Decision Support, Knowledge Representation and Management in Medicine

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Summary

Objectives: Clinical decision-support systems (CDSSs) are being recognized as important tools for improving quality of care. In this paper, we review the literature to find trends in CDSSs that were developed over the last few decades and give some indication of future directions in developing successful, usable clinical decision-support systems.

Methods: We searched PubMed for papers that were published during the past five years with the words Decision Support Systems appearing in the title and used our own knowledge of the field for earlier work.

Results: The goals of developers of modern CDSSs are to develop systems that deliver needed information and could be integrated with the healthcare's organizational dynamics. Such CDSSs form part of knowledge-management activities that healthcare organizations employ in order to excel. During the past few decades, we have witnessed a gradual maturation of knowledge representation formalisms and the needed infrastructure for developing integrated CDSSs, including electronic health record systems (EHR), standard terminologies, and messaging standards for exchange of clinical data. The demand for CDSSs that are effective and that will evolve as circumstances change gave rise to methodologies that guide developers on the construction and evaluation of CDSSs.

Conclusion: Although there exist many approaches for representing, managing and delivering clinical knowledge, the design and implementation of good and useful systems that will last and evolve are still active areas of research. The gradual maturation of EHR and infrastructure standards should make it possible for CDSSs implementers to make major contributions to the delivery of healthcare.

1. Introduction

Two reports from the Institute of Medicine in the USA—*To Err is Human: Building a Safer Health System* [1] and *Crossing the Quality Chasm: A New Health System for the 21ˢᵗCentury* [2]—respectively called attention on serious patient safety concerns surrounding the large number of preventable medical errors and the sizable gaps between best practices and actual practices. Clinicians not only use their medical knowledge to make diagnostic and therapeutic decisions, but also coordinate patient care over time and among multiple providers and settings. These decision-making and coordination processes rely on accessing, understanding and using vast amount of knowledge and information. Being human, the clinicians cannot be expected to remember every relevant piece of information and relate to it during the care process. The *Crossing the Quality Chasm* report highlighted the potential of using information technology, and in particular clinical decision support systems (CDSSs), to aid clinicians in gathering relevant data, making clinical decisions, and managing medical actions more effectively, and thus achieving reduced practice errors, a higher standard of care, and reduced costs [2]. Many CDSSs are now in routine use in acute care settings, clinical laboratories, educational institutions, and are incorporated into electronic medical record systems [3]. Systematic reviews of CDSSs show that, when effective, CDSSs change processes of care (e.g., appropriate ordering of tests, correct drug dosing), but few studies have reported that the use of CDSSs led to better patient outcomes [4-6].

Therefore it is important that we understand the challenges facing developers of CDSS. We focused our review of the CDSS literature to find trends in CDSSs that were developed over the years. For this purpose, we defined several topics that we believe are important for developing successful, usable clinical decision support systems. Following a life-cycle approach, the first topic focuses on the goals of CDS, as it is the vision that drives the way by which CDSSs will be developed, implemented, integrated with the environment, and evaluated. The next two topics focus on positioning CDSSs as part of a knowledge-management enterprise and explaining the modeling tasks that are required to analyze and represent the knowledge of CDSSs. The following topic addresses design considerations that are important for the success of CDSSs. Next, we review current standardization efforts, which are important for integration of CDSSs as part of an organization's health information system. The last topic addresses evaluation of CDSSs – a step that is both a quality control mechanism and the start of a new cycle in the development of effective CDSSs.

2. The Goal of Clinical Decision Support

Broadly speaking, a CDSS is any computer program designed to help health professionals make clinical decisions. A standard textbook in medical informatics [7] characterizes CDSSs as tools for information management, for focusing attention, and for providing patient-specific recommendations. Looking at research on CDSSs, we can see that the perception of CDSSs has shifted over the years. Early CDSSs used statistical methods (e.g., de Dombal's abdominal pain program [8]), decision analysis [9], and rule chaining (e.g., the MYCIN program [10]). Medical sociologists have characterized these systems as embodying a vision where medical decision making are information-processing activities which computers, with appropriate formalized knowledge and encoded algorithms, can perform at the level of clinicians or even better than clinicians can [11]. The goal of the systems was to excel in the complex tasks of differential diagnosis and therapy planning. Thus, evaluations of these systems involved comparing the performance of the CDSSs with those of novice or expert physicians [12, 13]. The implementations of these rationalistic technological interventions required a "disciplined practice" where clinicians enter well-defined input data at appropriate times and the output of the systems is realizable in the clinic [11]. The conflict between these requirements and the evolving, contingent, emergent nature of medical work contributed toward difficulties in the adoption of CDSSs [14]. Instead of seeing CDSSs as vehicles for rationalizing medicine, developers of modern CDSSs are more likely to take a *socio-technical* approach, which recognizes that introduction of CDSSs needs to take into account their potential affect on the division of work among care providers and how CDS would shape and, in turn, be shaped by the organ-izational structure and practices of providers [15]. In this context, the goals of modern CDS go beyond the original focus of producing expert-level advisories and extend to include support for tasks such as producing better documentation, retrieving relevant literature, and facilitating communication among providers. These additional goals contribute toward improving the overall quality of care.

In his review from 1994, Miller notes the differences between the CDSSs of the early 1970's and those of the 1990's [16]. The trends that Miller saw in the 1990's— a shift toward specialized and focused system, interacting systems that are integrated into the clinical environment and workflow, and the importance of evaluating CDSSs and designing them to be cost-effective—are also seen in systems that were developed during the last decade. In addition, researchers now recognize the need to consider patient preferences [17] and base the knowledge represented in CDSSs on evidence [18].

3. The Relationship among Decision Support, Knowledge Representation and Knowledge Management

In a recent review [19], Stefanelli characterized knowledge management in healthcare organizations as those practices that, through more effective utilization of their knowledge assets, facilitate an organization's competitive advantage in a highly dynamic environment, where medical knowledge changes rapidly and where providers and patients interact in distributed and collaborative processes. In this view, CDSSs are part of a knowledge-management toolkit that a healthcare organization can employ to deliver the "right knowledge to the right people in the right form at the right time" [20]. To accomplish this objective, developers of CDSSs have two knowledge-management tasks: (1) a process-oriented task that elucidates the organization goals, the information flow and the work flow, the roles and responsibilities, and the communication and co-ordination patterns of the care process in which a CDSS system has to operate and (2) a knowledge-modeling task in which modelers represent the medical knowledge that enables the CDSS to deliver appropriate decision-support services during the care process. Quaglini and colleagues developed the concept of care-flow management system (CfMS) [21] to allow explicit specification of how decision support is integrated with the clinical workflow.

The process-oriented task overlaps with the traditional requirement analysis in software engineering. Many methodologies have been developed for helping system analysts elicit an understanding of business processes, their participants, and their information needs, and translating them into a set of functional/design requirements of an information system that should be developed to support the organization. The most widely used methodology for eliciting and specifying design requirements in the industrial world is the Unified Modeling Language [22]. In [23], Osheroff and colleagues take a more informal approach, where they developed a workbook that implementers of a CDSS can use to work through the process of identifying stakeholders, determining the goals and objectives of the CDSS, cataloging the host information system's capabilities, and selecting, deploying, and monitoring specific CDS interven-

tions. Osheroff et al. emphasize the need to identify opportunities for CDS and to incorporate different types of CDS within clinical workflow. Berg and Toussanint [24], on the other hand, argue that implementing new information and communication technology is always a process-improvement project where the CDS intervention necessarily changes existing practices. Thus, the main challenge in implementing CDS is not so much trying to fit CDS into existing workflow, as it is managing the ongoing process of organizational development that was triggered by the CDS intervention.

The knowledge-modeling task involves elicitation, representation, sharing, evolution, and delivery of knowledge (or knowledge-based DS) to users. In the knowledge management literature, Nonaka and Takeuchi built a theory of knowledge management on the basis of the distinction between tacit and explicit knowledge [25]. Tacit knowledge is implicit in human's capability to perform particular tasks and cannot be expressed easily. It is context-specific and personal. Tacit and explicit knowledge are converted from each other during social processes: tacit-to-tacit (socialization), tacit-to-explicit (externalization), explicit-to-explicit (combination), and explicit-to-tacit (internalization). The medical field has elaborate schemes for production and dissemination of medical knowledge, in which tacit and explicit knowledge are inter-converted. For example, the development of clinical practice guidelines involves synthesis of opinions of expert panels and evidences explicitly reported in the literature. In this case, knowledge elicitation is a combination of tacit-to-explicit and explicit-to-explicit processes (formalization of guidelines, evidence synthesis, consensus-building, and learning), while delivering CDS is a form of ex-

plicit-to-explicit knowledge conversion (combining knowledge with data to generate specific recommendations) [26]. An important goal of CDSSs is to produce interventions that change clinicians' behaviors, with the final aim of helping clinicians to internalize these changes – an explicit-to-tacit conversion.

Eliciting knowledge from experts is a difficult process. A number of methodologies, such as the repertory grid method, based on personal construct psychology [27], have been developed. However, these methodologies are not routinely used to elicit medical knowledge. Instead, more traditional ways to elicit knowledge are used, such as literature review, interviews, observation of experts at field setting, examining experts at work while they "think aloud", and questionnaires. In addition, specialized methods have been developed to elicit knowledge, depending on its representation formalism. For example, rules can be elicited from experts using automated questioning [28], or they can be discovered from databases using various forms of data mining and machine learning [29]. Machine learning techniques have been used to learn classifications from examples that have been classified by experts (see next section).

Knowledge representation provides a means for expressing knowledge in a way that can be interpreted and reasoned with by humans and machines. We discuss knowledge representations for CDSSs in more detail in Section 4. Represented knowledge may be leveraged by using it in more than one institution, achieving knowledge sharing. Sharing is enhanced through standards. Some of the standards that form the infrastructure for CDSSs are covered in Section 5. Another form of knowledge sharing is sharing of executable knowledge components from which CDSSs can be assembled [30]. Medical knowledge is ever evolving;

new risk factors, drugs, diagnostic tests, clinical studies, pathogen incidence, and drug resistance are some examples of knowledge changes. When knowledge evolves, its representation needs to be updated for the CDSS to provide appropriate recommendations. An updated knowledge base is released for use in a new version. This necessitates mechanisms for version management so that reasoning can relate to the information existing in different versions, which may be used by different people at a single point in time, or can be used in retrospective studies. Version management of medical knowledge representations has been researched mainly in the domain of ontology evolution [31], vocabulary versioning [32, 33] and versioning of computer-interpretable guidelines [34]. As in versioning of non-medical knowledge models, basic change operations are derived from the basic elements of knowledge models and enable adding, removing, and changing those elements. Research in the medical domain emphasizes the recording of reasons for making the changes, so that users of the updated knowledge will be more apt to understand and embrace the changes.

Delivery of knowledge for CDS involves not only provision of patient-specific recommendations but also retrieval of reference information and guidance. Information retrieval systems vary in their indexing and mark-up techniques and search methods. For example, Berrios and colleagues [35] developed a method for indexing medical knowledge according to questions that the knowledge source answers. The questions are formed as combinations of four basic concepts: pathology, manifestation, investigation, and therapy (e.g., how does chemotherapy therapy compare with hormonal therapy in the setting of pregnancy (manifestation)?).

An example of a system that allows alternative search mechanisms for retrieving information is MedlineQuery ByExample (MedQBE), a research workbench for implementing and evaluating information retrieval strategies. It was evaluated by testing a feedback algorithm that builds upon PubMed's "related articles" feature [36].

4. Representation Formalisms for CDSSs

CDSSs use a variety of knowledge representation formalisms, but research in knowledge representation is not the driving force in CDS work in recent years; many of the representations used in current systems, such as clinical algorithms, mathematical pathophysiological models, Bayesian statistical systems and influence diagrams, neural networks, fuzzy set theory, and symbolic reasoning or "expert" systems, have been around since the 1970's [37] and 1980's [16]. Most of the current CDSSs use one or more of these formalisms for representing and reasoning with medical knowledge. In this section, we discuss some noticeable trends in the use of these knowledge representation formalisms for decision support. In the last decade, ontologies have often been used to formalize a shared understanding of a domain. In knowledge engineering, the term **ontology** is used to mean definitions of concepts in a domain of interest and the relationships among them ("a specification of a conceptualization of a domain" [38]). An ontology enables software applications and humans to share and reuse the knowledge consistently. Ontologies, as represented in a formal language such as frames or description logic, allow logical inference over the set of con-

cepts and relationships to provide decision support and explanation facilities [39]. Ontologies can be complemented by other knowledge representation formalisms, such as rules, which have been used to create medical knowledge bases since the 1970's. Such knowledge bases encode non-numeric qualitative models where symbolic reasoning is performed to reach abstract conclusions about a case (e.g., what therapy should be given, what is the probable organism causing an infectious disease) [7]. In recent years, ontologies have been often used to represent clinical guidelines. Evidence-based clinical guidelines are systematically-developed statements to assist practitioner and patient decisions about appropriate healthcare for specific clinical circumstances [40]. They aim to improve clinical care, to reduce practice errors and to save costs. Clinical guidelines have been around since the 1970's, yet the movement toward a safer, evidence-based medical practice has brought a resurgence of interest in them. In the last decade, much of the research on CDSSs has focused on developing formalisms for modeling clinical guidelines (computer-interpretable guidelines, CIGs). A number of these formalisms represent guidelines in ontologies of task-network models [41], in which guideline recommendations are hierarchically decomposed into networks of component tasks that unfold over time. Typical tasks involve medical actions (e.g., medication prescriptions), data queries, and clinical decision. Many decision-support systems that are based on these formalisms have been implemented in recent years [42, 43]. Much of the current research emphasizes the importance of modeling the integration of a CDSS with the organizational workflow and information systems. Formalisms such as EON, SAGE, PRODIGY, GLIF3, and GLARE include

a patient data model intended to facilitate interfacing the guideline model with an EMR [41]. The Guide/NewGuide and SAGE formalisms represent relevant organizational aspects, including available resources, organizational roles that perform activities (e.g., a clinician ordering a prescription), care setting, and timing constraints.

As acquiring knowledge from experts is difficult, a plethora of CDSSs have been developed in recent years using machine-learning (ML) techniques. These techniques can discover knowledge automatically by learning from examples. One of the most common ML techniques is neural nets. Neural nets are a network of interconnected simple processing elements. The net's global behavior is determined by the connections between the processing elements and element parameters. Neural nets recognize patterns in the input data and classify the input. The knowledge discovered by ML techniques is focused and usually involves a classification of examples. Examples of CDSSs that have been developed using ML techniques include learning of pulmonary gas exchange parameters to support the selection of inspired oxygen fraction [44], automated interpretation of diagnostic heart images [45], and determining preterm birth risk [29]. Many of the recently developed CDSSs are based on models that support probabilistic reasoning. Examples include decision theoretic models, such as Bayesian networks [46], influence diagrams [47], and decision trees [48]. These models are specifically designed for reasoning under uncertainty – a common theme in medical decisions in which the outcome of decision alternatives is uncertain. A comprehensive decision model includes representations for decisions (alternative actions), state variables that describe the states of the world,

preferences, and relationships among states of the world. These relationships may be probabilistic, logical, or qualitative [49]. Unlike decision trees, Bayesian networks and influence diagrams can express conditional dependencies in a manner that is accessible to humans as well as computational reasoning.

Many of the current CDSSs still use rules as the representation formalism. Rules are most suitable for expressing single medical decisions and are often implemented as alerts and reminders [50]. Most of the rule-based systems support categorical (deterministic) reasoning, but some use fuzzy rules to support reasoning under uncertainty. An example of such a system is care plan on-line (CPOL), an intranet-based chronic disease care planning system for general practitioners [51]. In this system, fuzziness is manifested in interpretation of quantitative data, formulation of recommendations, and unequal importance of clinical indicators. To incorporate fuzziness, CPOL represents guidelines as fuzzy *If. . .Then* rules and attaches a membership function to each linguistic variable. In this way, concepts like *underweight* and *overweight patients* and *those rapidly loosing weight* can be represented.

5. Factors Leading to Successful CDSS Implementations

The large variety of knowledge representations and reasoning methods enable the creation of sophisticated CDSSs but do not guarantee their successful implementation. This led to a literature that provides general recommendations on how to develop successful CDSSs [17, 18, 23, 52-55]. Many of these papers list the following factors

as being important for success of CDSSs: (1) decision support should be computerized rather than paper-based, (2) workflow integration should be considered, (3) timely advice should be provided, (4) clinical effects and costs of the system should be evaluated, and (5) the system should be developed with an ability to be maintained and extended. In the context of knowledge representation and management, workflow integration involves representation of organizational knowledge to facilitate the integration of CDSS with clinical workflow, as discussed in section 4. The maintenance of CDSSs includes maintenance of the knowledge and its evolution, as discussed in section 3.

The Evidence and Decision Support track of the 2000 AMIA Spring Symposium examined the challenges in realizing the promise of CDSS-facilitated evidence-based medicine. They elicited the following recommendations for developers of evidence adaptive CDSS [18]: (1) capture evidence in machine-interpretable knowledge bases; (2) develop maintainable foundations for computer-based decision support; (3) evaluate the clinical effects and costs of CDSSs; (4) integrate the system into workflow; and (5) establish public policies that provide incentives for implementing CDSSs.

Bates and coauthors [52] suggest Ten Commandments for effective clinical decision support: (1) Speed Is Everything, (2) Anticipate Needs and Deliver in Real Time, (3) Fit into the User's Workflow, (4) Little Things Can Make a Big Difference, (5) Recognize that Physicians Will Strongly Resist Stopping, (6) Changing Direction Is Easier than Stopping, (7) Simple Interventions Work Best, (8) Ask for Additional Information Only When You Really Need It, (9) Monitor Impact, Get Feedback, and Respond, and (10) Manage

and Maintain Your Knowledge-based Systems.

Wetter [53] lists the following factors as being important for achieving successful implementations: (1) timely advice, (2) workflow integration, (3) integration into IT environment, (4) flexibility, (5) response to user needs, (6) physicians' ability to change the knowledge base, and (7) maintenance and extension.

Kawamoto and coauthors [54] systematically reviewed the literature in order to determine why some clinical decision support systems succeed while others fail. They identified 22 factors repeatedly suggested in the literature as important determinants of a system's ability to improve clinical practice, and evaluated 15 of these features in randomized controlled trials of clinical decision support systems. They identified four of these features as independent predictors of a system's ability to improve clinical practice: (1) automatic provision of decision support as part of clinician workflow, (2) provision of a direct recommendation rather than just an assessment that is presented to the clinician for consideration, (3) provision of decision support at the time and location of decision making, and (4) computer-based generation of decision support, rather than paper-based.

Ruland and Bakken [17] report a model for developing, implementing, and evaluating CDSSs that include patients' perspectives of their health problems and preferences for treatment and care (shared decision support). The model includes eight steps: (1) identify the clinical decision problem by determining the relative importance of functional performance dimensions to patients, (2) define the purpose, users, and clinical context, (3) define the dimensions of the decision problem, (4) select a measurement technique for eliciting

patient preferences, (5) validate measurement technique, (6) determine the application platform, (7) address practice implementation issues, and (8) identify outcome measures and methods for outcome evaluation.

6. Current Standardization Efforts

To be effective and successful, CDSSs need to be integrated into health information systems that supply the patient data CDSSs need, that allow CDSSs to respond to decision-support opportunities in clinicians' workflow, and that supply applications such as alerting mechanisms and order entry systems that allows effective delivery of decision-support services. Thus, implementations of CDSSs are greatly aided by standardization in information system infrastructure, including standard terminology, data model, data exchange format, and other clinical information systems services. Developing and promoting such standards is the work of standard development organizations (SDOs), of which Health Level 7 (HL7) and CEN are most relevant for CDSS developers.

HL7 is an ANSI-accredited organization devoted to developing standards for clinical and administrative data sharing. Its mission is to provide standards for the exchange, management and integration of data that support clinical patient care and the management, delivery and evaluation of healthcare services. The HL7 Clinical Decision Support Technical Committee (CDSTC), in particular, is working on issues related to single-patient-focused health-care decision-support formalism. Its members have defined the Arden Syntax for Medical Logic Module as an HL7 stand-ard for representing and sharing clinical knowledge that expresses single medical decisions. Standardization in other decision-support formalisms is still in progress. Much work has been done to define a messaging standard for "info-button" queries at the point of care to retrieve context-sensitive information [56]. So far, the CDSTC has not tried to develop a standard for clinical guidelines. Instead, the CDSTC focuses on the development of standards for infra-structural components that can be used by different decision-support components, including an expression language for decision criteria and a virtual medical record (i.e., a view of a patient medical record that is simplified for decision-support purposes). Recently, the GELLO expression language (http://cslxinfmtcs.csmc.edu/hl7/arden/2004-09-ATL/v3ballot_gello_aug2004.zip) was successfully balloted by HL7's CDSTC for incorporation as a standard. CEN (http://www.cenorm.be/cenorm/index.htm) is the European Committee for Standardization. CEN's mission is to promote voluntary technical harmonization in Europe in conjunction with worldwide bodies and its partners in Europe. CEN's *Technical Committee 251* handles medical informatics, including work on (1) communications: information models, messaging and smart cards, (2) terminology, (3) security, safety and quality, and (4) technology for interoperability (devices).

7. Evaluation of CDSSs

The complexity of medical practices and the high cost of implementing CDSSs make evaluation of CDSSs both a challenge and a necessity. Among many possible definitions of evaluation, we adopt one that views the evaluation of a CDSS as the process of collecting and analyzing data about a CDSS for the purpose of answering certain questions [57]. The range of questions that can be posed for possible evaluation is enormous and the evaluation methodology is necessarily tied to the questions being asked. It is therefore not surprising that different researchers raise different questions and suggest different evaluation methodologies. Friedman and Wyatt formulated a framework for evaluation in terms of (1) the interests of stakeholders (e.g., user, developer, patient, and funding institutions) in the CDSS, (2) the need for an information resource, and the development process, intrinsic structure, function, and effect of that resource, and (3) the objectivist and subjectivist approaches to study design [58]. The **objectivist** method requires careful measurements of outcome variables where the presence or absence of CDS interventions is the independent variable. At the heart of the objectivist approach is the quantitative measurement of performance while guarding against biases such as Hawthorne effect[1] or secular trends[2] [57]. Objectivist evaluation may measure the "inherent performance" of a CDSS [59] that compares the output of a system against a gold standard or some other validated systems, or it may focus on the clinical impact, both in terms of process and outcome variables, as published evaluation studies of CDSSs have typically done [5]. Garg and colleagues identified 100 randomized and non-randomized controlled trials that evaluated the effect of implementing a CDSS compared with care provided without a CDSS. The

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[1] Hawthorne effect is the possibility that clinicians performance may improve if they know that they are being studied

[2] "Secular trends" refers to changes of dependent variables over time, where the changes are outside the control of investigators.

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variables that were measured included practitioner performance (where 62 out of 97 studies reported improvement with CDSSs) and patient outcomes (where 7 out of 53 studies reported improvement with CDSSs).

The results of systematic reviews such as [5] need to be read with caution. First, publication bias tends to favor projects that report successful outcomes. Second, as Wears and Berg points out in their editorial accompanying the paper [60], the lack of improved performance could be due to any number of factors, such as human-computer interface problems or lack of time or support among colleagues. Furthermore, they noted that most of the systems being studied were evaluated by developers of these systems. When evaluators were not also the system developers, the proportion of systems reporting improvement dropped significantly.

Wears and Berg's critique of the dominant objectivist evaluation strategy reflects the tension between the socio-technical and the more technologically-oriented objectivist views of CDS discussed above. Unlike the objectivist view, the socio-technical approach views clinical work as "fundamentally interpretative, interruptive, multitasking, collaborative, distributed, opportunistic, and reactive" [60] and the implementations of CDSSs as systems involving organizational dynamics and power relationships. Objectivist evaluation methodologies necessarily cannot capture the qualitative relationships that, in the socio-technical view, are critical determinants of a computer system's success or failure; often it is difficult to distinguish effects caused by the CDSS from effects caused by the change in the work practices induced by the implementation of CDSS. In contrast to the objectivist approach to evaluation, the **subjectivist** approach

to evaluation borrows from ethnography and uses techniques such as participant observations, interviews, and analysis of documents and artifacts to study the impact of introducing a CDSS on the clinical work in its natural setting [58]. A recent example that illustrates the use of the subjectivist methodology is an observational study of the effect of introducing computerized physician order entry on the workflow in an intensive-care unit [61]. The researchers found that the introduction of the system caused an increase in the number of coordination and verification requirements, sharing of login sessions by different users, and disruptions of workflow due to the geographical locations of the clinical workstations. The need to combine qualitative and quantitative evaluation methods in order to study different dimensions of clinical information systems is becoming apparent [62]. However, such multi-method evaluation is still uncommon [63].

8. Conclusion

This paper reviews some major themes in developing and deploying CDSSs. We saw, in recent years, the emergence of a powerful critique of the technology-centric vision of CDSSs. This critique is rooted in a conception of medical work as contingent and emergent, where clinical data and decisions are re-interpreted as clinicians manage the trajectory of a patient's problem and where clinicians' professional expertise and autonomy permit them to make decisions independently of any fixed protocol. According to this conception, the provision of decision-support services must be conscious of social roles and be consistent with the distributed nature of the care process, and not focus

on the mind of a single decision maker. Yet, at the same time, the imperatives of standardization and the accelerated rate of knowledge production also mean that clinicians must accommodate themselves to the requirements of automated decision support. We are in the midst of a transitional period where, although there exist many approaches for representing, managing and delivering clinical knowledge, we do not know a-priori how to design and implement good and useful systems that will last and evolve. In addition, the shift in the conceptualization of the goal of CDS raises evaluation questions, which require new methodologies that integrate the insights from different approaches that exist currently.

This is an incredibly exciting time for implementers of CDSSs. For years, workers in medical informatics and artificial intelligence developed advanced knowledge representation, knowledge management, and reasoning methods to create sophisticated diagnostic and therapy-management systems. Yet few of the early systems ever saw successful deployment. With the gradual maturation of electronic health record systems, the emergence of standard terminologies and messaging standards for exchange of clinical data, and the widespread recognition that CDS should play a crucial role in reducing medical errors and in improving the quality of healthcare and the efficiency of the healthcare delivery system, implementers of CDSS are poised to make major contributions to the delivery of healthcare.

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