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# Contemporary CDSS Frameworks and A Case Study of Smart CDSS

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## Abstract

Clinical Decision Support System (CDSS) plays imperative role in emulating decision making, providing evidence based decisions and solving complex medical problems from over 50 years. It has enormous impacts on quality of care, patient safety and avoidance of medical errors. CDSS are generally categorized into four major types, phases or stages namely standalone, integrated, standard-based and services oriented. In this article, the state of the art of CDSS systems is studied, and Smart CDSS that has been developed by the authors is presented as an example clinical scenario. This work describes, targeted scope of smart CDSS and working process including knowledge acquisition, knowledge execution, and integration with existing clinical workflows. Smart CDSS is incorporated with two complex and important domain including dementia and head and neck cancer workflows for testing and evaluations which achieve an impact on both improving patient care and reducing medical cost. We conclude that the smart CDSS can be integrated into any existing clinical workflow and have the capability to be extended to any desired disease.

## I. Introduction

The rise and advancement of AI and ICT technology has increased the requirement for intelligent healthcare applications and services. Technology advancement attracts research community and led to the inception of clinical decision support system (CDSS) and e-health applications and services. CDSS can typically be defined as "providing clinicians, patients or individuals with knowledge and person-specific or population information, intelligently filtered or presented at appropriate times, to foster better health processes, better individual patient care, and better population health"[1]. CDSS plays a pivotal role in improving patient care, facilitating and enhancing practitioner performance[2].

The main purpose of the CDS system is to improve quality of care, patient safety, and provide standardized diagnosis and treatment. Despite a long history of development, most of the systems evaluated in academia have not been realized in a real clinical practice environment which creates a gap between academia research and real medical practices, and most of the latest research reside and limited to research articles. To reduce this gap, the latest research needs to be implemented in real medical workflows. However, there are some hurdles in reducing this gap. The most prominent barriers have included heterogeneous healthcare workflow integration, lack of standard knowledge representation, complexity of knowledge representation languages, lack of frameworks for clinical knowledge transformation into executable knowledge bases, and physician fears regarding validity of the services related to the knowledge bases and quality of published guidelines[3].

To increase the benefits of CDSS, it needs to be part of the clinical workflow and can assist domain experts in making complex decisions about diagnosis and treatment. To be the part of clinical workflow, it needs to interact and share knowledge with other systems operating in the workflow. As mentioned by Adam et.al [2], based on the way in which CDSS interacts or decide not to interact with other systems has passed through four phases, standalone, integrated, standards-based and service model. Standalone systems ran solely from any other system. The advantages of these systems include easy to use, and have no dependency on other systems. However, the main disadvantages of these systems, it cannot be integrated with existing legacy system of the hospital. The hospitals required to run both, their legacy system and these CDSS system side by side which is cumbersome and difficult to interact with both systems. This leads to second phase and the requirement of a system that can collaboratively work with hospital existing systems known as integrated CDSS.

Integrated CDSS are systems that can be embedded and can work with the hospital existing system side by side. The fundamental advantage of these systems is, information needs to be stored in a single location and can be used by all systems in a hospital. The main drawback of these systems is, each hospital needs to have their own system and knowledge base. One hospital cannot use and understand knowledge base of the other hospital. The knowledge base is not shareable and understandable by other hospital's system. Also it is difficult to separate knowledge from code in these systems.

To overcome the disadvantages of phase two, the third phase of CDSS starts in 1989 [2]. The primary goal of this phase was to standardize CDSS system, so that it can be utilized and understand knowledge of any other hospital and health management system. The advantages of these systems include standardize knowledge representation. The knowledge of one system in a hospital can be shared and understood by other hospital. The disadvantages of these systems include limitation in encoding all type of knowledge. Also, defining a standard vocabulary like lab tests, drugs or procedures is a hurdle in these systems. Each hospital needs its own system, that needs to be understand by all user and needs maintenance cost as well.

The fourth phase of CDSS started in 2005 is known as service models. It is considered as most effective and state of the art approach. It separates clinical information system and CDSS component of an integrated decision support system and recombines them by using a standard API. The user needs to call API of the CDSS at any time if he is required assistance from CDSS. The major advantages of these systems include availability, easy integration, and separation of knowledge logic from its implementation. This approach overcomes the limitation of all previous types CDSS and combine advantages of them. It dramatically improves patient care and reduces healthcare cost.

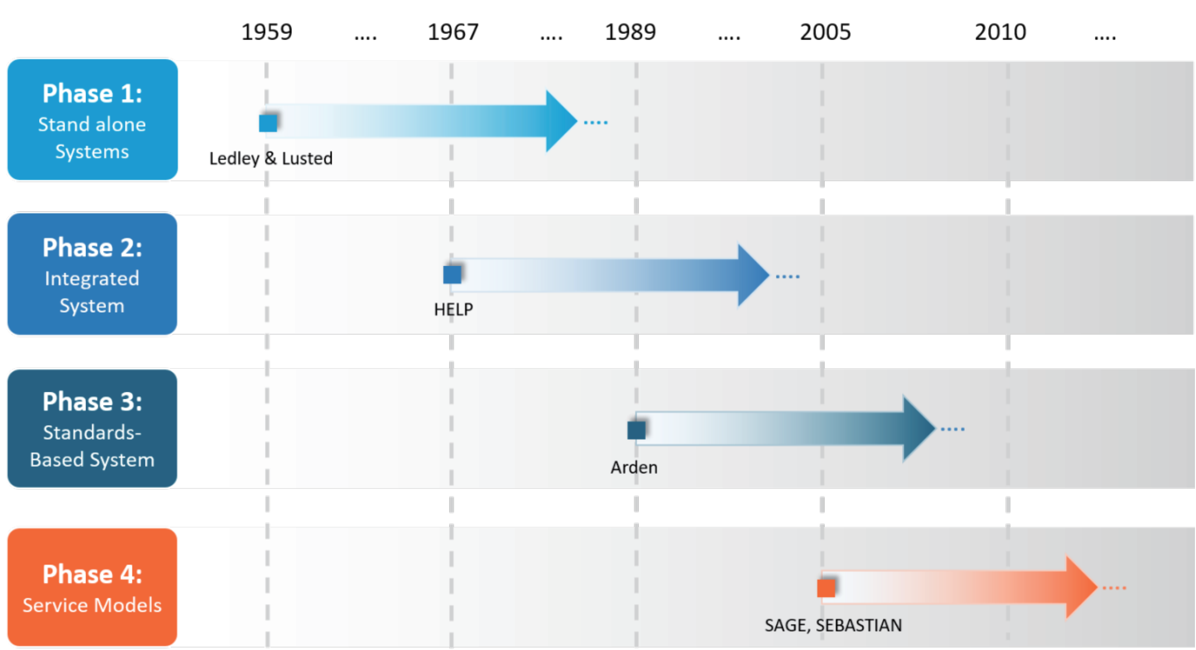


Figure 1. Four phases of CDSS

The aforementioned four phases as described by Adam et al. [2] and the first CDSS system of each phase is depicted in 〈Figure 1〉. Most of the systems developed after 2005 are Service Model oriented or used hybrid approaches. In this article, we present Smart CDSS, a state of the art, standard based and an integrated CDSS system that has an impact on improving patient health as well as reducing medical cost. It uses Health Level 7 (HL7) Arden syntax [4] standard. Smart CDSS can easily be expanded to any desired domain and can be integrated with any medical flow with a minimum effort. To acquire expert decision making capability, smart CDSS uses expert driven knowledge acquisition and provides knowledge authoring tool. On the other hand, to extract hidden pattern and get benefit of the patient's data, it utilizes machine learning and artificial intelligence techniques in data driven knowledge acquisition for generating its knowledge base. The complete working scenarios, knowledge extraction technique, knowledge execution and its impact will be described later in the upcoming sections of the article.

## Ⅱ. History of CDSS

The historical backdrop of CDSS begins in 1959 by Ledley et al. in a paper entitled "Reasoning Foundations of Medical Diagnosis" and have made colossal progression with the ascent of innovation[5]. The purpose of this work was to analyze medical diagnosis and reasoning process. They used probabilistic model along with set theory and Bayesian inference for medical diagnosis. In this research, the authors are inspired by the diagnosis process followed by human experts. The authors used an analog computer for sorting cards. These cards have diagnosis label and a series of punches representing symptoms of a case. The system diagnoses a disease by selecting a card having same punches as that of input symptoms. To add new diagnosis case to the system, the domain expert had to fill out and punch a card and feed it to the system card sorter.

In continuation, two years later in 1961 Warner et al. [6] proposed a mathematical model based system for heart defects detection and diagnosis. In this approach the authors used contingency tables for mapping patient available symptoms for diagnoses. The frequency of manifestation of each symptoms leads to diagnosis class. The systems' result was compared with gold-standard surgical diagnosis, and was found to compare favorably with experienced cardiologists.

Collen et al. [7] in 1964 developed a system for multiphasic screening and diagnosis. This system was inspired by Ledleys' system and was used at Kaiser Permanente. This system use cards that contain sign, symptoms, and questions. A card was given to the patient and he/she put the cards of question/symptoms to Yes and No boxes based on the available sign and symptoms. Based on the cards in Yes and No boxes, afterward the system processes these cards and identifies concerned disease.

Bleich et al. [8] proposed and developed a first ever therapy system in 1969. The system recommends therapy for acid base disorder along with diagnosis. The author targeted this domain because of its algorithmic nature. The system also has the capability to ask for missing information. During interaction with the system, if user provided information is not enough for the system to take any decision, the system request user for providing more information to reach to appropriate decision. The system produce human like evaluation note that propose management plan, evaluated and reviewed by domain expert afterward form verification.

Two years later in 1971, de Dombal et al. [9] developed abdominal complaints diagnosis system by using probabilistic model. The authors proved it as a significant system by achieving a diagnosis accuracy of 91.8% compared to a group of senior clinician's accuracy of 79.6%.

The influence of artificial intelligence inspired Shortliffe et al. [10] to propose rule based system MYCIN in 1975. MYCIN uses a new technique of backward chaining for prescribing antibiotics. Clinician enter known facts to the system. Based on the input facts the system either request additional facts or recommend optimal antibiotic therapy. It achieves 75% accuracy and the accuracy increases by adding additional rules to the knowledge base of the MYCIN.

Miller et al. [11] proposed a system ATTENDING, having different approach than all of the other existing systems by expecting proposed plan as input from user along with other inputs. The technique used in this system is considered as critiquing which is eventually used for hypertension and ventilator management while most of these early systems would broadly take input and provide recommendation of diagnosis or therapy. The user needs to insert proposed plan along with other parameters (sign and symptoms). The system reviews the input plan based on input symptoms and provides suggestion and comments about the plan.

The systems described heretofore are all limited to single domain. The system (INTERNIST-I) developed by Miller et al. [12] in 1985 provides decision support across entire filed of internal medicine. The system has a huge knowledge base comprised of 15 person years of work, having 500 disease profile and 3550 manifestations of disease. The system was evaluated by 19 standardized clinical exercises. One key contribution of the system was abstracting the complexity of the field into three concepts, evoking strength, frequency and import.

Right after INTERNIST, Barnett et al. [13] in 1987 developed a system known as DXplain. DXplain used white box approach for reasoning. The key contribution of this system was having the capability to explain its reasoning process, which increase the confidence of the user. The DXplain [14] is alive and available till now and fulfilling up to date requirement with easy to access web interface.

Gustafson et al. [15] in 1992 developed a system known as Comprehensive Health Enhancement Support System (CHESS) for supporting people facing health related crisis and concerns. It is a service oriented system that provides support in making tough decisions. CHESS delivers its services to user by referral to service providers and networking to experts and others facing the similar concerns. The major target area of CHESS includes Academic Crisis, Adult Children of Alcoholics, AIDS/HIV infection, Breast Cancer and Sexual Assault.

One of the most important consideration needs to take into account during treatment and medication is finding patient drug allergy. As same drug may have different effect on different patient and some patient may react to the drug. Therefore, Kuperman et al. [16] in 2003 developed a CDSS system for drug-allergy checking and improve patient safety. The system stores patients' medication information along with associated allergy in a standard format. Whenever care provider prescribes some medication to which the patient has allergy, the system generates alert and prevent care provider. Preventing allergic medication prescription improves patient safety.

In 2006, Lin et al. [17] developed a web based CDSS that uses verbal probability estimation to represent and reason about associated uncertainty in lower back pain. It has the capability to assess patients' information and recommend diagnosis consisting of one or multiple parts. Meanwhile, Tleyjeh et al. [18] devised a CDSS system known as VisualDX. The major area of interest of the VisualDX includes diagnosis and management of dermatologic disorders. It was developed by Logical Images intended to be used in medical and clinical care for different diagnosis based on morphologic finding and patient finding driven search. It also helps in increasing clinical awareness for recognition of bioterrorism, clinical warfare and radiation injuries.

In 2008, Mitus et al. [19] developed a system called InterQual which helps healthcare professional by applying evidence based medical care. It provides correctness of care decision support in care planning and management in medical and behavioral health. It also has the capability of knowledge sharing which reduce the unnecessary medical expenses. It provides recommendation in a timely, context specific and results oriented way with simple actionable rules. It delivers it services to any point of care by using API and can integrate with healthcare workflow through integrated toolkit. At the same time, Eom et al. [20] developed an ensemble-based CDSS known as AptaCDSS-E. AptaCDSS-E is an ensamble and hybrid system. It uses four machine learning classifiers namely Support vector machine, Neural network, Decision tree and Bayesian for diagnosing cardiovascular disease. The system achieves more than 94% accuracy, while having prediction interval difference less than 6%. The multiple classifier systems have greater accuracy as compared to the single classifier system as described by Wozniak et al. [21]. However, it requires more time and more resources. These systems are suitable for domain where accuracy is more important than execution time. On the other hand, the domain whose main concerns is time and can compromise on accuracy needs to use single classifier systems.

Samwald et al. [22] in 2012 developed a CDSS system that used standard knowledge representation for shareability purpose. One of the mostly used medical knowledge representation standard is known as Health Lever 7 (HL7) where Samwald used Arden Syntax standard of HL7. Among other advantages, one of the key feature is flexible list handling and same knowledge base can be used and understand by any other systems. Knowledge base of one system can be shared and used by other system. At the same time, Zhang, Yang, et al. [23] developed a real time CDSS with data stream mining. In their approach the authors have described a new design of data stream mining system that can analyze medical data stream and make real time prediction.

Assaf et al. [24] in 2013, use patient similarities by comparing their demographic, initial blood, electrocardiography measurements and medical history, and predict individual discharge diagnoses. In 2014, M.Berkan et al. [25] developed a hybrid CDSS for lung cancer known as Lung Cancer Assistant (LCA). The novel feature of LCA is its ability to provide rule-based and probabilistic decision support within a single platform. The rules are extracted from clinical guidelines while the probabilistic approach is based on Bayesian network trained on the English Lung Cancer Audit Database. Both of these researches promote higher resection rates and multimodality treatments.

In 2015, Robert C. et al. [26] developed a two-stage CDSS to recognize and stratify patients with sepsis in early stages. The first stage comprised of a cloud based clinical decision support with all-time surveillance to timely detect patient at risk. In this stage if a patient is identified at risk, the system notify patients' designated nurse, whom the contact is provided. The second stage consists of screening and stratification which is integrated into the patient record to provide evidence based accurate decision.

Ximeng et at. [27] proposed a new privacy-preserving patient-centric CDSS in 2016. In this system the past patient's data stored in cloud are used for naive Bayesian classifier training without leaking any individual patient medical data. The trained classifier is then used to compute the disease risk for new patients. The patients can retrieve the top-k disease name according to their preference. Additive homomorphic proxy aggregation scheme was used for user data protection which prevent user data leak and assure the patient data security and privacy.

Sperl-Hillen et al. [28] in 2017 developed a web based electronic health record integrated point of care CDSS known as CV Wizard that delivers personalized cardiovascular risk information to providers and patients in both low numeracy visual format as well as high numeracy quantitative format. It has high sustained use rates, high patient satisfaction, high primary care provider satisfaction and positive impacts on provider reported clinical processes regarding cardiovascular risk factor management.

Somayeh et al. [29] in 2018 developed heart diseases detection expert system by utilizing Fuzzy Analytic Hierarchy Process (AHP) and Fuzzy Inference System for evaluating patients' condition. The system calculates weights for different criteria that impact developing heart disease by Fuzzy AHP. Fuzzy Inference System based on calculated weights assesses and evaluates the likelihood of developing heart disease.

IBM Watson [30] has tremendous achievements in empowering health care professional and patients. It used a large amount of heterogeneous clinical resource including structured, unstructured, and visual resources to answer physician and patient queries. For producing relevant answer to the user query, it builds hypothesis and processes a huge amount of data to get most relevant answer to the user query by using deep neural network. It also provides knowledge studio and other tools to facilitate domain expert to discover hidden knowledge

Table 1. Features comparison of clinical decision support systems

| Approaches | Multimodal Knowledge Acquisition | Knowledge Shareability | Standard Based | Extensibility | Evidence Support | Service Model |
|---|---|---|---|---|---|---|
| R. S. Ledley [5] | No | No | No | Yes | No | No |
| H. R. Warner [6] | No | No | No | Yes | No | No |
| M. F. Collen [7] | No | No | No | Yes | No | No |
| H. L. Bleich [8] | No | No | No | Yes | No | No |
| F. T. Dombal [9] | No | No | No | Yes | No | No |
| E. H. Shortliffe [10] (MYCIN) | No | No | No | Yes | Yes | No |
| P. L. Miller [11] (ATTENDING) | No | No | No | Yes | No | No |
| R. A. Miller [12] (INTERNIST-I) | No | No | No | Yes | No | Yes |
| G. O. Barnett [13] (DXplain) | Yes | No | No | Yes | Yes | Yes |
| D. H. Gustafson [15] (CHESS) | No | No | No | Yes | No | Yes |
| G. J. Kuperman [16] | No | Yes | Yes | Yes | No | Yes |
| L. Lin [17] | No | No | No | Yes | No | Yes |
| I. M. Tleyieh [18] (VisualDX) | Yes | No | No | No | No | Yes |
| A. J. Mitus [19] (InterQual) | No | Yes | No | Yes | Yes | Yes |
| J. H. Eom [20] (AptaCDSS-E) | No | No | No | No | No | Yes |
| M. Samwald [22] | No | Yes | Yes | No | No | Yes |
| Y. Zhang [23] | Yes | No | No | No | No | Yes |
| A. Gottlieb [24] | No | No | No | Yes | Yes | Yes |
| M. B. Sesen [25] (LCA) | Yes | Yes | No | Yes | No | Yes |
| R. C. Amland [26] | No | No | No | No | Yes | Yes |
| X. Liu [27] | No | No | No | No | No | Yes |
| J. Sper-Hillen [28] (CV Wizard) | Yes | No | No | Yes | No | Yes |
| S. Nazari [29] | Yes | No | No | Yes | No | No |
| D. A. Ferrucci [30] (IMB Watson) | Yes | No | No | Yes | Yes | Yes |

and feed his expertise to the system.

Middleton et al. [31] has thoroughly analyzed the past 25 years retrospective and also has defined the next 25 years' vision of CDSS. In their study the authors have considered all six axes (data, knowledge, inference, architecture and technology, implementation and integration and users) for achieving their goal. Also in the next 25 years, all the barrier will be removed and CDSS will dramatically change the diagnosis and treatment procedure by adapting new techniques for all six axes.

To take advantages of technology improvement like in all other fields, medical domain utilizes the intelligence and advanced technology for taking intelligent decisions in the form of CDSS along with other utilization. Available features of the existing CDSS are compared and depicted in 〈table 1〉. CDSS brought tremendous improvement in diagnoses, treatment and reducing clinical cost. It utilized maximum resources for knowledge extraction to get maximum intelligence. It works side by side with domain experts and assist them in taking complex decisions in all domain and all stages. The confidence of domain experts on CDSS decision is increasing with the passage of time. On the basis of investigation of the existing work, traditional approaches used for knowledge acquisition, validation, and evolution are still not mature enough to address the following issues.

i. A toolset support to facilitate the knowledge acquisition for the domain experts.

ii. Validation of the knowledge acquired from diverse sources such as clinical practice guidelines (CPGs) and patient data.

iii. An evidence support for keeping the knowledge base up-to-date with global advancements in the domain.

To approach these issues, we propose a comprehensive framework called Smart CDSS that incorporates components for the solution of the issues mentioned above.

## Ⅲ. Smart CDSS: Example Clinical Scenarios

Smart CDSS is using clinical knowledge models and produces recommendation. As shown in 〈Figure 2〉, the scope of the Smart CDSS is to cover-up multiple diseases with respect to diagnosis, medication and treatment planning. The clinical knowledge for Smart CDSS comes from diverse sources – such as medical data and the clinical practice guidelines (CPGs) provided by domain expert. For example, the clinical knowledge is acquired from CPGs and plugged into home healthcare environment for medication intervention for dementia. In this way, the clinical knowledge is acquired from medical data as well as CPGs from treatment planning of oral cancer and for head and neck cancer.

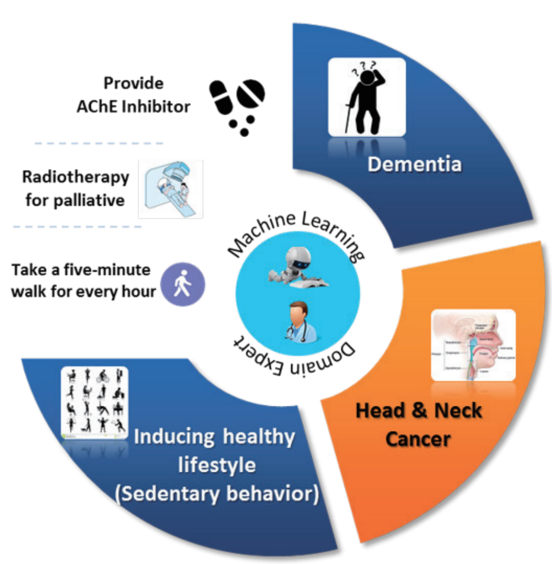


Figure 2. Smart CDSS Scope

In this article, we will introduce two scenarios of Smart CDSS for medications delivery and treatment plan as a contemporary framework for clinical decision support.

### 1. Medication Management at Home Health Environment

Smart CDSS framework with clinical knowledge module has capability to produce expert-based recommendations. 〈Figure 3〉 shows Smart CDSS as an external module to produce medication recommendation for patient with Alzheimer or dementia symptoms.

The flow of information and Smart CDSS medication recommendation is explained as follows:

- Overall Patient Care Environment is divided into five processing pools: i) Patient Activities, ii) Care-giver environment, iii) Home Health Care, iv) Recommendation, and v) Physician setup.
- Patient Activities covers all of the activities related to manage medication at patient site. The patient is provided with recommendation for medication based on his/her status.
- Caregiver environment is the core processes pool for medication management. The caregiver, initiate the medication delivery and management based on the prescribed medication plan or may change based on the status of the patient at time of medication delivery. The change in medication prescription needs proper approval and hence provides exact status of the patient to the physician. The caregiver interacts with Home Health Care environment to get patient status and initiate Recommendation pool to get suggested recommendation from Smart CDSS for update-prescriptions. After Smart CDSS recommendations, the updated prescriptions are approved from the physician. The approval process is comprehensive enough so that to make sure the medication delivery has authorized approval and managed on correct time.
- The Recommendation pool represents the Smart CDSS plugin to the patient care environment for medication recommendation. The clinical knowledge base

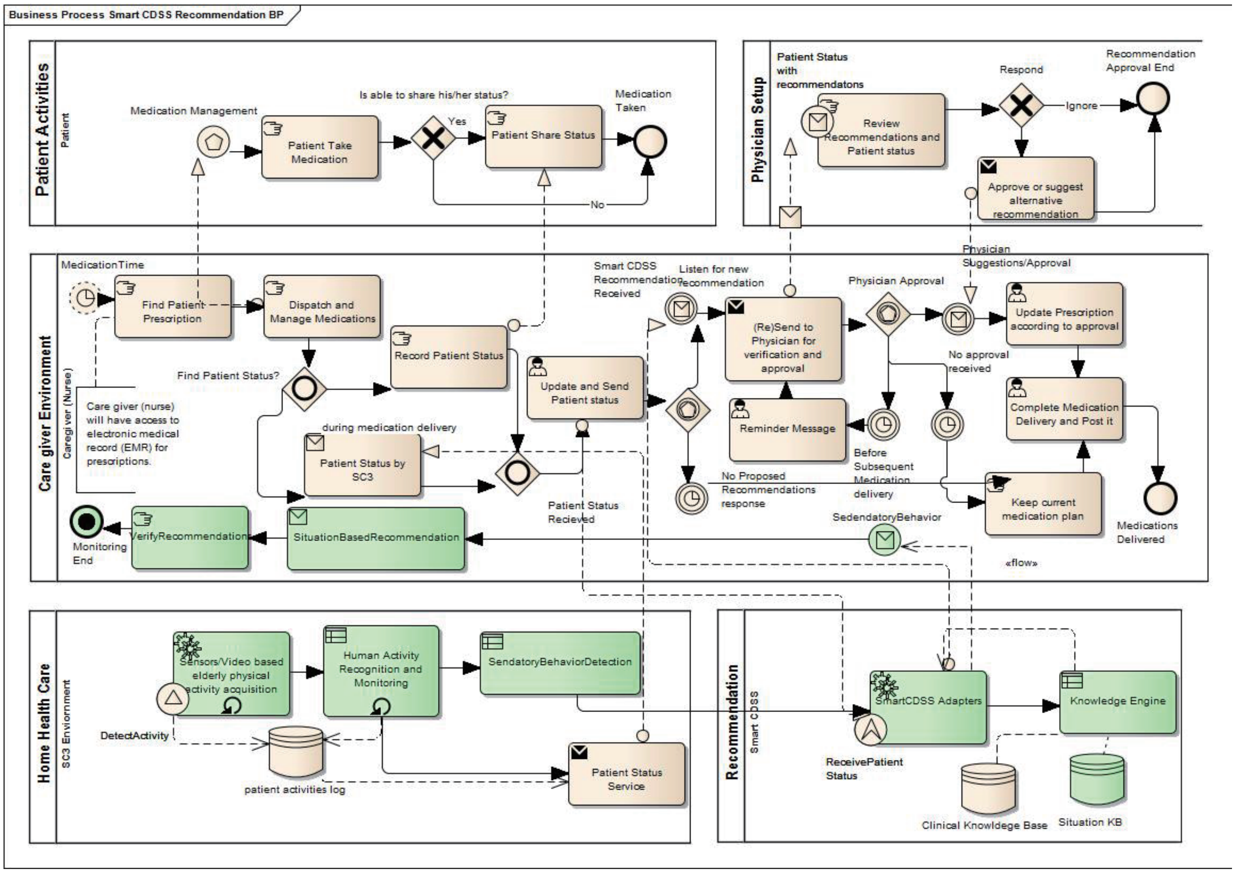


Figure 3. Smart CDSS Recommendation Process

comprises clinical rules relevant to disease specific medications (For Alzheimer and Dementia in this case).

- Home Health Care encapsulates the processes related to activity recognition modules of external platform. The environment is equipped with multimodal sensors and cameras' for detecting the behavior of patients and sharing status and any other sedentary behaviors with caregiver.
- The physician setup represents the remote services of physician for monitoring and approving the change in medication plan suggested by Smart CDSS shared via caregiver.
- Starting from the caregiver environment, the time-based medication delivery is started and the final medication is delivered to patient based on the patient status, suggested by Smart CDSS and off course approved by the physician.
- During all these medication management process, caregiver is facilitated to automatically find the patient status via the Home health care environment. The recommendation environment supports the final medication delivery.

While enabling automated recommendation via Smart CDSS, the overall platform is managing the medications for Alzheimer and dementia patients with semi-automated fashion by reducing less involvement of physician directly to the patient. This process reduces healthcare cost and improves patient care with efficient automated delivery process.

## 2. Diagnosis and Treatment Plan for Oral Cancer

Smart CDSS as a service was initially demonstrated for oral cavity cancer. Oral cavity cancer is the most frequently occurring disease in the head and neck site.

Smart CDSS was introduced to provide intervention during diagnosis of cancer stage and enable suggestion for appropriate treatment plan for oral cavity cancer patients. 〈Figure 4〉 covers up the main process flow of diagnosis and treatment plan at hospital.

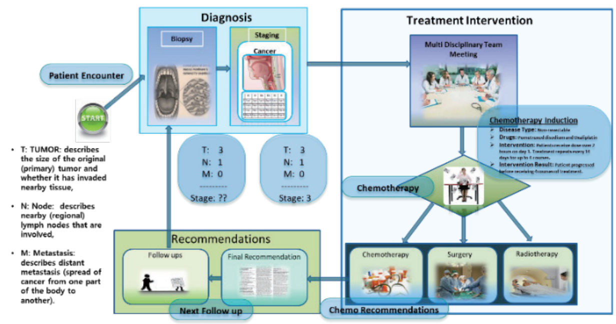

Figure 4. Head and Neck Cancer Diagnosis and Treatment Process

During oral cavity cancer treatment process, Smart CDSS interventions are introduced as follows:

- At initial stage during patient encounter, the patient basic symptoms are recorded. At this stage – Smart CDSS is passive.
- In order to proceed for any diagnosis decision, the physician orders several laboratory tests and other procedures. For example, in oral cancer biopsy is one of the procedures for diagnosis. At current stage CDSS can help but the scope of Smart CDSS is only processing the structured data and recommendation which are based on predefined CPGs.
- The clear distinction of the diagnosis is made after evaluating the various results from laboratory reports. The diagnosis is finalized by categorizing the cancer extent of spreading throughout the body site. The physician uses well-established tumor guidelines for categorizing the clinical stage. In Smart CDSS, the clinical knowledge is equipped with rule set following the TNM clinical staging guidelines. Physician estimate the T (Tumor), N (Node), and M (Metastasis) extent of cancer from different laboratory observations and submit it to the final clinical stage. The Smart CDSS provide final clinical stage based on the rule set in the knowledge base.
- After diagnosis, the treatment plan is the crucial task for physicians. In oral cancer, there can be more than one possible treatment plan but may differ with ultimate outcomes based on the patients' personal characteristics and other medical history. The tentative treatment plan includes Chemotherapy, Radiotherapy, Surgery and other combination of any of these preliminary treatments. In order to cope with this challenge, the team of physicians meets together and arranges a multidisciplinary conference. In conference, all the stakeholders – such as oncologist, radiologists, surgeons and other associated clinicians are invited. With their own opinion, all of the members suggest a treatment plan which may differ from each other. After carefully evaluating each treatment plan for expected outcome, they make consensus and finalize the treatment plan. At this stage, Smart CDSS support the decision-making by participating as a virtual doctor whose decision is purely based on the clinical knowledge comes from local evidences and CPGs. The Smart CDSS recommendation is also considered as an additional opinion and evaluated side-by-side with other opinions. Smart CDSS recommendation is worth as compared to individual opinions in terms as it accesses all relevant data of the patient, so for as other doctors have knowledge about particular symptoms of the patient. So if properly designed the clinical knowledge, Smart CDSS opinion can get trust as an expert's opinion in clinical decision making.
- After the treatment plan, the treatment is started and patient symptoms are evaluated where Smart CDSS helps in providing appropriate recommendation for next follow-ups with appropriate set of actions.
- The process of treatment is continued and may take several iterations, where Smart CDSS recommendations can help at each stage of the patient care.

The most important and challenging task for CDSS is the quality of knowledge acquisition. The next sections explain briefly about the process of knowledge acquisition.

## Ⅳ. Knowledge Acquisition of Smart CDSS

The most important aspect of Smart CDSS is unique approach for knowledge acquisition and final

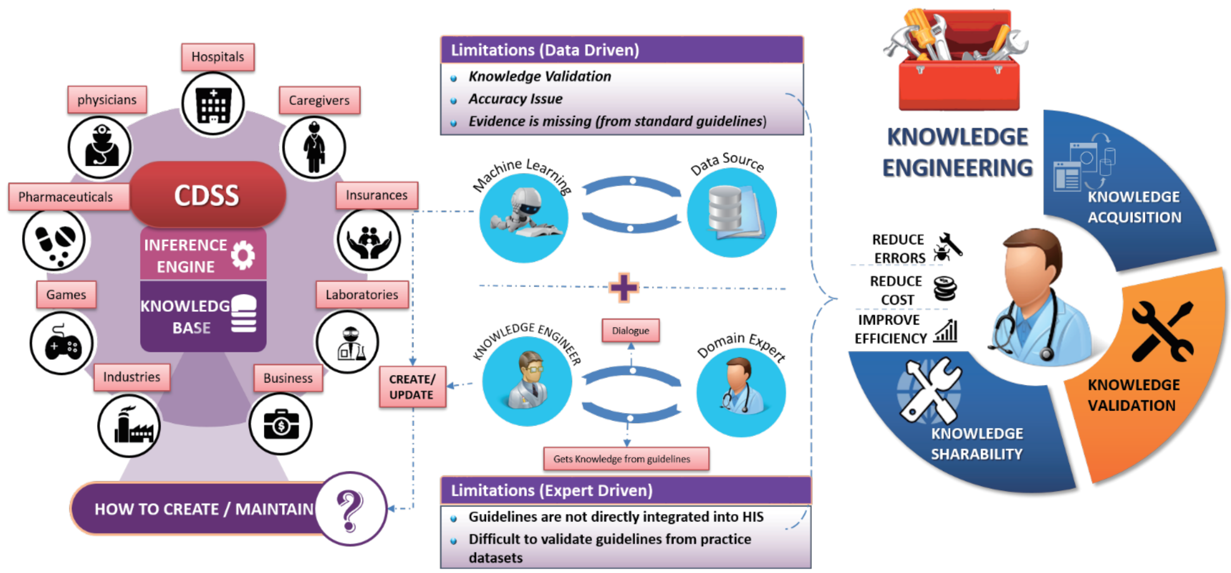


Figure 5. Smart CDSS Knowledge Acquisition Approach

recommendation model. Keeping in mind the importance of local evidences, Smart CDSS uses patient data to acquire the clinical model for recommendation using machine-learning approaches. At the same time, the clinical knowledge from CPGs is acquired. As an individual knowledge model, it has been revealed that the recommendation models are faced with many limitations. To cope with these limitations, Smart CDSS clinical knowledge is created by combining machine-learning model with CPGs model after rigorous validations. The abstract view of the individual approaches and motivation for combined approach is depicted in 〈Figure 5〉.

In order to get final executable knowledge for Smart CDSS, a model known as three-phase model is used[32]. The task performed at each phase is given as follows.

*Phase-1*: The use of quality document for knowledge extraction directly affects the performance of a system. CPGs are considered as one of the highest quality knowledge resource in healthcare domain. However for quality knowledge extraction, CPGs needs to be evaluated to assure the quality. Therefore, the first phase in smart CDSS identifies the quality of CPGs. The CPGs are selected and analyzed by team of physicians and computer scientists and produce the initial clinical knowledge model (CKM). 〈Figure 6〉 depicts the main concept of inspection of acquiring knowledge from CPGs.

*Phase-2*: To maximize advantages and complete the knowledge base, we utilized patient data for finding hidden pattern and knowledge in the data. Therefore, we are using the conventional machine learning approaches and create prediction model (PM) from existing patient data. In case of oral cavity cancer, we have used dataset of 1229 patient to create PM with overall accuracy of 71%. The PM and CKM are combined with rigorous validation process and produce the final refined clinical knowledge model (R-CKM).

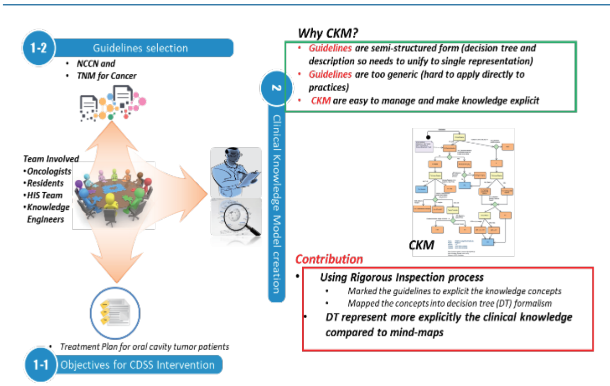


Figure 6. Clinical Knowledge Model Creation

*Phase-3*: The R-CKM is converted into final sharable and executable knowledge – called MLM (medical logic modules). The final executable knowledge is also known as computer interpretable guidelines (CIGs) if the knowledge is created from CPGs. From R-CKM (as candidate for CPGs) to MLMs (candidate CIGs), there are various options to generate the final knowledge. For Smart CDSS we use multiple dependent MLMs with Root and sub-MLMs approach.

Using this approach, we achieve high reusability, single request for data when needed, and allows modular approach for MLM design. The only key challenge we are facing is to define scope of logic per MLM and equal distribution of the knowledge concepts among multiple MLMs.

To prove our superiority on other system the comparison of other approaches compared to our approach with full descriptions are provided in ⟨Figure 7⟩.

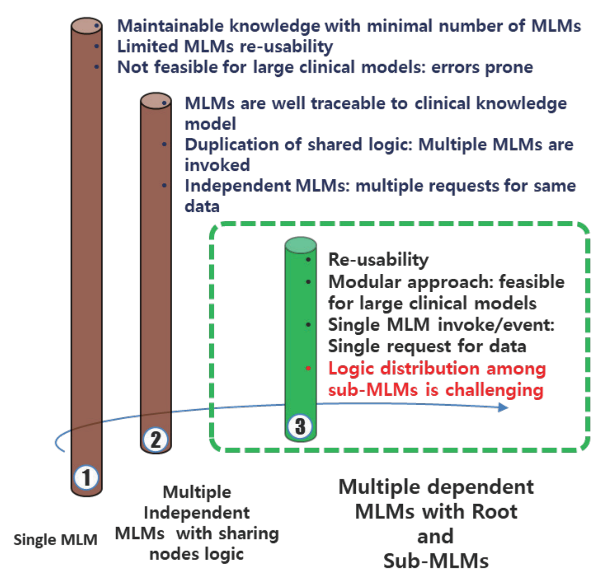


Figure 7. MLM generation strategies.

Conversion of the R-CKM into MLMs is a complex and tedious task. To hide the complexity and facilitate the domain expert in converting the R-CKM into MLMs, we also provide the Intelligent Knowledge Engineering Toolkit (I-KET). The I-KET is equipped with state of the art and easy to use interface, which allows domain expert to easily convert the R-CKM into MLMs. In general, the I-KET provides couple of features in managing the final MLMs. ⟨Figure 8⟩ depicts the high-level feature description of I-KET.

The I-KET has improved the physician performance 28-times greater than the commercially available

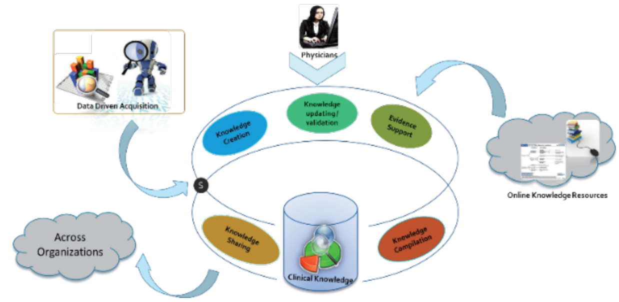


Figure 8. I-KET Features

knowledge acquisition toolset. Furthermore, it also facilitates in validation of rules by eliminating most of the errors including syntax errors that comes with complexity of knowledge acquisition toolset[33].

## V. Architectural View of Smart CDSS

Smart CDSS follow hybrid architectural approach for knowledgebase and recommendation sharing. It consumes the event in healthcare system as CDSS intervention and produces the recommendation using service model with HL7 vMR as standard interfaces. At the same time, the knowledge is encoded as standard sharable knowledge using HL7 medical logic modules (MLM) following HL7 Arden Syntax specification in conjunction with HL7 vMR specification for data model.

In addition to the recommendation framework, Smart CDSS is also equipped with state of the art knowledge acquisition toolkit – called I-KET[34]. Moreover, Smart CDSS is also integrated to online evidence based support using KnolwegeButton tool. ⟨Figure 9⟩ depicts the high level architecture of Smart CDSS and subsequent section briefly highlights the functions of each component. For detailed overview of each component, readers are recommended to consult the already published papers mentioned as references in the corresponding module section.

***Knowledge Engine***: Smart CDSS knowledge engine is the core component which holds the sharable knowledge represented in set of MLMs using HL7 Arden Syntax. The key novelty of the knowledge representation is two-fold: i) the encoded MLMs are following HL7 vMR standard to enable

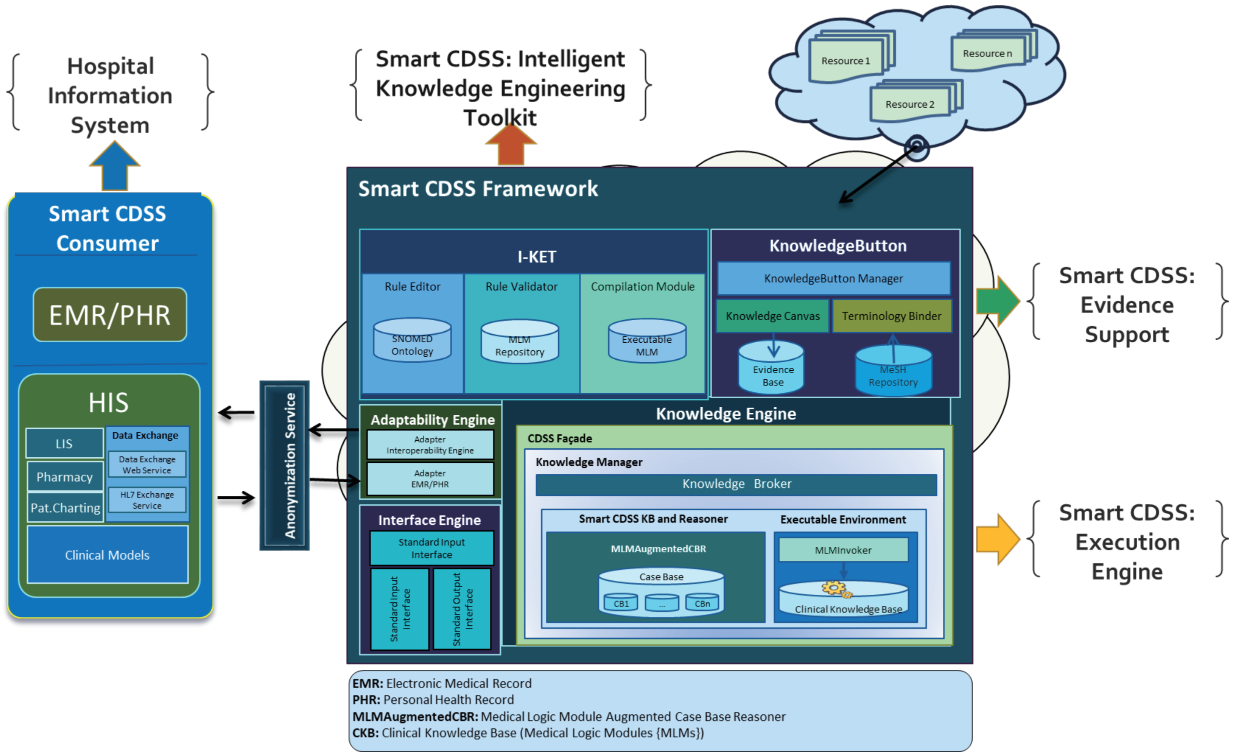


Figure 9. Smart CDSS Architectural View

directly pluggable knowledge for HIS systems conform to any HL7 standards, and ii) the MLMs are supported with novel validation mechanism to ensure consistency in the evolving and rapidly changing medical knowledge.

The first key feature is implemented as integral part of the Execution Environment where the validation process is implemented as case base reasoning enabled rule base validation mechanism – known as MLM Augment CBR. Moreover, assistive components such as Knowledge Manager provide flexibility in scheduling appropriate MLM for execution and inter-communicating the CDSS intervention in the coordinating components.

*I-KET*: Intelligent Knowledge Engineering Toolkit is key supporting tool for knowledge acquisition[34]. It uses a novel approach of reconciling various standard models such as HL7 vMR, SNOMED CT vocabulary, and domain models used at healthcare organization. The reconcile model – known as Semantic Reconciliation Model (SRM) enables creation of sharable knowledge which is interoperable with healthcare system workflows. Moreover, the concepts are reconciled with local domain, so the domain experts are allowed to use localized concepts in knowledge creation. The I-KET automatically converts the knowledge rules written in local concepts into standard MLMs.

*KnowledgeButton*: KnowledgButton is supporting toolset which provide additional evidence for generated recommendations[34]. It consumes the knowledge module – i.e. MLM, which is used in recommendation and construct standard query for PubMed. The query results are filtered against quality criteria indigenously developed in the toolset and present the most relevant study that may have close association to the generated recommendations.

*Adaptability Engine and Interface Engine*: Adaptability Engine (AE) and Interface Engine (IE) are two key components which play role in integration of healthcare system to the Smart CDSS. AE has the capability of providing conversion between HL7 vMR and other HL7 standards such as HL7 CDA. The implementation of this module is well tested with HL7 CDA[35]. IA is defining the key interfaces of Smart CDSS following standard input and output specifications of the HL7 vMR standards. These key interfaces are also exposed to external healthcare system for interacting with Smart CDSS.

## VI. Conclusion

This work presented state of the art CDSS systems and their effectiveness in improving patient health and reducing medical cost. The systems presented in this article have adopted unique and distinguished approach for achieving their desired goal and target. This study found out few of the outstanding issues still exists in the traditional approaches used for knowledge acquisition, validation, and evolution. As a case study, we presented our smart CDSS, its knowledge acquisition with authoring techniques, knowledge execution with guideline enabled data driven validation, and knowledge evolution with scientific evidence adaption from biomedical literature.

Future work will expand this work to include more sophisticated methods for knowledge acquisition including dialog mechanism. The dialogue facility will facilitate the user to intervene by talking to the system. Also, the system will be exposed to incremental knowledge acquisition with a real-time validation approach. Furthermore, it will also consider the automatic knowledge verification technique to verify the generated MLM.

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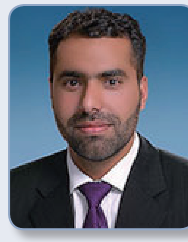

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