, some participants expressed concerns about privacy and confidentiality issues when using the i-SDM system, as they did not feel sufficiently reassured that the SDM AI system would not share or exploit their personal health information.

8.2 Participants' Unwillingness to Participate in the SDM Process

Two cancer patients (P13, P22) and one clinician (C8, Cancer) participant from Study 2 expressed unwillingness to participate in the SDM process. The patients who rejected SDM stated that is seemed like an excessive burden and responsibility, and they wanted healthcare professionals to make a knowledgeable decision without asking for the patients' opinions. These patients felt that their lack of knowledge or other issues such as language barriers would make the SDM process uncomfortable and ineffective, and they did not regard systems such as i-SDM as useful for mitigating these concerns.

The clinician who rejected SDM stated that having to negotiate with patients about treatments could lead to "*suboptimal*" (C8, Cancer) outcomes, that most patients lacked the background necessary to understand medical information and make a good decision, and that engaging in SDM would be a tremendous time burden on already overstrained clinical staff. C8 also pointed out that "*misinformation in clinical cancer settings is counterproductive, especially considering the strong emotional reactions patients have to a cancer diagnosis*" (C8, Cancer). From this point of view, the educational function of SDM could create mental health challenges if patients find the information to be overwhelming or alarming. In addition, however, the clinician was also very skeptical about the AI's ability to provide accurate and accessible information, leading to the view that it would produce misinformation or simply increase the burden on clinicians when striving to optimize treatment decisions and convince patients of the need for these treatments. These strong opinions indicate that SDM processes may not be suitable for all patients or clinicians. While a better explanation of how the technology works might alleviate some of this hesitancy, it is unlikely to make much of a difference in the perspectives of those who are fundamentally adverse to any kind of SDM approaches.

8.3 The Role of AI in Overcoming Cancer Disparities

Cancer patients require a great deal of family or caregiver support, which may include extra physical and mental care [99]. While most of the cancer patients in the current study had strong support networks and the opportunity to receive the most up-to-date medical care, this is not the case for other patients who might lack healthcare insurance, be socially marginalized, and/or live in under-served areas [93]. These differences in access to healthcare resources and information significantly increase cancer outcome disparities [36].

One of the advantages of systems such as i-SDM is that they are inexpensive and easily distributed to provide the same cutting-edge medical analyses and healthcare information support to all patients and clinical practitioners. By incorporating high-quality medical translations, they may also be useful in overcoming language barriers between patients and clinicians. This can assist in the goal of ensuring that every patient has access to the resources and knowledge needed to make informed decisions about their care and to navigate their medical journey with empowerment. Offering comprehensive and easily accessible information, the step-wise SDM AI system aligns with the working principles identified in Study 1, ensuring it meets the criteria for desired patient engagement. This interactive system is designed to accommodate users with varying levels of clinical knowledge. The i-SDM approach acknowledges the importance of the psychosocial and emotional dimensions in medicine, providing clinical information, opportunities for dialogue about lifestyle factors and personal concerns, and links to community support networks.

8.4 Implications for Human–Computer Interaction (HCI) research on AI in Healthcare

Our studies' findings address gaps in prior SDM deployment in clinical practice, particularly concerning older adult cancer patient populations. These findings propose four main implications for informing HCI research on AI integrations in healthcare settings:

First, one of the greatest strengths of AI-based systems in this context is to assist in creating clear and personalized **explanations** of medical information and good **communication** between patients and clinicians. Although most of our patient participants ultimately concurred with their clinicians' recommended treatment, the AI-based system helped them to better understand this choice and gave them opportunities to discuss with clinicians how the decision related to their personal priorities. The transparent and detailed explanations provided by AI gave the older adult cancer patients easy-to-understand information so that they could better grasp how clinicians are making decisions. This helped to remove some of the communication burdens from clinicians while simultaneously promoting discussion and contributing to a patient-centered clinical paradigm.

Second, participants did not believe that AI systems would ever be able to substitute for clinicians' decision-making. Instead, AI should serve to provide **educational** and **informational** resources. By providing personalized analytics and well-vetted data, AI can help both patients and clinicians to confirm their understanding of medical needs and treatment options, leading to an informed, mutually agreed-upon decision. When grounded in clear and comprehensive data sources and accessible explanations, AI-based technologies can help patients and clinicians to feel more confident about these decisions.

Third, researchers should focus on the ability of AI to provide **personalized** predictions, which can be more informative for patients and clinicians compared to generic data summaries. For example, treatment outcomes for patients who have various comorbidities (combinations of different health conditions) may differ significantly from the overall treatment outcome statistics. AI can assist in immediately providing data that is tailored to such individual factors.

Fourth, both patients and clinicians are likely to have concerns about relying on AI technologies for medical information, and theses concerns need to be addressed by technology developers to promote confidence and **acceptance**. Such tools can benefit by providing simple explanations to users about "*how AI works*" to help establish trust in the clinical AI system. Transparency concerning the training data source, model accuracy, potential biases in the ML model, and the privacy of patient's data can all contribute strongly to promoting user acceptance of the technology. Trust may also be enhanced by a well-designed interface that walks users through the information step-by-step instead of presenting overwhelming up-front complexity.

9 LIMITATIONS AND FUTURE WORK

A notable limitation in this work is that both Study 1 and Study 2 used a small and unrepresentative participant sample, consisting primarily of Caucasians with a high extent of educational attainment, living in a high-income university town. Further research will be needed to confirm the findings for a more diverse participant sample and for a wider range of healthcare settings. Participants without higher education degrees may face greater challenges in accessing healthcare, and may have different informational needs and different perspectives on the patient–clinician relationship. The specific patient diseases and clinician specialties included in our participant sample may also have affected the findings. Further research will be needed to confirm the findings for a more diverse participant sample and for a wider range of healthcare settings. In particular, participants without higher education degrees may face greater challenges in accessing healthcare, and may have different informational needs and different perspectives on the patient–clinician relationship.

Moreover, the recruitment process for Study 2 targeted cancer survivors; i.e., patients who have already completed their cancer treatment decisions. This may have introduced bias in the results regarding attitudes and opinions on SDM, in comparison to patients who are still actively engaged in the clinical decision-making process. It should be noted that clinical decision-making becomes increasingly complex as patients age, due to the involvement of multiple comorbidities and their previous medical history, and patients who are in poor health may be less able or interested to participate in SDM. The hypothetical cancer case that we used when presenting the i-SDM technology to participants was relatively simple and involved a limited number of treatment options. More development and testing will be needed to evaluate the utility of the technology for patients and clinicians who are dealing with more advanced and complex medical conditions.

In addition to considering a broader and more diverse participant sample, we recommend that future studies in this area should closely examine individual differences in technology use, and consider different medical diagnoses (more or less complex) as a variable. An important focus for future work is reaching a more nuanced understanding of how technology can be optimally leveraged in the SDM process. While our study has shed light on the benefits and usability of the prototype i-SDM system, it would be valuable to examine its use in actual patient–clinician interactions to help determine its effectiveness and how it can be better tailored to meet users' needs. This will pave the way for design improvements to better align the system with the requirements of both patients and clinicians.

Hence, it is crucial to acknowledge that different types of cancer present unique challenges and considerations. Each cancer field has its own characteristics, treatment modalities, and patient populations, which can significantly influence the dynamics of SDM and the role of technology. To account for these variations, future work should involve step-wise comparisons and analysis specific to certain types of cancer. By focusing on specific cancer contexts, we can delve into the nuances and intricacies of SDM and technology utilization within those domains, further refining our understanding and tailoring interventions accordingly.

10 CONCLUSION

Our study demonstrated the potential of a patient-centered SDM AI system for empowering older adult cancer patients in the cancer decision-making process. Study 1 revealed patient and clinician participants' views and needs in relation to SDM, eliciting ten important factors that should be considered when making a treatment decision. SDM was found to be effective in enhancing communication and relationships between older adult cancer patients and their clinicians. Study 2 gathered feedback and insights about the design of the i-SDM system and its prospects for improving patient satisfaction. The majority of the older adult cancer patient and clinician participants viewed the i-SDM system as potentially useful and effective, especially in its role of reducing the burden on clinicians as they communicate complex medical knowledge. The aging-friendly multi-stage SDM process provided empowerment and support for older adult cancer patients during challenging times by breaking down complex decision-making. i-SDM was also shown to enhance clinical efficiency and improve healthcare experiences in this understudied population. The overall findings contribute to the research literature on healthcare support technologies and advance a promising vision for sustainable patient–clinician SDM dialogues. Emphasizing the crucial role of transparent explanations, accessibility, and trust-building, the paper provides useful insights for healthcare and AI communities, and points toward potential directions for future HCI research in the context of older adult cancer patients.

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REFERENCES

[1] [n. d.]. International Patient Decision Aids Standards (IPDAS) Collaboration. http://ipdas.ohri.ca/
[2] [n. d.]. Surgery for Prostate Cancer. https://www.cancer.org/cancer/types/prostate-cancer/treating/surgery.html
[3] João Abrantes, Maria João Silva, José Meneses, Catarina Oliveira, Francisco Maria Calisto, and Ross Filice. 2023. *External validation of a deep learning model for breast density classification.* https://doi.org/10.26044/ecr2023/C-16014
[4] Naseem Ahmadpour, Phillip Gough, Melanie Lovell, Philip Austin, Philip Poronnik, Wendy Qi Zhang, Judy Kay, Bob Kummerfeld, Tim Luckett, Martin Brown, Jane L. Phillips, and Meera Agar. 2023. How can HCI support end-of-life care? Critical perspectives on sociotechnical imaginaries for palliative care. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3544549.3585768
[5] Anshu Ankolekar, Ben G. L. Vanneste, Esther Bloemen-van Gurp, Joep G. van Roermund, Evert J. van Limbergen, Kees van de Beek, Tom Marcelissen, Victor Zambon, Matthias Oelke, Andre Dekker, Cheryl Roumen, Philippe Lambin, Adriana Berlanga, and Rianne Fijten. 2019. Development and validation of a patient decision aid for prostate Cancer therapy: from paternalistic towards participative shared decision making. *BMC Medical Informatics and Decision Making* 19, 1 (July 2019), 130. https://doi.org/10.1186/s12911-019-0862-4
[6] Robert Aronowitz and Jeremy A. Greene. 2019. Contingent Knowledge and Looping Effects - A 66-Year-Old Man with PSA-Detected Prostate Cancer and Regrets. *The New England Journal of Medicine* 381, 12 (Sept. 2019), 1093–1096. https://doi.org/10.1056/NEJMp1811521
[7] Seljelid B, Varsi C, Solberg Nes L, Øystese Ka, and Børøsund E. 2022. Feasibility of a Digital Patient-Provider Communication Intervention to Support Shared Decision-Making in Chronic Health Care, InvolveMe: Pilot Study. *JMIR formative research* 6, 4 (April 2022). https://doi.org/10.2196/34738 Publisher: JMIR Form Res.
[8] Atallah Baydoun, Angela Y Jia, Nicholas G Zaorsky, Rojano Kashani, Santosh Rao, Jonathan E Shoag, Randy A Vince, Leonardo Kayat Bittencourt, Raed Zuhour, Alex T Price, Theodore H Arsenault, and Daniel E Spratt. 2023. Artificial intelligence applications in prostate cancer. *Prostate cancer and prostatic diseases* (June 2023). https://doi.org/10.1038/s41391-023-00684-0
[9] Christiane Bieber, Knut Georg Müller, Klaus Blumenstiel, Achim Hochlehnert, Stefanie Wilke, Mechthild Hartmann, and Wolfgang Eich. 2008. A shared decision-making communication training program for physicians treating fibromyalgia patients: Effects of a randomized controlled trial. *Journal of Psychosomatic Research* 64, 1 (Jan. 2008), 13–20. https://doi.org/10.1016/j.jpsychores.2007.05.009
[10] Mary Jo Bitner, Amy L. Ostrom, and Felicia N. Morgan. 2008. Service Blueprinting: A Practical Technique for Service Innovation. *California Management Review* 50, 3 (April 2008), 66–94. https://doi.org/10.2307/41166446
[11] Clarence Braddock, Pamela L. Hudak, Jacob J. Feldman, Sylvia Bereknyei, Richard M. Frankel, and Wendy Levinson. 2008. "Surgery is certainly one good option": quality and time-efficiency of informed decision-making in surgery. *The Journal of Bone and Joint Surgery. American Volume* 90, 9 (Sept. 2008), 1830–1838. https://doi.org/10.2106/JBJS.G.00840
[12] C. H. Braddock, S. D. Fihn, W. Levinson, A. R. Jonsen, and R. A. Pearlman. 1997. How doctors and patients discuss routine clinical decisions. Informed decision making in the outpatient setting. *Journal of General Internal Medicine* 12, 6 (June 1997), 339–345. https://doi.org/10.1046/j.1525-1497.1997.00057.x
[13] Matthias Braun, Patrik Hummel, Susanne Beck, and Peter Dabrock. 2021. Primer on an ethics of AI-based decision support systems in the clinic. *Journal of Medical Ethics* 47, 12 (Dec. 2021), e3–e3. https://doi.org/10.1136/medethics-2019-105860 Publisher: Institute of Medical Ethics Section: Original research.
[14] D. S. Brody. 1980. The patient's role in clinical decision-making. *Annals of Internal Medicine* 93, 5 (Nov. 1980), 718–722. https://doi.org/10.7326/0003-4819-93-5-718
[15] Wouter Bulten, Kimmo Kartasalo, Po-Hsuan Cameron Chen, Peter Ström, Hans Pinckaers, Kunal Nagpal, Yuannan Cai, David F. Steiner, Hester van Boven, Robert Vink, Christina Hulsbergen-van de Kaa, Jeroen van der Laak, Mahul B. Amin, Andrew J. Evans, Theodorus van der Kwast, Robert Allan, Peter A. Humphrey, Henrik Grönberg, Hemamali Samaratunga, Brett Delahunt, Toyonori Tsuzuki, Tomi Häkkinen, Lars Egevad, Maggie Demkin, Sohier Dane, Fraser Tan, Masi Valkonen, Greg S. Corrado, Lily Peng, Craig H. Mermel, Pekka Ruusuvuori, Geert Litjens, Martin Eklund, and PANDA challenge consortium. 2022. Artificial intelligence for diagnosis and Gleason grading of prostate cancer: the PANDA challenge. *Nature Medicine* 28, 1 (Jan. 2022), 154–163. https://doi.org/10.1038/s41591-021-01620-2
[16] Eleanor R. Burgess, Ivana Jankovic, Melissa Austin, Nancy Cai, Adela Kapuścińska, Suzanne Currie, J. Marc Overhage, Erika S Poole, and Jofish Kaye. 2023. Healthcare AI Treatment Decision Support: Design Principles to Enhance Clinician Adoption and Trust. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–19. https://doi.org/10.1145/3544548.3581251
[17] Carrie J. Cai, Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. 2019. "Hello AI": Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (Nov. 2019), 104:1–104:24. https://doi.org/10.1145/3359206
[18] Francisco Maria Calisto, João Fernandes, Margarida Morais, Carlos Santiago, João Maria Abrantes, Nuno Nunes, and Jacinto C. Nascimento. 2023. Assertiveness-based Agent Communication for a Personalized Medicine on Medical Imaging Diagnosis. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–20. https://doi.org/10.1145/3544548.3580682
[19] Francisco Maria Calisto, Nuno Nunes, and Jacinto C. Nascimento. 2020. BreastScreening: On the Use of Multi-Modality in Medical Imaging Diagnosis. In *Proceedings of the International Conference on Advanced Visual Interfaces (AVI '20)*. Association for Computing Machinery, New York, NY, USA, 1–5. https://doi.org/10.1145/3399715.3399744
[20] Francisco Maria Calisto, Nuno Nunes, and Jacinto C. Nascimento. 2022. Modeling adoption of intelligent agents in medical imaging. *International Journal of Human-Computer Studies* 168 (Dec. 2022), 102922. https://doi.org/10.1016/j.ijhcs.2022.102922
[21] Kristin L. Carman, Pam Dardess, Maureen Maurer, Shoshanna Sofaer, Karen Adams, Christine Bechtel, and Jennifer Sweeney. 2013. Patient And Family Engagement: A Framework For Understanding The Elements And Developing Interventions And Policies. *Health Affairs* 32, 2 (Feb. 2013), 223–231. https://doi.org/10.1377/hlthaff.2012.1133 Publisher: Health Affairs.
[22] Cathy Charles, Tim Whelan, Amiram Gafni, Leonard Reyno, and Cristina Redko. 1998. Doing Nothing is No Choice: Lay Constructions of Treatment Decision-making Among Women with Early-stage Breast Cancer. *Sociology of Health & Illness* 20, 1 (1998), 71–95. https://doi.org/10.1111/1467-9566.00081 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1467-9566.00081.
[23] Jung-Chen Chen, Shang-Feng Tsai, and Shih-An Liu. 2023. A retrospective study of differences in patients' anxiety and satisfaction between paper-based and computer-based tools for "Shared Decision-Making". *Scientific Reports* 13, 1 (March 2023), 5187. https://doi.org/10.1038/s41598-023-32448-0 Number: 1 Publisher: Nature Publishing Group.
[24] Simon Cook, Cosmin Munteanu, Efthymios Papadopoulos, Howard Abrams, Jennifer N. Stinson, Eric Pitters, Douglas Stephens, Margaret Lumchick, Urban Emmenegger, Rama Koneru, Janet Papadakos, Armin Shahrokni, Sara Durbano, Ines Menjak, Rajin Mehta, Kristen Haase, Raymond Jang, Monika K. Krzyzanowska, Craig Dale, Jennifer Jones, Manon Lemonde, Shabbir Alibhai, and Martine Puts. 2023. The development of an electronic geriatric assessment tool: Comprehensive health assessment for my plan (CHAMP). *Journal of Geriatric Oncology* 14, 1 (Jan. 2023), 101384. https://doi.org/10.1016/j.jgo.2022.09.013
[25] Juliet Corbin and Anselm Strauss. 2008. *Basics of qualitative research: Techniques and procedures for developing grounded theory, 3rd ed.* Sage Publications, Inc, Thousand Oaks, CA, US. https://doi.org/10.4135/9781452230153 Pages: xv, 379.
[26] Burhan Coskun, Gokhan Ocakoglu, Melih Yetemen, and Onur Kaygisiz. 2023. Can ChatGPT, an Artificial Intelligence Language Model, Provide Accurate and High-quality Patient Information on Prostate Cancer? *Urology* (July 2023). https://doi.org/10.1016/j.urology.2023.05.040

[27] Maarten Cuypers, Hoda H. M. Al-Itejawi, Cornelia F. van Uden-Kraan, Peep F. M. Stalmeier, Romy E. D. Lamers, Inge M. van Oort, Diederik M. Somford, Reindert Jeroen A. van Moorselaar, Irma M. Verdonck-de Leeuw, Lonneke V. van de Poll-Franse, Julia J. van Tol-Geerdink, and Marieke de Vries. 2020. Introducing Decision Aids into Routine Prostate Cancer Care in The Netherlands: Implementation and Patient Evaluations from the Multi-regional JIPPA Initiative. *Journal of Cancer Education* 35, 6 (Dec. 2020), 1141–1148. https://doi.org/10.1007/s13187-019-01572-9

[28] Anita Das, Arild Faxvaag, and Dag Svanæs. 2011. Interaction design for cancer patients: do we need to take into account the effects of illness and medication?. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. Association for Computing Machinery, New York, NY, USA, 21–24. https://doi.org/10.1145/1978942.1978946

[29] Carol E. DeSantis, Kimberly D. Miller, William Dale, Supriya G. Mohile, Harvey J. Cohen, Corinne R. Leach, Ann Goding Sauer, Ahmedin Jemal, and Rebecca L. Siegel. 2019. Cancer statistics for adults aged 85 years and older, 2019. *CA: A Cancer Journal for Clinicians* 69, 6 (2019), 452–467. https://doi.org/10.3322/caac.21577 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3322/caac.21577.

[30] Clark DuMontier, Kah Poh Loh, Enrique Soto-Perez-de Celis, and William Dale. 2021. Decision Making in Older Adults With Cancer. *Journal of Clinical Oncology* 39, 19 (July 2021), 2164–2174. https://doi.org/10.1200/JCO.21.00165

[31] Safa ElKefi and Onur Asan. 2021. How technology impacts communication between cancer patients and their health care providers: A systematic literature review. *International Journal of Medical Informatics* 149 (May 2021), 104430. https://doi.org/10.1016/j.ijmedinf.2021.104430

[32] Glyn Elwyn, Marie Anne Durand, Julia Song, Johanna Aarts, Paul J. Barr, Zackary Berger, Nan Cochran, Dominick Frosch, Dariusz Galasiński, Pål Gulbrandsen, Paul K. J. Han, Martin Härter, Paul Kinnersley, Amy Lloyd, Manish Mishra, Lilisbeth Perestelo-Perez, Isabelle Scholl, Kounosuke Tomori, Lyndal Trevena, Holly O. Witteman, and Trudy Van der Weijden. 2017. A three-talk model for shared decision making: multistage consultation process. *BMJ (Clinical research ed.)* 359 (Nov. 2017), j4891. https://doi.org/10.1136/bmj.j4891

[33] Glyn Elwyn, Steve Laitner, Angela Coulter, Emma Walker, Paul Watson, and Richard Thomson. 2010. Implementing shared decision making in the NHS. *BMJ (Clinical research ed.)* 341 (Oct. 2010), c5146. https://doi.org/10.1136/bmj.c5146

[34] Csaba Fasi. 2022. Application of Artificial Intelligence in Administrative Decision-making. In *Proceedings of the Central and Eastern European eDem and eGov Days (CEEeGov '22)*. Association for Computing Machinery, New York, NY, USA, 147–152. https://doi.org/10.1145/3551504.3551555

[35] Sahar Fazeli, Judith Sabetti, and Manuela Ferrari. 2023. Performing Qualitative Content Analysis of Video Data in Social Sciences and Medicine: The Visual-Verbal Video Analysis Method. *International Journal of Qualitative Methods* 22 (Jan. 2023), 16094069231185452. https://doi.org/10.1177/16094069231185452 Publisher: SAGE Publications Inc.

[36] Harold P. Freeman. 2006. Patient Navigation: A Community Based Strategy to Reduce Cancer Disparities. *Journal of Urban Health* 83, 2 (March 2006), 139–141. https://doi.org/10.1007/s11524-006-9030-0

[37] Kenneth Yamikani Fukizi. 2023. Collaborative Decision-Making Assistant for Healthcare Professionals: A Human-Centered AI Prototype Powered by Azure Open AI. In *Proceedings of the 6th ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (COMPASS '23)*. Association for Computing Machinery, New York, NY, USA, 118–119. https://doi.org/10.1145/3588001.3609370

[38] Fania R. Gärtner, Hanna Bomhof-Roordink, Ian P. Smith, Isabelle Scholl, Anne M. Stiggelbout, and Arwen H. Pieterse. 2018. The quality of instruments to assess the process of shared decision making: A systematic review. *PLoS ONE* 13, 2 (Feb. 2018), e0191747. https://doi.org/10.1371/journal.pone.0191747

[39] Pola Hahlweg, Martin Härter, Yvonne Nestoriuc, and Isabelle Scholl. 2017. How are decisions made in cancer care? A qualitative study using participant observation of current practice. *BMJ Open* 7, 9 (Sept. 2017), e016360. https://doi.org/10.1136/bmjopen-2017-016360 Publisher: British Medical Journal Publishing Group Section: Patient-centred medicine.

[40] Yuexing Hao, Zeyu Liu, Monika Safford, Rulla Tamimi, and Saleh Kalantari. 2023. An Exploratory Study of Shared Decision-Making (SDM) for Older Adult Patients with Chronic Diseases. In *Companion Publication of the 2023 Conference on Computer Supported Cooperative Work and Social Computing (CSCW '23 Companion)*. Association for Computing Machinery, New York, NY, USA, 12–16. https://doi.org/10.1145/3584931.3607023

[41] Ian Hargraves, Annie LeBlanc, Nilay D. Shah, and Victor M. Montori. 2016. Shared Decision Making: The Need For Patient-Clinician Conversation, Not Just Information. *Health Affairs* 35, 4 (April 2016), 627–629. https://doi.org/10.1377/hlthaff.2015.1354 Publisher: Health Affairs.

[42] Sarah T. Hawley and Reshma Jagsi. 2015. Shared Decision Making in Cancer Care: Does One Size Fit All? *JAMA Oncology* 1, 1 (April 2015), 58–59. https://doi.org/10.1001/jamaoncol.2014.186

[43] Judith H. Hibbard, Jean Stockard, Eldon R. Mahoney, and Martin Tusler. 2004. Development of the Patient Activation Measure (PAM): conceptualizing and measuring activation in patients and consumers. *Health Services Research* 39, 4 Pt 1 (Aug. 2004), 1005–1026. https://doi.org/10.1111/j.1475-6773.2004.00269.x

[44] Rowena Hill, Lucy R. Betts, and Sarah E. Gardner. 2015. Older adults' experiences and perceptions of digital technology: (Dis)empowerment, wellbeing, and inclusion. *Computers in Human Behavior* 48 (July 2015), 415–423. https://doi.org/10.1016/j.chb.2015.01.062

[45] Aubri Hoffman, Laura Crocker, Aakrati Mathur, Deborah Holman, June Weston, Sukhkamal Campbell, Ashley Housten, Andrea Bradford, Shilpi Agrawala, and Terri L. Woodard. 2021. Patients' and Providers' Needs and Preferences When Considering Fertility Preservation Before Cancer Treatment: Decision-Making Needs Assessment. *JMIR Formative Research* 5, 6 (June 2021), e25083. https://doi.org/10.2196/25083 Company: JMIR Formative Research Distributor: JMIR Formative Research Institution: JMIR Formative Research Label: JMIR Formative Research Publisher: JMIR Publications Inc., Toronto, Canada.

[46] Chloe E. Holden, Sally Wheelwright, Amélie Harle, and Richard Wagland. 2021. The role of health literacy in cancer care: A mixed studies systematic review. *PLOS ONE* 16, 11 (Nov. 2021), e0259815. https://doi.org/10.1371/journal.pone.0259815 Publisher: Public Library of Science.

[47] Maia Jacobs, Jeremy Johnson, and Elizabeth D. Mynatt. 2018. MyPath: Investigating Breast Cancer Patients' Use of Personalized Health Information. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (Nov. 2018), 78:1–78:21. https://doi.org/10.1145/3274347

[48] Maia L. Jacobs, James Clawson, and Elizabeth D. Mynatt. 2015. Comparing Health Information Sharing Preferences of Cancer Patients, Doctors, and Navigators. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*. Association for Computing Machinery, New York, NY, USA, 808–818. https://doi.org/10.1145/2675133.2675252

[49] Alistair E. W. Johnson, Lucas Bulgarelli, Lu Shen, Alvin Gayles, Ayad Shammout, Steven Horng, Tom J. Pollard, Sicheng Hao, Benjamin Moody, Brian Gow, Li-wei H. Lehman, Leo A. Celi, and Roger G. Mark. 2023. MIMIC-IV, a freely accessible electronic health record dataset. *Scientific Data* 10, 1 (Jan. 2023), 1. https://doi.org/10.1038/s41597-022-01899-x Number: 1 Publisher: Nature Publishing Group.

[50] Natalie Joseph-Williams, Robert Newcombe, Mary Politi, Marie-Anne Durand, Stephanie Sivell, Dawn Stacey, Annette O'Connor, Robert J. Volk, Adrian Edwards, Carol Bennett, Michael Pignone, Richard Thomson, and Glyn Elwyn. 2014. Toward Minimum Standards for Certifying Patient Decision Aids: A Modified Delphi Consensus Process. *Medical Decision Making* 34, 6 (Aug. 2014), 699–710. https://doi.org/10.1177/0272989X13501721 Publisher: SAGE Publications Inc STM.

[51] Lena Josfeld, Christian Keinki, Carolina Pammer, Bijan Zomorodbakhsch, and Jutta Hübner. 2021. Cancer patients' perspective on shared decision-making and decision aids in oncology. *Journal of Cancer Research and Clinical Oncology* 147, 6 (June 2021), 1725–1732. https://doi.org/10.1007/s00432-021-03579-6

[52] Patrick Kelly, David Ada Adama, Isibor Kennedy Ihianle, Pedro Machado, and Richard I. Otuka. 2023. Exploring the Role of Fear in Human Decision Making. In *Proceedings of the 16th International Conference on PErvasive Technologies Related to Assistive Environments (PETRA '23)*. Association for Computing Machinery, New York, NY, USA, 505–510. https://doi.org/10.1145/3594806.3596590

[53] Lotta Kuosmanen, Maija Hupli, Satu Ahtiluoto, and Elina Haavisto. 2021. Patient participation in shared decision-making in palliative care – an integrative review. *Journal of Clinical Nursing* 30, 23-24 (2021), 3415–3428. https://doi.org/10.1111/jocn.15866 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jocn.15866.

[54] Min Hun Lee, Daniel P. Siewiorek, Asim Smailagic, Alexandre Bernardino, and Sergi Bermúdez i Badia. 2021. A Human-AI Collaborative Approach for Clinical Decision Making on Rehabilitation Assessment. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3411764.3445472

[55] Jessy Lin, Nicholas Tomlin, Jacob Andreas, and Jason Eisner. 2023. Decision-Oriented Dialogue for Human-AI Collaboration. https://doi.org/10.48550/arXiv.2305.20076 arXiv:2305.20076 [cs].

[56] Jieyuan Liu. 2020. Artificial Intelligence and Data Analytics Applications in Healthcare General Review and Case Studies. In *Proceedings of the 2020 Conference on Artificial Intelligence and Healthcare (CAIH2020)*. Association for Computing Machinery, New York, NY, USA, 49–53. https://doi.org/10.1145/3433996.3434006

[57] France Légaré, Stéphane Ratté, Karine Gravel, and Ian D. Graham. 2008. Barriers and facilitators to implementing shared decision-making in clinical practice: Update of a systematic review of health professionals' perceptions. *Patient Education and Counseling* 73, 3 (Dec. 2008), 526–535. https://doi.org/10.1016/j.pec.2008.07.018

[58] France Légaré and Philippe Thompson-Leduc. 2014. Twelve myths about shared decision making. *Patient Education and Counseling* 96, 3 (Sept. 2014), 281–286. https://doi.org/10.1016/j.pec.2014.06.014

[59] Dee Mangin, Cathy Risdon, Larkin Lamarche, Jessica Langevin, Abbas Ali, Jenna Parascandalo, Gaibrie Stephen, and Johanna Trimble. 2019. 'I think this medicine actually killed my wife': patient and family perspectives on shared decision-making to optimize medications and safety. *Therapeutic Advances in Drug Safety* 10 (April 2019). https://doi.org/10.1177/2042098619838796 Place: London Publisher: Sage Publications Ltd WOS:000463608900001.

[60] Ittay Mannheim, Ella Schwartz, Wanyu Xi, Sandra C. Buttigieg, Mary McDonnell-Naughton, Eveline J. M. Wouters, and Yvonne van Zaalen. 2019. Inclusion of Older Adults in the Research and Design of Digital Technology. *International Journal of Environmental Research and Public Health* 16, 19 (Jan. 2019), 3718. https://doi.org/10.3390/ijerph16193718 Number: 19 Publisher: Multidisciplinary Digital Publishing Institute.

[61] Meghan K. Mattos, Jessie S. Gibson, Dan Wilson, Laura Jepson, Soojung Ahn, and Ishan C. Williams. [n. d.]. Shared decision-making in persons living with dementia: A scoping review. *Dementia-International Journal of Social Research and Practice* ([n. d.]). https://doi.org/10.1177/14713012231156976 Place: London Publisher: Sage Publications Ltd WOS:000935985300001.

[62] Tamara L. McCarron, Karen Moffat, Gloria Wilkinson, Sandra Zelinsky, Jamie M. Boyd, Deborah White, Derek Hassay, Diane L. Lorenzetti, Nancy J. Marlett, and Thomas Noseworthy. 2019. Understanding patient engagement in health system decision-making: a co-designed scoping review. *Systematic Reviews* 8, 1 (April 2019), 97. https://doi.org/10.1186/s13643-019-0994-8

[63] Scott Mayer McKinney, Marcin Sieniek, Varun Godbole, Jonathan Godwin, Natasha Antropova, Hutan Ashrafian, Trevor Back, Mary Chesus, Greg S. Corrado, Ara Darzi, Mozziyar Etemadi, Florencia Garcia-Vicente, Fiona J. Gilbert, Mark Halling-Brown, Demis Hassabis, Sunny Jansen, Alan Karthikesalingam, Christopher J. Kelly, Dominic King, Joseph R. Ledsam, David Melnick, Hormuz Mostofi, Lily Peng, Joshua Jay Reicher, Bernardino Romera-Paredes, Richard Sidebottom, Mustafa Suleyman, Daniel Tse, Kenneth C. Young, Jeffrey De Fauw, and Shravya Shetty. 2020. International evaluation of an AI system for breast cancer screening. *Nature* 577, 7788 (Jan. 2020), 89–94. https://doi.org/10.1038/s41586-019-1799-6 Number: 7788 Publisher: Nature Publishing Group.

[64] Michael J. Barry, MD, Susan Edgman-Levitan, PA, and Karen Sepucha, PhD. 2018. Shared Decision-Making: Staying Focused on the Ultimate Goal. *Catalyst Carryover* 4, 5 (Sept. 2018). https://doi.org/10.1056/CAT.18.0097 Publisher: Massachusetts Medical Society.

[65] Supriya G. Mohile, Mostafa R. Mohamed, Huiwen Xu, Eva Culakova, Kah Poh Loh, Allison Magnuson, Marie A. Flannery, Spencer Obrecht, Nikesha Gilmore, Erika Ramsdale, Richard F. Dunne, Tanya Wildes, Sandy Plumb, Amita Patil, Megan Wells, Lisa Lowenstein, Michelle Janelsins, Karen Mustian, Judith O. Hopkins, Jeffrey Berenberg, Navin Anthony, and William Dale. 2021. Evaluation of geriatric assessment and management on the toxic effects of cancer treatment (GAP70+): a cluster-randomised study. *Lancet (London, England)* 398, 10314 (Nov. 2021), 1894–1904. https://doi.org/10.1016/S0140-6736(21)01789-X

[66] Margarida Morais, Francisco Maria Calisto, Carlos Santiago, Clara Aleluia, and Jacinto C. Nascimento. 2023. Classification of Breast Cancer in Mri with Multimodal Fusion. In *2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI)*. 1–4. https://doi.org/10.1109/ISBI53787.2023.10230686 ISSN: 1945-8452.

[67] Katelyn Morrison, Donghoon Shin, Kenneth Holstein, and Adam Perer. 2023. Evaluating the Impact of Human Explanation Strategies on Human-AI Visual Decision-Making. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (April 2023), 48:1–48:37. https://doi.org/10.1145/3579481

[68] Nora Moumjid, Amiram Gafni, Alain Brémond, and Marie-Odile Carrère. 2007. Shared decision making in the medical encounter: Are we all talking about the same thing? *Medical Decision Making* 27 (2007), 539–546. https://doi.org/10.1177/0272989X07306779 Place: US Publisher: Sage Publications.

[69] Annette M. O'Connor, John E. Wennberg, France Legare, Hilary A. Llewellyn-Thomas, Benjamin W. Moulton, Karen R. Sepucha, Andrea G. Sodano, and Jaime S. King. 2007. Toward the 'tipping point': decision aids and informed patient choice. *Health Affairs (Project Hope)* 26, 3 (2007), 716–725. https://doi.org/10.1377/hlthaff.26.3.716

[70] Cecilia Panigutti, Andrea Beretta, Fosca Giannotti, and Dino Pedreschi. 2022. Understanding the impact of explanations on advice-taking: a user study for AI-based clinical Decision Support Systems. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery, New York, NY, USA, 1–9. https://doi.org/10.1145/3491102.3502104

[71] Ravi B. Parikh, Christopher Manz, Corey Chivers, Susan Harkness Regli, Jennifer Braun, Michael E. Draugelis, Lynn M. Schuchter, Lawrence N. Shulman, Amol S. Navathe, Mitesh S. Patel, and Nina R. O'Connor. 2019. Machine Learning Approaches to Predict 6-Month Mortality Among Patients With Cancer. *JAMA Network Open* 2, 10 (Oct. 2019), e1915997. https://doi.org/10.1001/jamanetworkopen.2019.15997

[72] Sun Young Park, Pei-Yi Kuo, Andrea Barbarin, Elizabeth Kaziunas, Astrid Chow, Karandeep Singh, Lauren Wilcox, and Walter S. Lasecki. 2019. Identifying Challenges and Opportunities in Human-AI Collaboration in Healthcare. In *Conference Companion Publication of the 2019 on Computer Supported Cooperative Work and Social Computing (CSCW '19)*. Association for Computing Machinery, New York, NY, USA, 506–510. https://doi.org/10.1145/3311957.3359433

[73] Lia Patrício, Daniela Sangiorgi, Dominik Mahr, Martina Čaić, Saleh Kalantari, and Sue Sundar. 2020. Leveraging service design for healthcare transformation: Toward people-centered, integrated, and technology-enabled healthcare systems. *Journal of Service Management* 31, 5 (2020), 889–909. Publisher: Emerald Publishing Limited.

[74] Ruth E. Pel-Littel, Bianca M. Buurman, Marjolein H. van de Pol, Jos W. R. Twisk, Linda R. Tulner, Mirella M. Minkman, Wilma J. M. Scholte Op Reimer, and Julia C. M. van Weert. 2023. Effects of a shared decision making intervention for older adults with multiple chronic conditions: the DICO study. *BMC medical informatics and decision making* 23, 1 (March 2023), 42. https://doi.org/10.1186/s12911-023-02099-2

[75] A. H. Pieterse, M. C. M. Baas-Thijssen, C. a. M. Marijnen, and A. M. Stiggelbout. 2008. Clinician and cancer patient views on patient participation in treatment decision-making: a quantitative and qualitative exploration. *British Journal of Cancer* 99, 6 (Sept. 2008), 875–882. https://doi.org/10.1038/sj.bjc.6604611 Number: 6 Publisher: Nature Publishing Group.

[76] Arwen H. Pieterse, Anne M. Stiggelbout, and Victor M. Montori. 2019. Shared Decision Making and the Importance of Time. *JAMA* 322, 1 (July 2019), 25–26. https://doi.org/10.1001/jama.2019.3785

[77] Martin Pinquart and Paul R. Duberstein. 2004. Information needs and decision-making processes in older cancer patients. *Critical Reviews in Oncology/Hematology* 51, 1 (July 2004), 69–80. https://doi.org/10.1016/j.critrevonc.2004.04.002

[78] Martine T. E. Puts, Brianne Tapscott, Margaret Fitch, Doris Howell, Johanne Monette, Doreen Wan-Chow-Wah, Monika Krzyzanowska, Nathasha B. Leighl, Elena Springall, and Shabbir M. Alibhai. 2015. A systematic review of factors influencing older adults' decision to accept or decline cancer treatment. *Cancer Treatment Reviews* 41, 2 (2015), 197–215. https://doi.org/10.1016/j.ctrv.2014.12.010

[79] Shriti Raj, Toshi Gupta, Joyce Lee, Matthew Kay, and Mark W Newman. 2023. "It can bring you in the right direction": Episode-Driven Data Narratives to Help Patients Navigate Multidimensional Diabetes Data to Make Care Decisions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–16. https://doi.org/10.1145/3544548.3581073

[80] Suhila Sawesi, Mohamed Rashrash, Kanitha Phalakornkule, Janet S. Carpenter, and Josette F. Jones. 2016. The Impact of Information Technology on Patient Engagement and Health Behavior Change: A Systematic Review of the Literature. *JMIR Medical Informatics* 4, 1 (Jan. 2016), e4514. https://doi.org/10.2196/medinform.4514 Company: JMIR Medical Informatics Distributor: JMIR Medical Informatics Institution: JMIR Medical Informatics Label: JMIR Medical Informatics Publisher: JMIR Publications Inc., Toronto, Canada.

[81] Dena Schulman-Green, Emily Cherlin, Renee Capasso, Sarah S. Mougalian, Shiyi Wang, Cary P. Gross, Preeti S. Bajaj, Katherine Eakle, Sharmi Patel, Karin Douglas, and Kerin Adelson. 2020. Patient and Family Caregiver Considerations When Selecting Early Breast Cancer Treatment: Implications for Clinical Pathway Development. *The Patient - Patient-Centered Outcomes Research* 13, 6 (Dec. 2020), 683–697. https://doi.org/10.1007/s40271-020-00426-7

[82] Mina S. Sedrak, Rachel A. Freedman, Harvey J. Cohen, Hyman B. Muss, Aminah Jatoi, Heidi D. Klepin, Tanya M. Wildes, Jennifer G. Le-Rademacher, Gretchen G. Kimmick, William P. Tew, Kevin George, Simran Padam, Jennifer Liu, Andrew R. Wong, Andrea Lynch, Benjamin Djulbegovic, Supriya G. Mohile, and William Dale. 2021. Older adult participation in cancer clinical trials: A systematic review of barriers and interventions. *CA: A Cancer Journal for Clinicians* 71, 1 (Jan. 2021), 78–92. https://onlinelibrary.wiley.com/doi/abs/10.3322/caac.21638 Publisher: American Cancer Society.

[83] L. Aubree Shay and Jennifer Elston Lafata. 2014. Understanding patient perceptions of shared decision making. *Patient Education and Counseling* 96, 3 (Sept. 2014), 295–301. https://doi.org/10.1016/j.pec.2014.07.017

[84] Sarah J. Shoemaker, Michael S. Wolf, and Cindy Brach. 2014. Development of the Patient Education Materials Assessment Tool (PEMAT): A new measure of understandability and actionability for print and audiovisual patient information. *Patient Education and Counseling* 96, 3 (Sept. 2014), 395–403. https://doi.org/10.1016/j.pec.2014.05.027

[85] Venkatesh Sivaraman, Leigh A Bukowski, Joel Levin, Jeremy M. Kahn, and Adam Perer. 2023. Ignore, Trust, or Negotiate: Understanding Clinician Acceptance of AI-Based Treatment Recommendations in Health Care. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–18. https://doi.org/10.1145/3544548.3581075

[86] Helen Smith. 2021. Clinical AI: opacity, accountability, responsibility and liability. *AI & SOCIETY* 36, 2 (June 2021), 535–545. https://doi.org/10.1007/s00146-020-01019-6

[87] A. M. Stiggelbout, A. H. Pieterse, and J. C. J. M. De Haes. 2015. Shared decision making: Concepts, evidence, and practice. *Patient Education and Counseling* 98, 10 (Oct. 2015), 1172–1179. https://doi.org/10.1016/j.pec.2015.06.022

[88] Sally Thorne, John L. Oliffe, and Kelli I. Stajduhar. 2013. Communicating shared decision-making: Cancer patient perspectives. *Patient Education and Counseling* 90, 3 (March 2013), 291–296. https://doi.org/10.1016/j.pec.2012.02.018

[89] Lyndal J. Trevena, Carissa Bonner, Yasmina Okan, Ellen Peters, Wolfgang Gaissmaier, Paul K. J. Han, Elissa Ozanne, Danielle Timmermans, and Brian J. Zikmund-Fisher. 2021. Current Challenges When Using Numbers in Patient Decision Aids: Advanced Concepts. *Medical Decision Making: An International Journal of the Society for Medical Decision Making* 41, 7 (Oct. 2021), 834–847.

https://doi.org/10.1177/0272989X21996342
[90] Octavian Sabin Tătaru, Mihai Dorin Vartolomei, Jens J. Rassweiler, Oșan Virgil, Giuseppe Lucarelli, Francesco Porpiglia, Daniele Amparore, Matteo Manfredi, Giuseppe Carrieri, Ugo Falagario, Daniela Terracciano, Ottavio de Cobelli, Gian Maria Busetto, Francesco Del Giudice, and Matteo Ferro. 2021. Artificial Intelligence and Machine Learning in Prostate Cancer Patient Management—Current Trends and Future Perspectives. *Diagnostics* 11, 2 (Feb. 2021), 354. https://doi.org/10.3390/diagnostics11020354
[91] Julia C. M. van Weert, Barbara C. van Munster, Remco Sanders, René Spijker, Lotty Hooft, and Jesse Jansen. 2016. Decision aids to help older people make health decisions: a systematic review and meta-analysis. *BMC Medical Informatics and Decision Making* 16, 1 (April 2016), 45. https://doi.org/10.1186/s12911-016-0281-8
[92] Himanshu Verma, Jakub Mlynar, Roger Schaer, Julien Reichenbach, Mario Jreige, John Prior, Florian Evéquoz, and Adrien Depeursinge. 2023. Rethinking the Role of AI with Physicians in Oncology: Revealing Perspectives from Clinical and Research Workflows. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–19. https://doi.org/10.1145/3544548.3581506
[93] Elizabeth Ward, Ahmedin Jemal, Vilma Cokkinides, Gopal K. Singh, Cheryll Cardinez, Asma Ghafoor, and Michael Thun. 2004. Cancer Disparities by Race/Ethnicity and Socioeconomic Status. *CA: A Cancer Journal for Clinicians* 54, 2 (2004), 78–93. https://doi.org/10.3322/canjclin.54.2.78 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3322/canjclin.54.2.78.
[94] Thomas H. Wieringa, Rene Rodriguez-Gutierrez, Gabriela Spencer-Bonilla, Maartje de Wit, Oscar J. Ponce, Manuel F. Sanchez-Herrera, Nataly R. Espinoza, Yaara Zisman-Ilani, Marleen Kunneman, Linda J. Schoonmade, Victor M. Montori, and Frank J. Snoek. 2019. Decision aids that facilitate elements of shared decision making in chronic illnesses: a systematic review. *Systematic Reviews* 8, 1 (May 2019), 121. https://doi.org/10.1186/s13643-019-1034-4
[95] World Health Organization. 2016. *Patient engagement.* World Health Organization. https://apps.who.int/iris/handle/10665/252269
[96] Qian Yang, Yuexing Hao, Kexin Quan, Stephen Yang, Yiran Zhao, Volodymyr Kuleshov, and Fei Wang. 2023. *Harnessing Biomedical Literature to Calibrate Clinicians' Trust in AI Decision Support Systems.* https://doi.org/10.1145/3544548.3581393
[97] Qian Yang, Aaron Steinfeld, and John Zimmerman. 2019. Unremarkable AI: Fitting Intelligent Decision Support into Critical, Clinical Decision-Making Processes. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3290605.3300468
[98] Bo Zhang, Huiping Shi, and Hongtao Wang. 2023. Machine Learning and AI in Cancer Prognosis, Prediction, and Treatment Selection: A Critical Approach. *Journal of Multidisciplinary Healthcare* 16 (June 2023), 1779–1791. https://doi.org/10.2147/JMDH.S410301
[99] Shaodian Zhang, Erin O'Carroll Bantum, Jason Owen, Suzanne Bakken, and Noémie Elhadad. 2017. Online cancer communities as informatics intervention for social support: conceptualization, characterization, and impact. *Journal of the American Medical Informatics Association* 24, 2 (March 2017), 451–459. https://doi.org/10.1093/jamia/ocw093

A APPENDIX

A.1 Step-wise Heatmap Analysis

Figure 4: Heatmap visualizations for each step of i-SDM prototype.

A.2 Cue Labels Analysis across Steps in Study 2

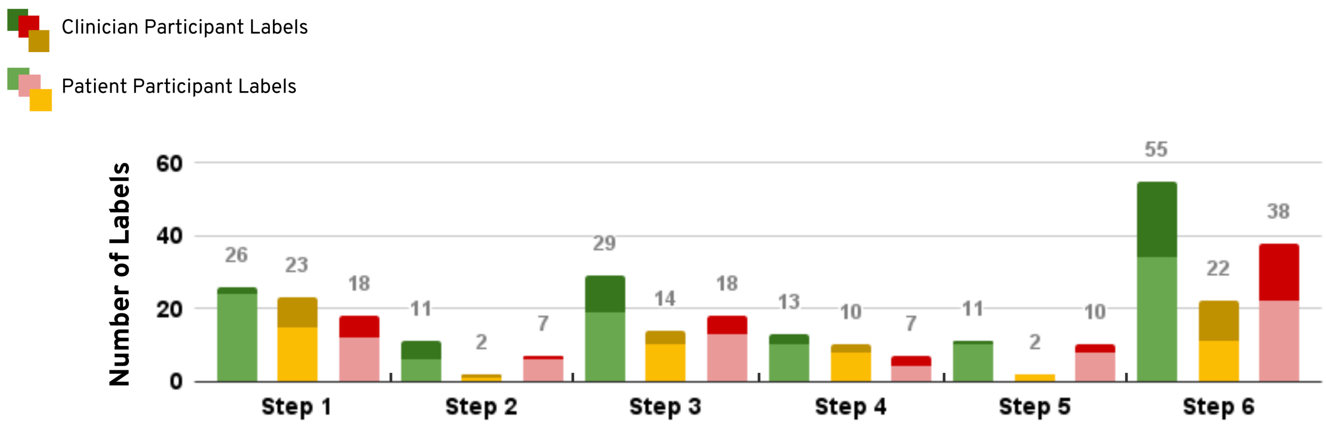

Figure 5: Barplot illustration of positive, neutral, and negative labels across all six steps. The barplot presents cue label data collecting from seven clinician participants (darker bars) and eighteen patient participants (lighter bars) in Study 2. Green, yellow, and red bars correspond to positive, neutral, and negative cue labels. The grey numbers above each bar indicate the total number of labels for the total number of code labels of each stage.