Modeling information flows in clinical decision support: key insights for enhancing system effectiveness

RECEIVED 20 July 2015
REVISED 23 October 2015
ACCEPTED 26 October 2015
PUBLISHED ONLINE FIRST 5 February 2016

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ABSTRACT

A fundamental challenge in the field of clinical decision support is to determine what characteristics of systems make them effective in supporting particular types of clinical decisions. However, we lack such a theory of decision support itself and a model to describe clinical decisions and the systems to support them. This article outlines such a framework. We present a two-stream model of information flow within clinical decision-support systems (CDSSs): reasoning about the patient (the clinical stream), and reasoning about the user (the cognitive-behavioral stream). We propose that CDSS "effectiveness" be measured not only in terms of a system's impact on clinical care, but also in terms of how (and by whom) the system is used, its effect on work processes, and whether it facilitates appropriate decisions by clinicians and patients. Future research into which factors improve the effectiveness of decision support should not regard CDSSs as a single entity, but should instead differentiate systems based on their attributes, users, and the decision being supported.

Keywords: decision-support systems, clinical, workflow, decision making, user-computer interface

PROBLEM

Friedman stated that a fundamental theorem of medical informatics is that a person working in partnership with an effective information resource is often "better" than that same person working unassisted.[1] In the field of clinical decision-support systems (CDSSs), this implies that a clinician working with the aid of a CDSS makes better decisions than a clinician working without one. However, it is clear that some CDSSs are ineffective. A recent review surprisingly showed that only 58% of published randomized clinical trials of CDSSs demonstrated improved processes of care or patient outcomes,[2] and some have even led to poorer outcomes,[3] even though they were thought to be well-engineered for clinical use. Thus, a fundamental challenge for CDSS research is to identify those characteristics that lead to successful systems. Because we lack a vocabulary to describe and differentiate decision-support systems, we are unable to predict which systems are likely to succeed. Published studies on CDSS effectiveness report on only a small number of factors, which are often arbitrarily chosen and defined.

To put it simply, despite over five decades of research, our discipline lacks a theory of decision support. This means that we do not know the full range of issues to teach our students about CDSSs, we cannot reliably predict which systems will prove effective, and – most importantly – we cannot give evidence-based advice to CDSS designers about how to maximize their chances of creating effective systems. Worse, we cannot describe all of the relevant features of a specific CDSS using a language or criteria that are widely accepted and that others will understand. Potentially relevant factors originate from disparate fields such as computer science and psychology, which are often considered in isolation. Accordingly, in this article, we introduce a new model of information flow in clinical decision support, based on Ahituv's generic model of information flow.[4] This model, termed the "Two-Stream Model," describes the range of issues encompassed by the field of CDSS and helps identify factors that are likely to influence CDSS effectiveness.

MODELING A CLINICAL DECISION

Ahituv proposed a simple information flow model in which the *state of an object* is observed to collect *data* about it, the data are interpreted to obtain *information*, the information is used to make a *decision*, and the decision is used to act to change the state of the object.[4] Figure 1 shows a first, simplified instantiation of this model for healthcare domains, based on Wyatt.[5] The decision "domain" is the patient. We can measure the patient's temperature (data), interpret the result as a fever (information), and decide whether treatment is needed (decision). A CDSS uses a formalized knowledge base to interpret the data.[6] The CDSS can offer either a conclusion about the state of the patient ("what is true," eg, a diagnosis) or an explicit recommendation ("what to do").[7]

In much of the work on CDSSs, the advice is simply presented to the user with an implicit assumption that this is sufficient to prompt the recipient to act appropriately. However, we know from decades of psychology research[8] that this assumption is naïve. The fundamental function of a CDSS is to support the clinical decisions of the user. Consequently, interaction with the user is a fundamental part of the system's design. In early CDSSs, this led to adding features such as an explanation of the reasoning behind the advice given by the system.[9,10]

MODELING THE PRESENTATION OF ADVICE

We can represent a CDSS's interaction with the user with a second instantiation of Ahituv's model (Figure 2). The CDSS can observe user activity such as a mouse click (data), interpret this activity as reading the patient record (information), and decide how to present the message (decision). Data about the user may also include more permanent information, such as the user's role (patient, general practitioner, specialty, etc.), demographics (eg, expertise), or the user's interaction history (eg, their responses to earlier messages). In most CDSSs, decisions on how and when to present advice are based only on implicit knowledge of the problem domain and the clinical workflow. However, CDSSs can also incorporate explicit models of cognition that

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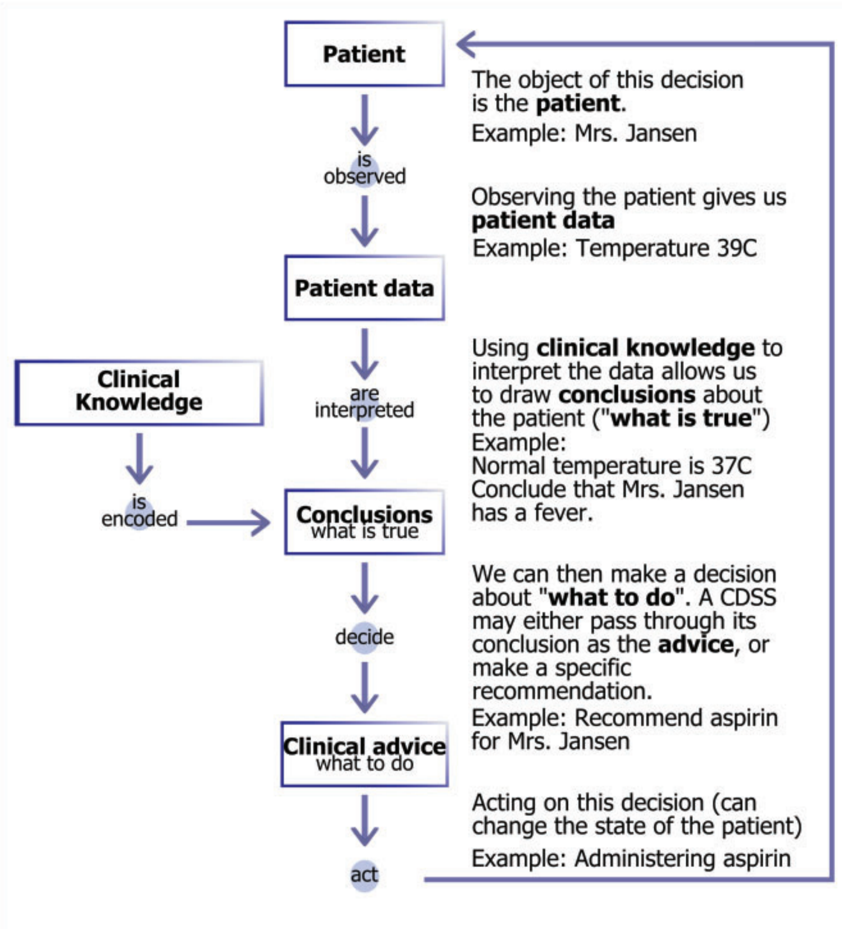
Figure 1: The Ahituv model applied to a clinical decision. The doctor (or the clinical decision-support system) observes the patient, resulting in data that are interpreted using clinical knowledge to reach a conclusion about the patient ("what is true"), which can be used as the basis for a decision (about "what to do"). Naturally, this is a simplified example; an actual clinical decision would incorporate many more observations about the patient, such as the chief complaint, history of present illness, and a review of the problem list, as well as the patient's preferences.



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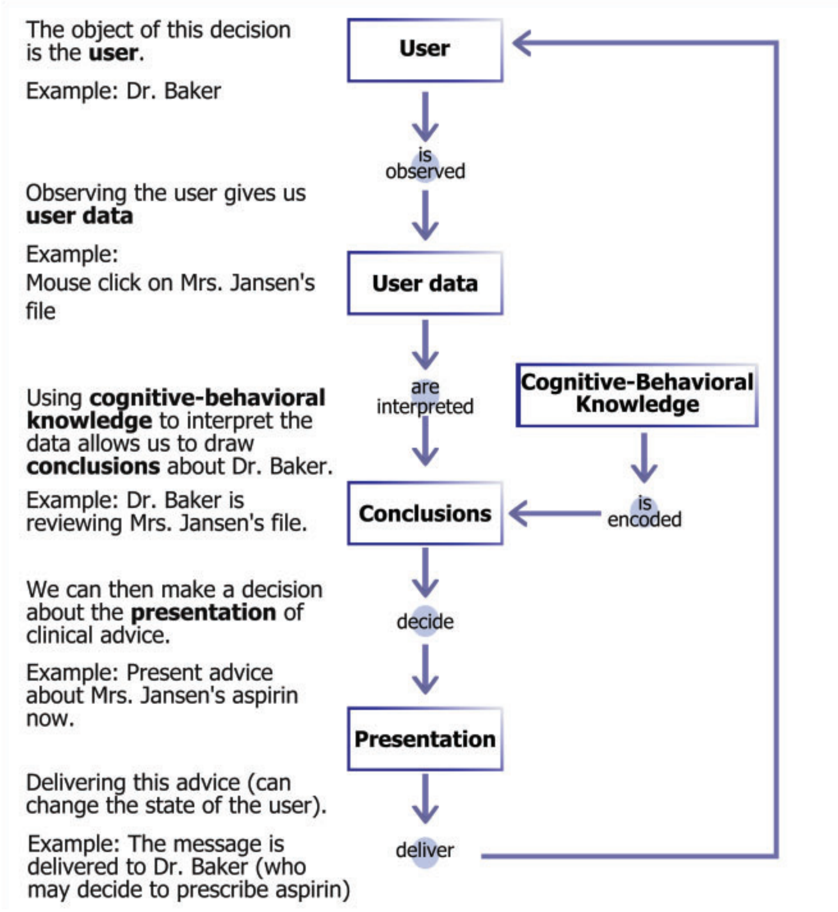
include memory, reasoning strategies, and domain knowledge[11] while interacting with socio-cultural behaviors and behavior-change theory, as well as with domain epistemology and work related policies,[12] and, potentially, with mental models of the CDSS and its interaction with users.[13] This "cognitive-behavioral knowledge" can be used to improve the fluency of the user-CDSS interaction, the system's model of the user, and its model of the decisions that it is designed to support.

MODELING A DECISION-SUPPORT SYSTEM

The two information flow models we have presented are joined together to create our proposed new model of a decision-support interaction, incorporating both "streams" (Figure 3). The conclusions about the patient determine the *content*, but can also help determine other aspects of the message (the *timing*, *channel*, *format*,[14] *form of notification*, and *interaction functions*). The content may also include an explanation of the system's reasoning, evidence, etc. The *timing* is the time of the delivery of the message (in the workflow or relative to the time of the decision – eg, before the decision in a consulting system, and after the decision in a critiquing system), and the *channel* is the route of the delivery (eg, the electronic patient record). The *format* of the message includes aspects such as color, placement, or whether the message is presented in a dialog box.[15] The *form of notification* is the way of notifying the user that new advice is available, and the *interaction functions* are the options the user has for interacting with the message (eg, a "click-to-order" option). Aspects of the advice, such as clinical intent[16,17] or severity of harm,[18] can also influence the presentation of the message.[19]

In Figure 3, the user is presumed to be a clinician, and, thus, the user in this model includes both cognitive factors and the clinical context, along with the associated workflows. Likewise, relevant aspects of patients include not only their clinical state (complaints, relevant history, etc.) but also their preferences and wish to be involved in the decision process. The information cycle is closed when the user *interacts* with the patient. Most patient data come from clinical documentation, although, increasingly, data come directly from patients (eg, patient self-assessments), and data about the clinician-patient interaction itself could help support shared decision making. To represent a CDSS designed for patient self-management or shared decision making, the Patient and User can be unified in the model. The encoded knowledge (both clinical and cognitive-behavioral), combined with the inference

Figure 2: The Ahituv model applied to a decision on how to present clinical decision-support system advice to the user. The system collects data about the user, interprets this information to reach a conclusion about the user's activities, and then determines if, when, and how advice should be presented as a message to the user.



engine used to interpret the data, constitute the *decision-support system*. The CDSS has properties beyond those of its component parts.[6,7] The cue for the system to begin its reasoning process is the *trigger*,[20] which can be a specific item of user data (eg, a mouse click triggering a passive system) or of patient data (eg, the arrival of a test result that triggers an active system).

IMPLICATIONS

We believe that this new model has direct utility for educators, researchers, and system developers and will indirectly benefit CDSS users, patients, and health systems (Table 1).

As an educational tool, our model defines the scope of topics in the field and the relationships among them. For researchers and developers, the model suggests a categorization for properties of the system that can influence its effectiveness. Table 2 presents a simplified example, using the MYCIN system.[21] Such a categorization is useful for understanding the success or failure of a particular implementation and addressing emerging CDSS issues, such as automation bias.[22] It can also act as a checklist for system developers, to help them make conscious choices about the kind of support that should be offered. For example, studying the barriers to correct action can help determine what behavior changes are needed.[23] The model can be applied to determine if and how a CDSS can facilitate such changes, as well as iteratively applied by observing how the users respond to the CDSS. In this situation, we must consider how best to frame the advice, how to present evidence, whether to repeat the message and "escalate" its delivery if it is not followed, etc. Table 2 provides an example checklist; however, it should be understood that further research is needed to complete the list of attributes for each element of the model.

For patients, CDSS users (both patients and clinicians), and health systems, the use of this framework should lead to more acceptable, sustainable, and effective decision support; better engagement of users and patients with decisions; and, ultimately, more effective and safer healthcare systems. The model suggests two ways of classifying decisions and, thus, types of decision support. Decisions may be differentiated based on their clinical content (eg, diagnostic, work-up, or treatment advice) or on cognitive-behavioral properties (eg, explicit vs implicit reasoning or the nature of clinical errors). Likewise, types of decision support may be categorized based on their clinical intent (the clinical stream) or the method of their presentation (the cognitive-behavioral stream). Incorporating data about both specific patients and users (eg, health literacy level or medical specialty) should help us tailor CDSS advice further. For example, individual users may have

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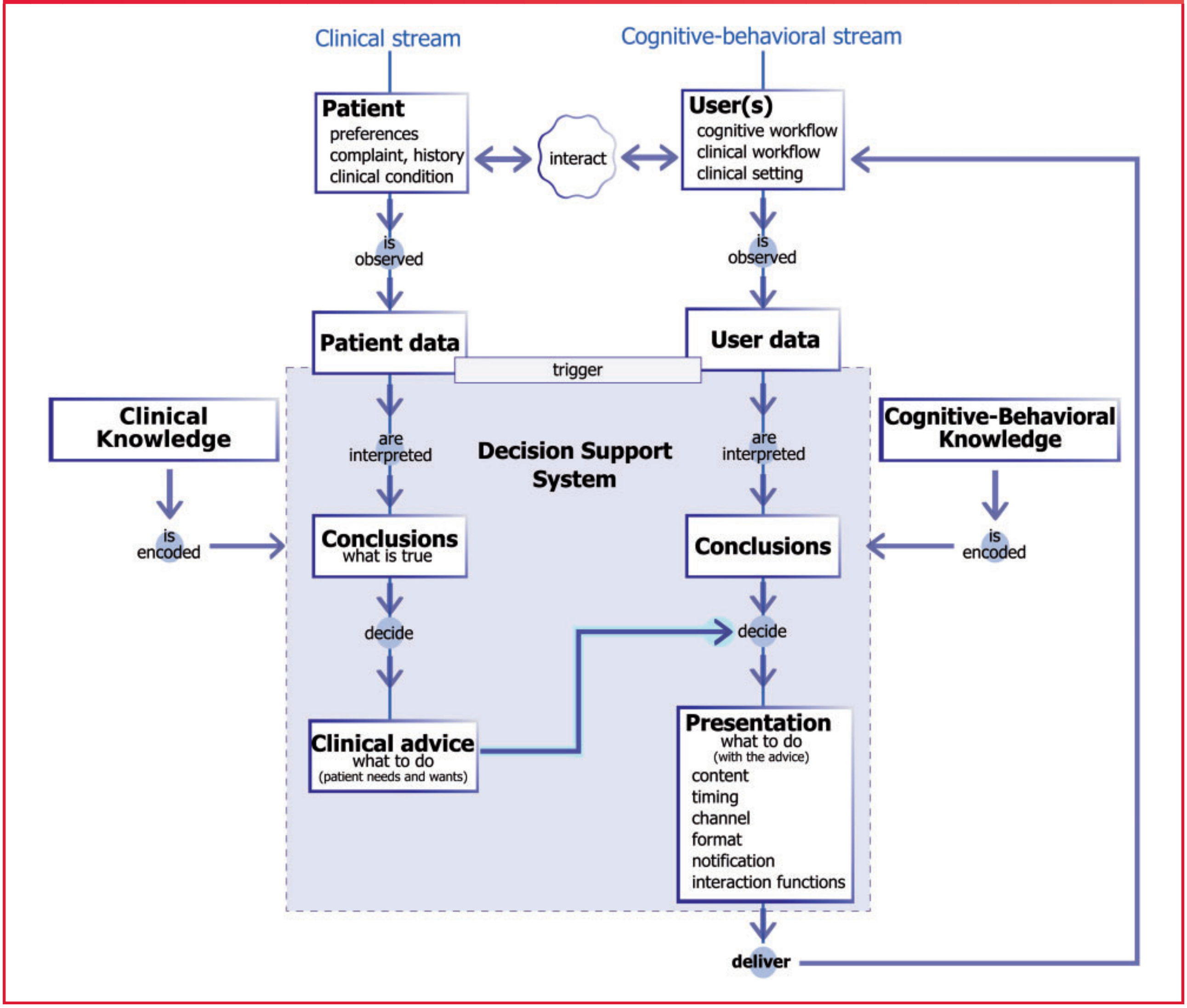
Figure 3: The complete model. The two streams interact such that the conclusion about the patient (clinical advice) is the basis for the content of the message delivered by the clinical decision-support system, but can also guide the decision about how the message should be presented. When it is delivered to the user, this message has the potential to affect the user's thoughts and behavior. The user then may or may not act on the advice during their interaction with the patient, depending, in part, on how the message containing the advice is presented. If the patient is the user (in a self-management system) or one of the users (in a shared decision-making system), then the message has the potential to directly influence the patient's actions. Clinical and Cognitive-Behavioral Knowledge are encoded into the knowledge representation of the Decision Support System, which is then used to interpret the data, draw conclusions, and decide what advice to present to the user and how to present it.



different approaches to the same decision and may, consequently, need different kinds of support. Currently, we cannot make evidence-based recommendations about what types of support are effective for which types of decisions, but our proposed model opens up these topics for more detailed research exploration.

The two streams of the model suggest two categories for evaluating the effectiveness of a CDSS. On the clinical stream, we assess the quality of the advice provided by the CDSS as a process measure[24] and sometimes clinical outcomes. On the cognitive-behavioral stream, we often measure guideline adherence or other process indicators, but mainly as intermediaries of clinical outcomes. We rarely assess the quality of the presentation of the advice or the effect of the CDSS on the user and workflow. One can imagine a system that improves a measure such as guideline adherence, but at the cost of a great deal of time and cognitive overload. Likewise, one can imagine a CDSS that has no net effect on guideline adherence, but allows clinicians to achieve the same adherence rate with considerably less effort. Such a system may be very effective at supporting decisions, but, if we neglect to make the right measurements, its success may be overlooked.

Further theoretical and empirical work is needed to formalize the concepts, components, and applications of this model. The first step is to create a typology for each element of the model, populating this typology with potential effect modifiers and confounders drawn from the

Table 1: Likely Benefits of the New CDSS Model for Different Stakeholder Groups

CDSS stakeholder group	Likely benefits of the new CDSS model
Medical informatics educators and students	Clarity regarding how to think about, describe, and classify decision-support systems (eg, classification by type of clinical advice, presentation, and/or cognitive model); better-designed research and the emergence of a robust evidence base about which design factors and implementation characteristics determine the acceptability and impact of the CDSS.
CDSS researchers	A language to describe CDSS features and to classify CDSSs; a principled underlying model of CDSSs that helps researchers frame experimental studies.
CDSS developers	A typology of CDSS; identification and linkage of key design features with typical use cases; the emergence of an empirically based set of predictive design principles for effective CDSSs, analogous to the principles of materials or construction used by engineers when they design bridges or aircraft.
CDSS users	CDSSs that fit better with user needs, habits, and workflows and require less cognitive work; more accurate and consistent decisions, leading to safer, more effective care and improved patient outcomes
Patients	CDSSs that fit better with the patient's needs as a user and as a participant in his or her own care, as well as the patient and clinician's need for systems that support shared decision making, clinicians who pay more attention to the patient and less attention to the computer; decisions that are more reliable and lead to better outcomes and fewer complications.
Health systems	CDSSs that are predictably more cost-effective and less disruptive to clinical work.

CDSS, clinical decision-support system.

Table 2: Examples of Use of the Model to Describe a Classical CDSS (MYCIN) and to Create a Checklist for CDSS Developers

Model elements	MYCIN system	Example checklist for developers
Patient	Hospitalized patients with severe bacterial infections. Demographics, allergies, background conditions (eg., compromised host?), etc.	Patient population. Relevant attributes (chief complaint, history of present illness, problem list, preferences, wish to be involved in decisions, etc.)
Clinical knowledge	Clinical experts. Bacterial identification and empirical antibiotic choice.	Source(s) and types of clinical knowledge required.
Patient data	Gender, age, current diagnosis, vital signs, bacterial morphology, culture site, etc. Entered by user (not integrated with EHR).	Data elements: Sources and types of data elements. Interpretation/action if data element is missing.
Conclusions	Identity of organism, underlying inferences, and degree of certainty.	Types of conclusions the system can draw.
Clinical advice	Whether to treat, choice of antibiotic(s), and strength of recommendation.	Types and wording of advice the system can present.
Decision-support system	Rules represented as LISP expressions and an associated inference engine.	Knowledge representation and reasoning mechanisms to be used.
Trigger	Initiated by a user seeking advice (clinician).	Data or interaction that triggers the system to begin processing.
User(s)	Clinician(s) requiring infectious disease consultation (expertise in other areas).	Role (patient, patient + doctor, junior doctor, specialist, etc.). Setting (home, ward, ICU, etc.). Clinical workflow (clinical activity and tasks). Cognitive workflow (sequence of data capture and reasoning).
Cognitive-behavioral knowledge	Need to communicate in natural language; need for explanation of reasoning; need to manage and convey uncertainty.	Anticipated usage/workflow. Theory/strategy for support (expected utility, prospect theory, behavior change, etc.).
User data	Text input from user (eg, answering simple questions, entering data, user enters "why" or "how").	Static data (eg, role, supervisor, preferences). Dynamic data (mouse clicks, response to previous alerts, etc.).
Conclusions	User wants advice, an explanation, or help.	Conclusions that the system can draw about the user.
Presentation	Content: Conclusion and advice phrased in natural language Timing: Immediate Channel: Stand-alone system Format: Plain text Notification: Direct display Interaction functions: User may type "why" or "how" for explanation	How advice/output is presented to the user, in terms of: Content (eg, framing) Timing Channel Format Notification Interaction functions

CDSS, clinical decision-support system; EHR, electronic health record; ICU, intensive care unit.

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literature (including theories of decision-making in healthcare), and using the model to postulate new potential factors. The direction and strength of relationships among these factors and the impact of specific CDSSs can then be hypothesized and tested, which should lead to a principled, theoretical basis for describing distinct types of decision-support systems, and allow researchers and designers to predict the circumstances under which each type of CDSS is likely to be effective.

The Two-Stream Model presented in Figure 3 offers a classification of factors that can not only contribute to success or failure in a CDSS implementation but can also suggest conditions under which such events occur. Although we cannot yet provide evidence-based recommendations to CDSS designers on how to design effective systems, this model should act as a useful checklist of aspects to consider in the CDSS design process. The model also has clear utility for education by defining the competencies and range of issues encompassed by the field of CDSS. It also provides a framework and a common vocabulary to guide future research and to create an evidence base. The model implies that, rather than looking for factors that influence the effectiveness of CDSSs as a single homogenous entity, future systematic reviews should instead investigate *which types of decision support* will be effective for supporting *which types of clinical decisions* and, in turn, what factors define those types. Researchers should strive toward measuring the impact of the system on both the patient and cognitive-behavioral outcomes, including the impact on the user's cognitive load and work processes. This will allow us to recognize and learn from successful systems as we seek to create technologies that help both patients and clinicians.

CONTRIBUTORS

The model was conceived by S.M., A.A., and J.C.W., and evaluated and improved by E.H.S. and V.L.P. All authors contributed to the writing of this manuscript.

FUNDING

S.M. and A.A.H. are supported by the Improving Care of Vulnerable Elders (ICOVE) project (Netherlands Organization for Health Research and Development #311020302).

COMPETING INTERESTS

None.

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