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Commentary

Clinical decision support: Converging toward an integrated architecture

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1. Introduction

Multiple national initiatives [1], focus on cost cutting [2] and medical error reduction [3], and the need for healthcare quality improvement have given rise to the concept of Clinical Decision Support (CDS). The notion of CDS goes back to a concept called "medical data processing" in the 1960s [4], which for the first time entertained the idea that medical data processing by computers could make the physician's job easier. In order to utilize a computer program, the physician must learn how to communicate with it and how to correctly evaluate the information obtained from it. The medical data processing concept morphed into a concept called Clinical Medical Librarian (CML) in 1977 [5]. The objective of CML was to develop a librarian, called the informationist librarian [6], which acts as a clinical decision support consultant for patient care, identifying and addressing complex evidentiary needs of a clinical team. The CML services [7] were offered to provide information quickly to the physicians and other members of the healthcare team; to influence the information-seeking behavior of the clinicians; and to establish a special role of librarian in the clinical team. Guise et al. [6] point out that the current emphasis on cost-effective and high-quality care, with a strong focus on applying evidence-based guidance to decrease medical errors, has resulted in amplified interest in and demand for expert support to clinicians. Garg et al. ([2], p. 1223) found that "clinical decision support system improved practitioner performance in 62 (64%) of the 97 studies assessing this outcome, including 4 (40%) of 10 diagnostic systems, 16 (76%) of 21 reminder systems, 23 (62%) of 37 disease management systems, and 19 (66%) of 29 drug-dosing or prescribing systems".

Our analysis of review papers on clinical decision support, published over the last 20 years [8–15], reveals two things. First, there are too many definitions of CDS. Our review suggests that the literature has not provided a clear definition of CDS; rather, CDS has been defined in myriad ways [13,14]. For example, CDS has been defined as an Artificial Intelligence tool, an information retrieval mechanism, and a component of an Electronic Health Record (EHR) system. Second, there seems to be too many architectural frameworks in CDS. The issue is whether all these architectures are necessary, or whether they are converging toward a common, integrated architecture.

In this commentary, we present arguments in support of the architecture integration proposition. We emphasize that CDS borrows ideas and concepts from different fields, such as knowledge management; decision support systems (DSS); data warehousing and analytics; and Electronic Health Record (EHR) systems. We used extensive internet and library searches to collect journal articles on CDS going back to 1960s. CDS application information was collected from hospital web sites. EHR information was collected from vendor web sites, from our discussions with the vendor representatives, attending demonstrations of their EHR tools, and finally trying out several of them. Two of the authors acted as reviewers and analyzed articles in full text along with EHR tools and vendor web sites. The other authors evaluated the reviews to make sure that the articles are correctly represented in the paper. Such an exercise provided us with the information needed to evaluate the relevance of retrieved articles, and understand their main findings.

In Section 2, we review the CDS literature to identify the different CDS definitions. We argue that like DSS in Information Systems area, CDS evolution is dictated by the underlying tools and clinical decision support needs. In Section 3, we contend that the CDS architectural frameworks are converging toward integration by focusing on a representative sample of CDS architectures. We also argue that we need three essential components – information management, data analytics and knowledge management – for such an integrated architecture. In Section 4, we argue that an integrated architecture would provide an implementation mechanism to respond to the ten grand challenges posed in [13,14]. We conclude this commentary by summarizing our findings and outlining future directions in Section 5.

2. CDS definition: A moving target?

Ledley and Lusted [4] first introduced the notion of decision support in medical data processing:

> Medical data processing could aid certain aspects of medical diagnosis. The foundation of such effort rests on its use of AI

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tools with logical analysis on symptoms, or by using fast information retrieval of records for the biochemical and physiological indices or using statistical modeling techniques.

Johnston et al. [8] studied 793 citations from MEDLAR, EMBASE, SCISEARCH, and INSPEC databases in the period between 1974 and 1994, along with 28 controlled trials, and defined CDS as software that uses a knowledge base designed for use by a clinician involved in patient care as a direct aid to clinical decision making. Hunt et al. [9] used MEDLINE, EMBASE, INSPEC, SCISEARCH, and the Cochrane Library bibliographic databases from 1992 to March 1998 along with 68 controlled trials. They found that CDS could enhance clinical performance for drug dosing, preventive care, and other aspects of medical care. However, they did not find any convincing evidence for use of CDS in helping diagnosis. Hence, they defined CDS as a computer-based decision support system that could synthesize and integrate patient-specific information, perform complex evaluations, and present the results to clinicians in a timely fashion.

Osheroff et al. [17], on the other hand, defined CDS as a collection of support methods: documentation forms/templates, relevant data display, order creation facilitators, time-based checking and protocol/pathway support, reference information and guidance, and finally, reactive alerts and reminders. Garg et al. [2] examined MEDLINE, EMBASE, Evidence-Based Reviews databases (Cochrane Database of Systematic Reviews, ACP Journal Club, Database of Abstracts of Reviews of Effects, and Cochrane Central Register of Controlled Trials), and Inspec bibliographic databases from 1998 through September 2004. They defined CDS as an information system designed to improve clinical decision making, where characteristics of individual patients are matched to a computerized knowledge base, and software algorithms generate patient specific recommendations. Computer-generated recommendations are delivered to the clinician through electronic medical record, by pager, or through printouts placed in a patient's paper chart.

Chaudhry et al. [10] connected decision support with computerized reminders. They observed that the decision support functions were usually embedded in electronic health record systems frequently used in the outpatient setting or in computerized provider order-entry systems more often assessed in the inpatient setting. They looked at MEDLINE (1995 to 2004), Cochrane Central Register of Controlled Trials, the Cochrane Database of Abstracts of Reviews of Effects, and the Periodical Abstracts Database. They hand-searched personal libraries kept by content experts and project staff; and mined bibliographies of articles and systematic reviews for citations.

Berlin et al. [11] studied 58 randomized controlled trials from PubMed and the Cochrane Library from 1998 to 2003. They found that CDS systems can be decomposed into two groups: patient-directed systems and inpatient systems. A patient-directed system provides decision support for preventive care and health-related behaviors, while an inpatient system targets clinicians to provide online decision support and execution of recommendations. They define CDS as an information system that has a collection of features such as context, knowledge and data source, decision support, information delivery and workflow.

Following the style of creating taxonomy of features, Wright et al. [12] have described CDS as a collection of its decision support functionalities. They argue that the decision support features can be grouped into four categories: triggers, input data, interventions, and offered choices. Triggers are events that cause a decision support rule to be invoked. Input data are the data elements used by a decision support rule to make inferences. Interventions are possible actions that a decision support module can take, and offered choices are the choices that a clinician might have.

The definition of CDS, as is evident from above, has evolved from "medical data processing" to a collection of "decision support functionalities" that can be housed in any health care information system. However, we need to understand the reasons for the many changes in the definition of CDS. Note that the definition for decision support systems (DSSs) has also undergone several such changes, according to the information systems literature. We believe that the cause for the changes in the DSS definition is the evolution of the underlying tools. We support our argument by first describing a representative sample of DSS definitions from the literature.

The term "decision support system" was first introduced by Gorry and Scott Morton [18] 40 years ago. According to them, a DSS is a system that supports users/managers in unstructured decision-making situations. In their overview of the first DSS conference, Carlson and Scott Morton [19] state:

> The use of the term "decision support system" is relatively new and means different things to different people. For the purpose of this conference, it meant the flexible support of decision makers with computer-based information. In particular, we were interested in systems which provided useful support for problems with a lack of predefined structure. For all practical purposes, this type of computer support has not been available in the past (p. 2, [19]).

Keen and Scott Morton [20] extended the notion of generic operations and emphasized a need for the building blocks in a DSS. In their words:

> A DSS can be assembled selectively, drawing on those building blocks that offer the best combination of power, cost, turnaround time and suitability to the problem statement (p.13, [20]).

Several suggestions for these building blocks can be seen in the information systems literature. Haseman [19] and Donovan and Madnick [19] offered architectures, where the use of database management with analytical capabilities was shown to be useful for DSS. The idea of graphics as a component of DSS was introduced by Carlson and Sutton [21] in their GADS (Geodata Analysis and Display System) project. They argued that since decision makers have trouble describing a decision process, a DSS should use familiar representations to assist conceptualizations. Bonczek, Holsapple and Whinston [22] defined DSS as a collection of three interacting components: a language system to communicate between users and other components of DSS; a knowledge system acting as a repository of problem domain knowledge; and a problem-processing system linking the above two components with general problem manipulation capabilities required for decision support. Intelligent DSS [23] also employed artificial intelligence (AI) techniques to extend its capabilities to include knowledge system and problem processing system [22]. El-Najdawi and Stylianou [23] argued that an integration of the underlying tools is essential for an effective DSS.

Using a time line, we divide the history of DSS into seven eras: pre-Sixties, the Sixties, the Seventies, the Eighties, the Nineties, the 2000s and the 2010s (Fig. 1). The shaded boxes in brown depict important events in the DSS area. The shaded boxes in pink show its underlying tools, ranging from language development, modeling, database, web design to artificial intelligence. In the interest of space, we focus only on events that are relevant to our argument.

Even though DSS originated in the computer-aided models of pre-sixties needed for decision making and planning, much of the DSS activities were pushed by tool innovations in languages, data base systems, expert systems, statistical packages, web development, enterprise integration, etc. The concepts of data warehouses, online analytical processing (OLAP), and business

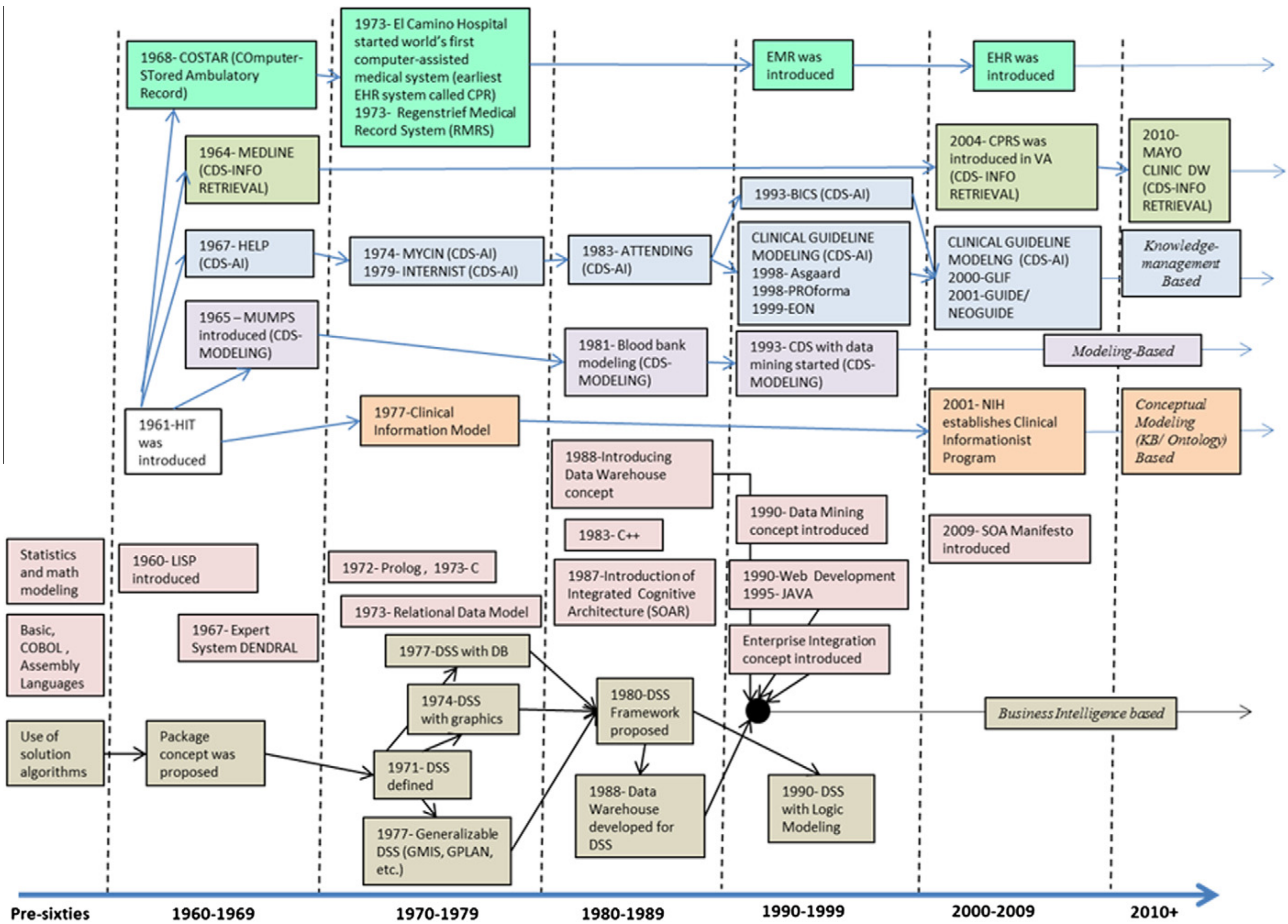

Fig. 1. Evolution timelines of clinical decision support and decision support systems.

intelligence (BI) came into focus in the early 1990s, concentrating on data integration at the organization level.

Tool innovation had a similar effect on CDS evolution. Just like the definition of DSS evolved due to a technology push, the definition of CDS has also evolved from simple "medical data processing" to a much more complex "decision support" system by always adopting newer technologies. As a result, like DSS, the definition of CDS has kept changing, along with its architecture.

Fig. 1 describes the architectural categories that CDS has evolved through: information management (information acquisition, storage and business-intelligence reporting) based, modeling (or data-analytics) based, and knowledge-management based. The information management category focuses on CDS activities that concentrate on capturing clinical, financial, and other types of healthcare data using EHR systems. Once such data sets are captured and stored in a data base or a data warehouse, information is retrieved and reports are generated using BI tools. The data analytics category is used to analyze data in many different ways. Finally, the knowledge-management based category focuses on the complexity of the clinical decision making domain and provides mechanisms to create knowledge bases using AI techniques that can used to develop knowledge base systems for CDS.

3. Convergence of CDS architectures

A direct impact of a constantly evolving CDS definition can be seen in the scores of CDS architectures developed over the last 40 years. The question is if we need all these architectures or if it is time to consider an integration of the different architectural categories. Even though many research articles have been published in CDS, not much emphasis has been placed on studying CDS architectures in a chronological fashion. The benefit of such a study is to narrow our efforts from understanding hundreds of architectures to considering a few categories of those architectures. Only Wright and Sittig [13,14] have studied the history of CDS architectures this way and grouped them into a set of categories whose characteristics can be described. They reviewed the CDS architectures from 1959 till 2007, and developed a model that describes the evolving nature of CDS architectures. They looked at architectures as a coupling mechanism between CDS and other healthcare information systems such as Electronic Health Record (EHR) systems, Computerized Physician Order Entry (CPOE) systems, and Computerized Patient Record System (CPRS) systems. The architecture categories used in their model are: standalone, integrated, service-based and standards-based.

In the standalone category, the CDS system is separate from any other system, that is, there is no coupling. Such systems do not need standardization, require relatively low clinical knowledge, and do not need real patient data. However, these systems are quite slow and are not very practical [13,14]. The integrated category, on the other hand, requires that CDS needs to be strongly coupled with other clinical information systems such as EHR and CPOE. In such systems, no new patient data need to be re-entered and alerts can be initiated. The major downside of the integrated architecture is that there is no easy way to share the systems or reuse their content. Service-based category uses loose coupling by offering clinical decision support as a service to the clinical information system. The objective is to isolate the clinical decision support activities from the clinical information system in the beginning and then recombine the decisions at the end. Finally, the standards-based category promotes the use of standards to represent, encode, store and share decision support content. The objective is to have standard coupling mechanisms among systems. However, such systems can get into trouble as there can be many standards resulting in hundreds of such systems. Encoding a standard can also create problems. Standards-based CDS is a special case of integrated and service-based architectures.

It is important to point out that both the integrated and service-based categories have one thing in common and that is they both support integration. The integrated CDS systems are usually designed to work together with other healthcare applications and are built by a common engineering team using a common application infrastructure, and are based on a common database schema. The service-based CDS systems, on the other hand, are connected using interface brokers, service-oriented architecture, etc. As coupling simply points to how CDS relies on other modules, it cannot detail the architecture. So, although Wright and Settig [13,14] promote the importance of integration, the article does not describe the architectural details of these CDS categories. As both categories support integration (each in a different way), we explore what constitutes an integrated architecture in CDS by studying the evolution of CDS architecture similar to the way DSS evolution was described in Section 2.

As described earlier, the tool innovation that took place since the sixties pushed the CDS architecture in three different directions. They include: information management, data analytics, and knowledge management. Each of these focuses on a specific functionality of a CDS system. Fig. 2 emphasizes this evolution in a chronological progression.

Historically, CDS architecture was created to focus on information management [24]. Information management in CDS involves information acquisition, storage, and retrieval using an EHR tool. The earliest EHR systems were installed at the Harvard Community Health Plan (HCHP): Computer STored Ambulatory Record (COSTAR) system in 1969 [25], Regenstrief Medical Record System (RMRS) in 1973 [26], and at the El Camino hospital in California in 1973. The objective of an EHR tool is to capture and store as much medical and patient data as possible. The ability to find data relevant to a problem is a basic form of CDS. For example, accessing a clinical laboratory test result is a retrieval task. Building on this basic capability, a clinical information system can transition increasingly into providing direct decision support about laboratory test results.

Systems such as Computerized Physician Order Entry (CPOE) and Computerized Patient Record System (CPRS) have also been introduced to capture patient encounter data. The information management aspects of CDS architecture have since evolved into systems that use data warehousing techniques by extracting, transforming, and loading clinical, financial, and other medical data sets into a data warehouse. Such systems are currently running at Mayo Clinic [27], at Denver Health [28], and at Emory [29]. Reporting and BI tools work on the data set stored in the data warehouse.

As most clinical judgments are not deterministic, a CDS system needs to recognize the inherent variability of medical data, the imprecision of tests and measurements, and the fact that many principles of practice are based on limited evidence. Due to these reasons, use of the modeling or data analytics architecture with mathematical and statistical modeling has flourished in the medical domain, in areas such as blood bank management, disease diagnosis, and genomic analysis. [30–33]. In recent years, various data mining tools [34–37] are also being used for analysis. We have clubbed data mining and statistical/mathematical modeling techniques together because they both help in healthcare data analysis.

Finally, the knowledge management-based CDS architecture focuses on capture and representation of knowledge from human experts. This area has been looked at in two ways. First, efforts were made to create diagnosis expert systems such as MYCIN [38] and INTERNIST [39,40] based on the LISP programming language introduced in the sixties, followed by other well-known systems such as ATTENDING [41] in the eighties and BICS [42] in the nineties. This architecture married the concepts of expert systems [43] with medical diagnosis and is currently quite predominant in CDS research areas like clinical guideline modeling and surgical process modeling [44–45]. For example, during the last 25 years, there have been steady attempts at supporting guideline-based care in an automated fashion [46]. These computer-interpretable clinical guideline (CIG) research efforts have ranged from developing tools such as ONCOCIN [47], Asgaard Project [48], PROforma [49], EON [50], GLIF [51], and Guide [52] to conceptual models [53]. Standardization can also be seen in the components that are common across different CIG tools [51]. Second, with the advent of the clinical information model in the seventies, there was a need to develop clinical knowledge. Over time, this approach has evolved into clinical knowledge base design with an objective to capture different types of clinical expertise [54–59]. Such a knowledge base can include diverse types of knowledge, ranging from definitions of medical concepts, clinical temporal patterns to complex procedural knowledge such as guidelines for diabetes and protocols for oncology patients.

How should we conceptualize the integration issues in CDS? Should we look at the integration of CDS with other healthcare systems, or should we look at the integration of the above-mentioned CDS functionalities? Many researchers [60–63] think that CDS is simply some functionality in existing health care information systems, such as EHR and CPOE systems. The integration here is at the module level and clinical work support is viewed as a collection of healthcare information systems including CDS. Instead, using [64], we describe CDS as a domain, where an integrated tool is needed so that it "provides clinicians, staff, patients, or other individuals with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health and health care" (p. 141, [64]). This definition supports our earlier observation of CDS evolution and enforces the idea that CDS is not simply a collection of monitoring, alert, trigger, modeling, prediction and information retrieval functionalities [2]. Rather, it is more of a domain that needs components such as information management, data analytics, and knowledge management. Fox et al. [65] also stress this point by suggesting the need for a theory in CDS. We argue that our decomposition of the CDS architecture into three components can be achievable by integrating decision theory, knowledge representation, process design, and organizational modeling.

4. Support for the convergence

The concept of integrated architecture for CDS has extensive support in many areas of CDS research. We start this discussion by pointing out that most of the ten "grand challenges" described in [16] provide support for the integrated CDS architecture concept. We also find that the integration concept has been used in the clinical data warehouse implementation projects in US hospitals. And finally, we find that many EHR vendors are embracing integration ideas into their EHR tools.

4.1. Support from the grand challenges

According to [16], the grand challenges need to be addressed if the anticipated benefits of the technology are to be achieved. We

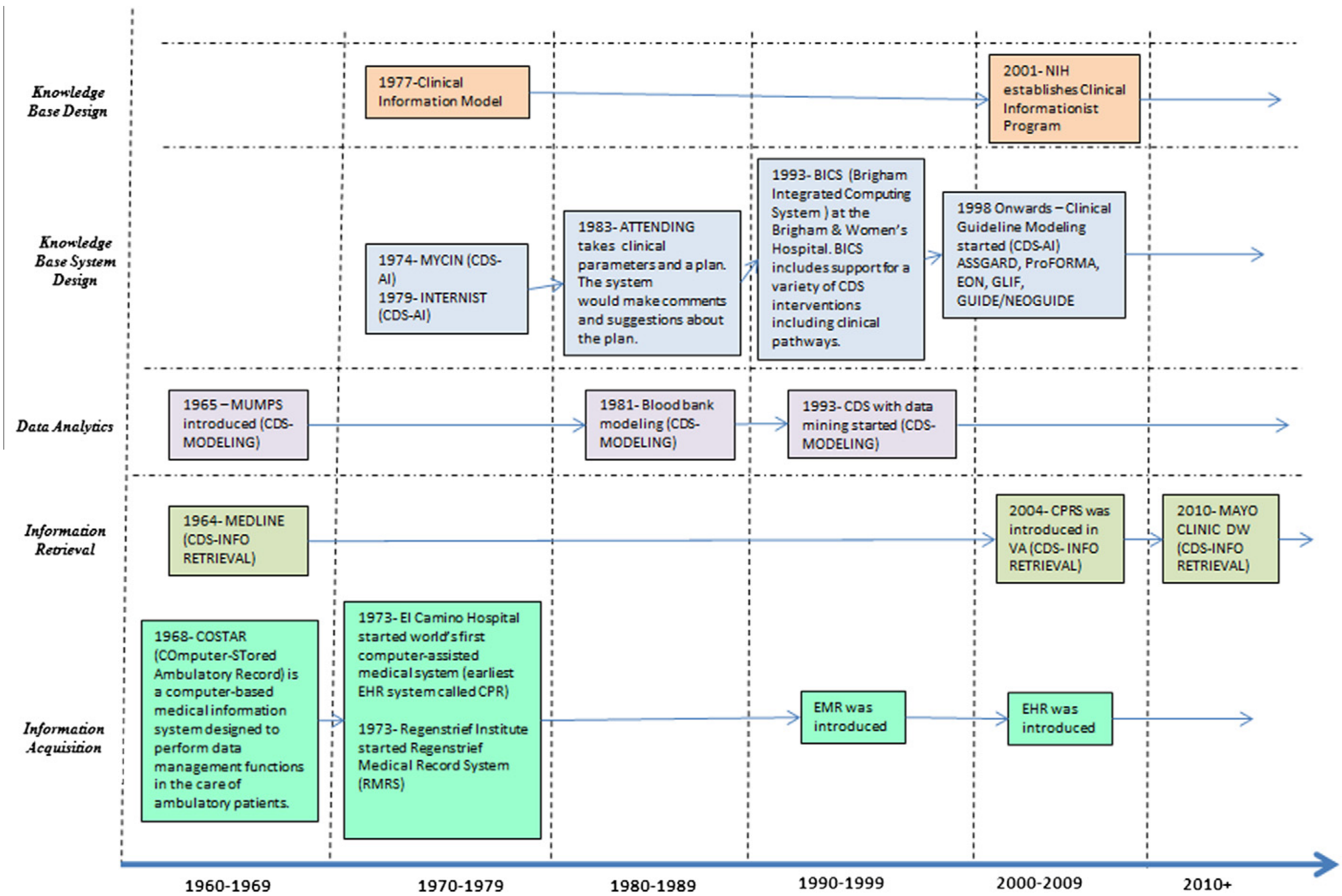

Fig. 2. Different architectural approaches in CDS domain.

argue in this section that the integrated CDS architecture concept can address many of these challenges.

Human computer interface (Challenge 1) is an important aspect in CDS for presentation of clinical decision support recommendations. Existing technologies have introduced many types of interfaces, such as smart reports with drag and drop capabilities, dashboards, and scorecards. Yet it is still unclear if these help in clinical workflow and clinical decision making. Patient data can be unstructured text (such as physician's notes), structured data (such as lab results), images, and structured text (such as patient information). According to [16], "No one can retain and process the entire content of a complicated patient's data; clinicians need to recall the most important facts and conclusions pertinent to the current situation." As a result, summarization of the data is needed (Challenge 2). The purpose of the summarization is to make all key data sets needed for optimal decision-making available to the decision makers. Different summaries are needed for different clinicians. The integrated CDS architecture addresses these two challenges with its inherent data warehousing capabilities, BI functionalities, and AI capabilities. The data warehouse in the integrated architecture supports the summarization of structured data by roll-up activities and providing drill-down features that can disaggregate the summary data set. In order to get this done, the data warehousing process needs to develop data cubes that can be utilized for many types of summarizations using the appropriate BI tools. Summarization at the text level is not easy and research is being done in the AI area [66,67].

Not much has been done in prioritization and filtering recommendations (Challenge 3), even though they are very important. They are still in the research stage [67]. On the other hand, text mining has been quite useful in studying the free-text information (Challenge 4) such as clinical notes. Some support has been developed to combine recommendations for patient with co-morbidities (Challenge 5) using data warehousing technology, structured data, and data mining. A similar type of technology (using data mining) can help mine large clinical data bases to develop new CDS patterns of recommendations (Challenge 7).

We feel that the current thrust in the use of healthcare information technology in areas such as Meaningful use (MU), Patient-centered Medical Home (PCMH), Accountable Care Organization (ACO), and the increasing need to report to Centers for Medicare & Medicaid Services (CMS) and other healthcare insurance payers will push to prioritize CDS content development and implementation (Challenge 6) across the country. Clinical work process also needs to be studied to understand how the best practices evolve and how they can be disseminated to others. The integrated architecture can be implemented using tight coupling or loose coupling (Challenge 9). Both styles need some standardization.

Centralized internet-accessible clinical decision support repository (Challenge 10) can be developed using an integrated architecture. The objectives of such an effort are: (a) to track outcomes across patient populations; (b) to track financial performance; (c) to support clinical research; (d) to improve clinical processes and practices; (e) to improve business processes and practices; (f) to report to regulatory bodies; and (g) to develop quality assurance. Such a repository can be created by employing data warehousing technology. The repository will have a centralized, standardized, and integrated collection of data extracted from numerous source systems. It would include scalable, extensible tools and processes

Table 1
EHR vendor tools and integrated CDS architecture.

CDS Architecture	CDS Infrastructure Components	Allscripts [73,74]	e-MD [75–77]	GE [78–83]	Next Gen [84,85]	McKesson [86–89]	Greenway [90,91]	e-ClinicalWorks [92–98]
Information management	CPOE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Document capture	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Clinical workflow management	Yes (integrated)	Yes (integrated)	Yes (integrated)	Yes (integrated)	Yes (integrated)	Yes (integrated)	Yes (integrated)
	e-prescribing	Yes	Supports surescript	Yes	Yes	Yes	Yes	Yes
	Practice management	Offers scheduling flexibility across patients, location and clinical needs; claims management; and drill down reporting	Can be customized; has many capabilities for billing and provides comprehensive reporting	Yes, connectivity to patient portal; sophisticated task management capabilities; extensive reporting facilities	Yes, has many capabilities for scheduling, billing and reporting	Yes, flexible scheduling, billing and reporting; comprehensive approach	Yes, integrated billing and scheduling; reporting is 3rd party offering	Yes, standard and extensive for billing, scheduling and reporting
	Data extraction, transformation and loading (ETL)	Has data migration and transform tools using Sunrise clinical analytics; data loading is done using a third party	No	Yes, ETL is available and is web-based	Not Known	Yes, extraction available; uses virtual document for transformation; customized loading service is available	Not Known	Not known
	OLAP services	Not known	Important; Not known	Yes	Not Known	Yes on OLAP	Not known	Not known
	BI and reporting services	In-built report writer; can be customized; real-time, flexible dashboard with drill-down capabilities; scorecard available	In depth and flexible reporting; dashboard capabilities available	Many kinds; Integrated patient scorecards	Yes, productivity reports	Yes, with drill down capabilities; alerts are available; dashboard and scorecard available	Yes, extensive; integrated and allows roll-up capabilities; dashboard capabilities available	Yes; flexible style; dashboard capabilities (focuses on patient dashboard)
	e-Communication	Secure and personalized	Has patient portal, etc.	Has patient portal connection	Has patient portal; has mechanism to converse with other providers	Web gateway	Yes, web based	Has patient portal
Data analytics	Data mining	Sunrise clinical analytics provides data mining	Not Known	Has tools to provide data for data mining	Yes	Some capabilities	Yes	Yes, built-in
	Text mining	Not known	Not known	Not known	Not known	Not known	Not known	Not known
	Statistical data analysis	Some	Some general statistics such as patient movement timings, etc.	Yes (allows to analyze payer transaction volume, etc.)	Some financial analysis	Yes	Not known	Not known
Knowledge management	Rule base	Has an in-built care guide	Has a rule manager	Yes	Yes	Yes	Yes	Yes
	Clinical expert system	Some	Some	Standard items such as drug-drug interactions, etc.	Yes, integrated	Yes, standard items	Yes, standard items	Yes
	Alerts	Yes	Yes, appointment alerts	Yes	Yes	Yes	Yes	Yes
	Trigger	Yes	Yes, scheduler manages patient triage	Yes	Yes	Yes	Yes	Yes (check excel)
	Clinical knowledge base	Provides comprehensive knowledge base	Integrated	Yes	Integrated	Web-based	Yes	Yes (for patients)
Integration	Strong coupling	Yes	Yes	Yes (strong security is emphasized)	Yes (strong security and data exchange)	Yes (strong security)	Yes (strong security)	Yes (strong security)
	Loose coupling	No SOA	No SOA	Not known	Not known	Not known	Not known	Not known

for transforming, integrating, and adding new data, and would employ the best of the breed, world-class BI reporting tool.

It is clear from our discussion above that the challenges, which are deemed technologically feasible right now, cannot be supported by any one component of the integrated architecture. This means that the CDS architecture must include information management, data analytics, and knowledge management components.

4.2. Support from clinical data warehousing projects

Clinical data warehouses (CDWs) are increasingly becoming a popular way to integrate data generated in a clinical setting and in other health care environments. A typical CDW integrates data from disparate data sources such as electronic medical records, clinical departmental systems, patient accounting, back office, research, and various other source systems. The goal of a CDW is to rapidly and cost-effectively unlock value from clinical, financial, and operational data to create better clinical and business insights through an integrated picture. CDW projects have been implemented in several hospitals, including Cook County Hospitals [68], New York-Presbyterian Hospital [69], and Mayo Clinic [27]; as well as in several research institutions such as Emory's administrative data warehouse [29], Stanford's Center for Clinical Informatics [70], Medical University of South Carolina [71], and Ohio State University [72].

Our analysis of these implementation projects show that data are sourced from a variety of sources with different computing environments for the purpose of integration. The data usually include pharmacy data, laboratory test results data, pathology reports data, radiology reports data, medical records, clinical encounters, diagnosis data, procedures and emergency department data. These CDW infrastructures use the information management dimension to extract data from these disparate sources, transform them into the proper format, and help load the data into the data warehouse. Data validity and quality issues are addressed to keep the data in the data warehouse consistent and trustworthy. Fairly large numbers of reporting and data analytics have been used to support quality improvement (such as cost accounting), research productivity and best-practices monitoring (such as checking redundant antibiotics), measurement of antibacterial utilization, and so on. Finally, knowledge management has been utilized quite effectively not only at the EHR level, but also in developing surveillance applications in hospitals that focus on rates of antibacterial resistance, potential infections, bloodstream infections, and other factors.

4.3. Support from EHR vendor tools

Finally, we examine several well-known EHR tools to determine if they support the integrated CDS architecture. We identified several well-known EHR tools in the United States using KLAS research[1] and HIMSS Analytics.[2] The list includes Allscripts, e-MD, GE, NextGen, McKesson, Greenway, and e-Clinicalworks. We interviewed the vendors of these tools to learn more about their products, followed by detailed demonstrations of their tools. Based on our understanding of these tools, available product literature, and vendor web sites, we list a set of attributes that describe the components of the CDS integration model (see Table 1).

We use nine attributes to describe the information management component, ranging from CPOE and document capture tools to reporting capabilities. We argue that these attributes collectively describe the CDS infrastructure for the information management component and range from data acquisition to reporting. In this list, we have included practice management as it is integral in managing information.

The data analytics component, on the other hand, includes analytic capabilities, ranging from statistical data analysis to data and text mining capabilities. These tools typically access data stored in the operational data base or in the data warehouse, and offer different types of data analysis. The knowledge base management includes capabilities that are essential for supporting clinical knowledge. Some examples include a rule base for clinical expert system, a clinical knowledge base, alerts, and triggers. Finally, coupling for integration is classified as strong coupling or loose coupling.

Based on these attributes, we created Table 1, which shows the coverage of the attributes by the EHR tools. It is quite obvious from Table 1 that almost all attributes for the three components are supported by these EHR tools. Certain attributes are worth mentioning here. With the current focus by the ONC to push for EHR adoption by practices, the EHR-part of the CDS is emerging as a place, where many of these functionalities (such as e-prescribing, CPOE, BI reporting and dashboards) are starting to reside. Components such as rule base, alerts, and triggers, which form the basis of clinical knowledge management are now totally integrated into these systems. The coverage of data analytics, however, is still very nascent and usually handled separately in supporting systems offered by the EHR vendors. Data warehousing capabilities focus on online analytical processing (OLAP). We envision that in future, data warehousing vendors such as Microsoft, Oracle, Teradata, and IBM, which are already integrating data warehousing features with data analytics, will tie up with EHR vendors to provide a seamless transition from data collection and knowledge management activities (OLTP paradigm) to analytics and reporting (OLAP paradigm). Many of these kinds of integration is already been happening in the customer relationship management (CRM) domain, where a database management system is getting integrated with reporting, analytics and knowledge management tools (see for example, Microsoft's Dynamics CRM tool with different analytics). Finally, we observe that current integration among these components (except the data warehousing part of the information management) is mostly geared toward strong coupling.

5. Conclusion

Even though many reviews have been published in the last 20 years, none of them have really looked at how CDS literature has been influenced by DSS research. In this opinion piece, we have discussed why there are so many CDS definitions and how the CDS architectures are slowly converging toward an integrated architecture. We have also argued for the need to integrate the three essential components of CDS – information management, knowledge management, and data analytics – and we found ample evidence that the CDS area is moving toward integration.

Based on our observations of the grand challenges, large hospital projects in the country, and our experience with EHR tools there still remain major gaps. Even though integration might be a goal of many, it is still complicated at the technology level, at the data level, and at understanding clinical work. At the technology level, work is still needed to integrate the OLTP systems with every OLAP capabilities. At the data level, traditional data types need to be integrated seamlessly with text and image data types. It is also unclear at this time how clinical work can be modeled in the right way so that the clinical decision rules are integrated with data to support optimal clinical decision making.

In concluding, we want to emphasize the importance of integration in CDS as we move toward a quality and performance-oriented healthcare world. It is difficult to develop effective quality performance reports and dashboards without a thorough integration at all levels of CDS.

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