Università degli Studi di Trieste

Corso di Laurea Magistrale in
INGEGNERIA CLINICA

# CLINICAL DECISION SUPPORT SYSTEMS

## Corso di Informatica Medica

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# DEFINITIONS

- "A computer program that helps physicians to make diagnoses."
- "Any computer program designed to help healthcare professionals to make clinical decisions. In a sense, any computer system that deals with clinical data or knowledge is intended to provide decision support."
- "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"

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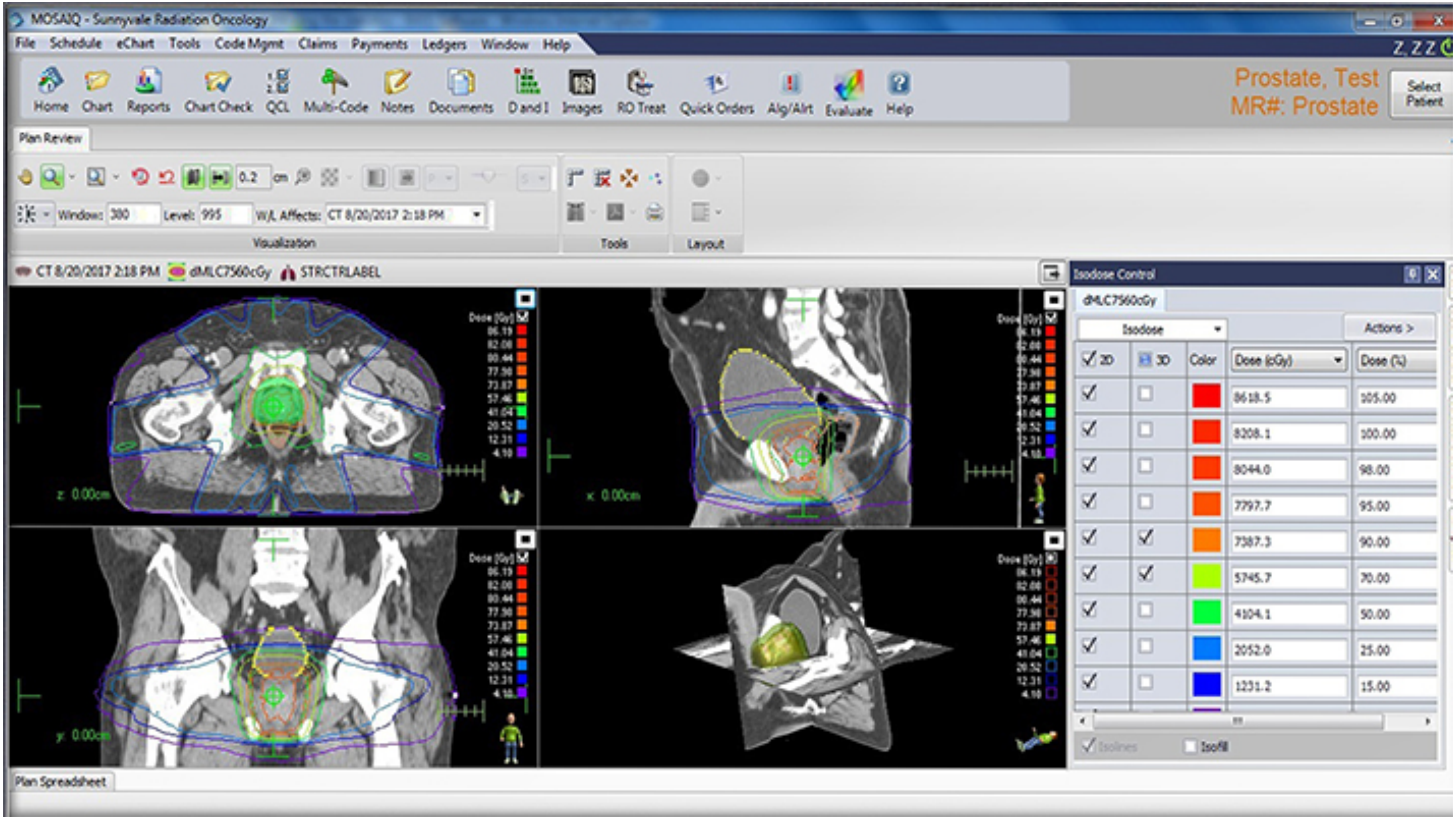
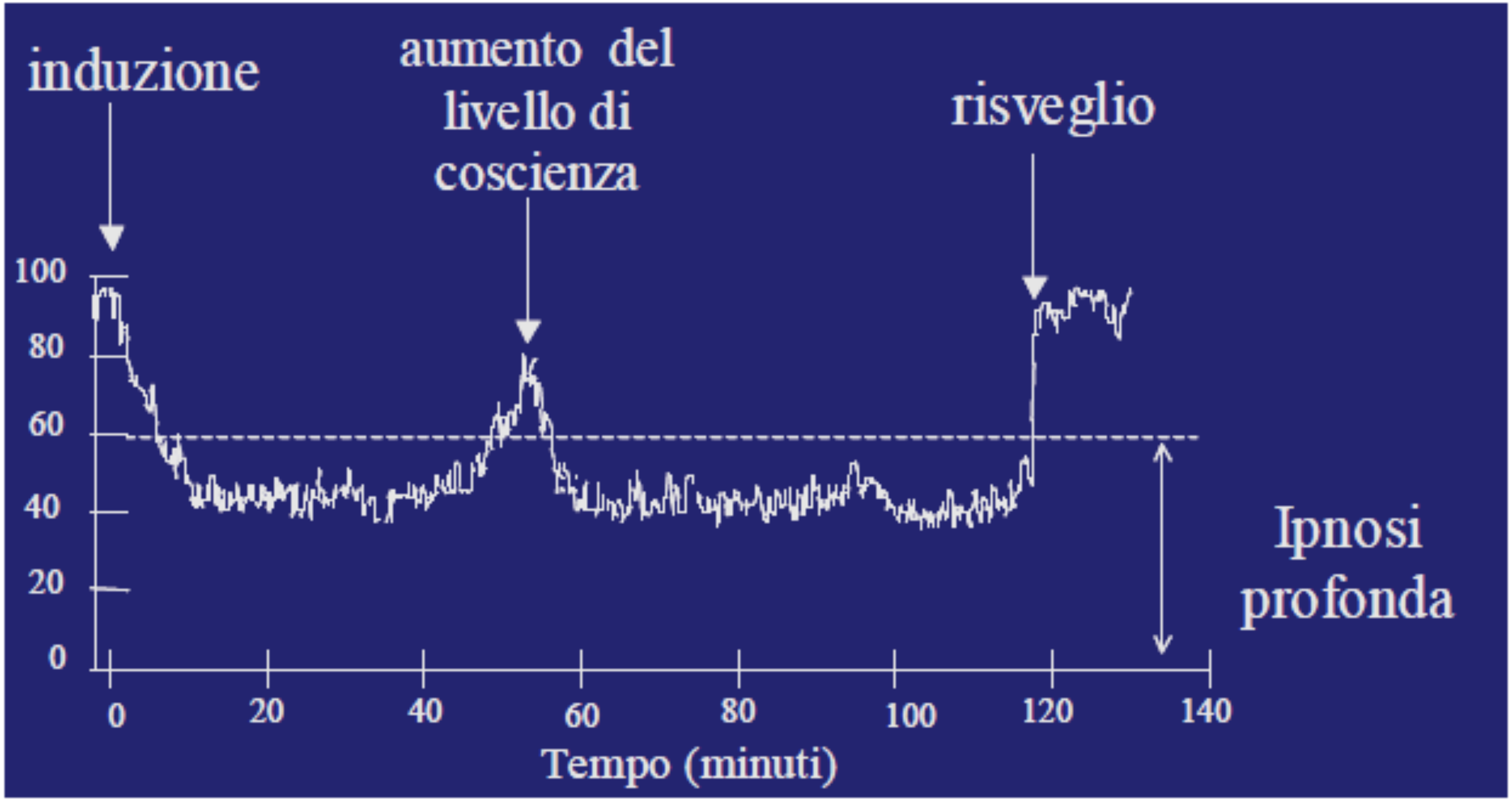
# EXAMPLE



# EXAMPLE



induzione
aumento del livello di coscienza
risveglio
100
80
60
40
20
0
0
20
40
60
80
100
120
140
Tempo (minuti)
Ipnosi profonda

# TYPES OF DECISIONS

## DIAGNOSIS →

- analyzing available data to determine the pathophysiologic explanation for a patient's symptoms

## DIAGNOSTIC PROCESS →

- deciding which questions to ask, tests to order, or procedures to perform and determining the value of the results relative to associated risks or financial costs.

## PATIENT'S MANAGEMENT →

- Treat or not?
- Which treatment?
- Patient's preference?
- Constraints?

## OTHER TYPES OF DECISIONS:

- Epidemiology
- Health policies
- Biomedical experiments

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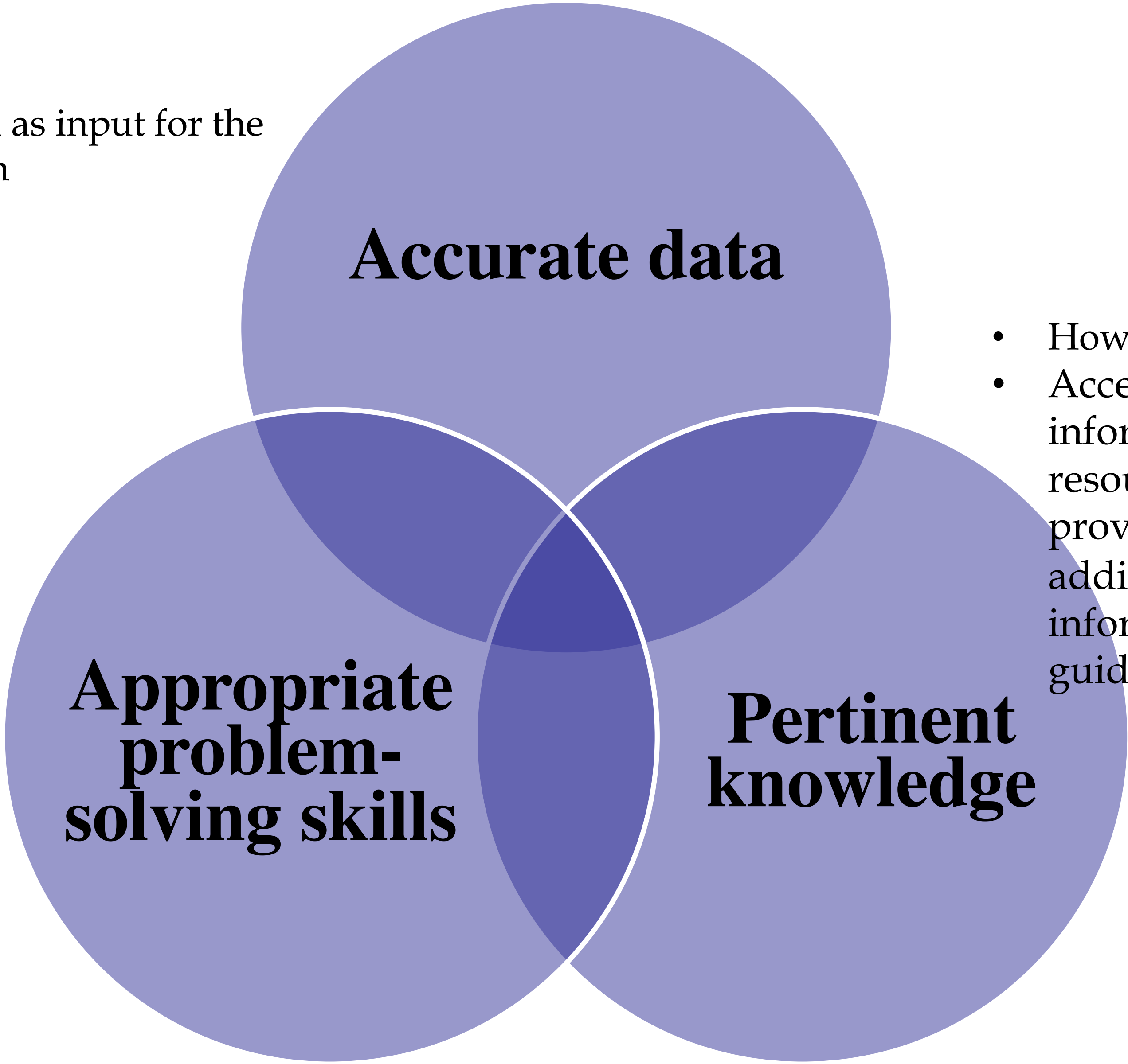
# REQUIREMENTS

Needed as input for the decision




- How to use data
- Access to information resources that provide pertinent additional information (e.g. guidelines)

- Set appropriate goals for a task
- Reason about the goals
- Evaluate trade-offs between costs and benefits

# DATA

- Data should be adequate but NOT EXCESSIVE
- Data should be processed and synthesized
- Additional data may confuse rather than clarify (e.g., operating room and intensive-care units)
- Quality of the available data →
  - Terminology Imprecision
  - Lack of standardized language
  - Precision of instrumentation
  - Need of data validation

# TOOLS

## TOOLS FOR ADVANCED INFORMATION MANAGEMENT

- Storage and management of information
- Augmentation tools
- Interpretation is left to clinician

## TOOLS FOR FOCUSING ATTENTION

- Alert and flags of abnormal values
- Reminders
- They use simple logics

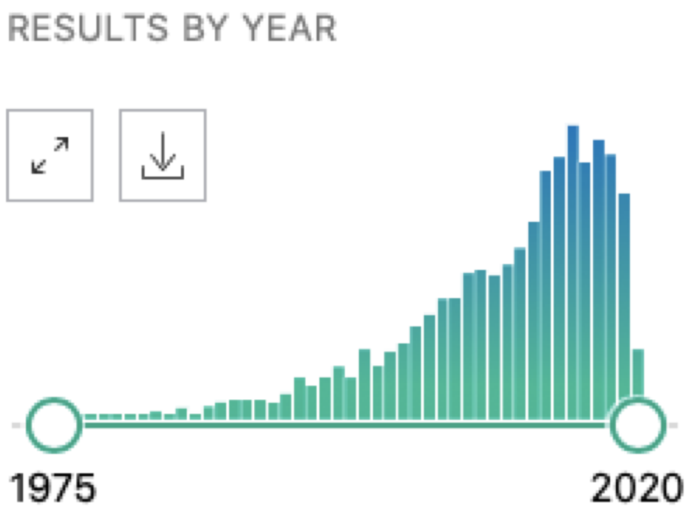
## TOOLS FOR PROVIDING PATIENT-SPECIFIC RECOMMENDATIONS

- Custom-tailored assessments or advice based on sets of patient specific data.
- They may follow simple logics (such as algorithms), may be based on decision theory and cost–benefit analysis, or may use numerical approaches only as an adjunct to symbolic problem solving.

# HISTORY

- Early 60s → experimental prototypes
- Three advisory systems from the 1970s are the pioneers:
  - deDombal's system for diagnosis of abdominal pain (de Dombal et al., 1972)
  - Shortliffe's MYCIN system for selection of antibiotic therapy (Shortliffe, 1976)
  - HELP system for delivery of inpatient medical alerts (Kuperman et al., 1991; Warner, 1979).
- Later development

PubMed.gov



# deDOMBAL



- Late 1960s, University of Leeds
- Computer-based decision aids using Bayesian probability
- The system was called Leeds abdominal pain system
- It used sensitivity, specificity, and disease-prevalence data for various signs, symptoms, and test results to calculate the probability of seven possible explanations for acute abdominal pain (appendicitis, diverticulitis, perforated ulcer, cholecystitis, small-bowel obstruction, pancreatitis, and nonspecific abdominal pain).
- High accuracy (91.8%) as compared to clinicians' diagnoses (65-80% accuracy). (Program's accuracy regarding appendicitis was 100%)
- However, it worked only in Leeds:
  - variation in the way that clinicians interpret the data that must be entered into the computer.
  - different probabilistic relationships between findings and diagnoses in different patient populations.

# MYCIN



- A consultation system on appropriate management of patients who have infections
- Not statistical approach but rule-based approach
- Knowledge of infectious diseases in MYCIN was represented as production rules:
  - knowledge derived from discussions with collaborating experts
  - Conditional statements that relate observations to associated inferences that can be drawn. MYCIN's power was derived

# EXAMPLE OF RULES

**Rule507**

| | | |
|---|---|---|
| IF: | 1) | The infection that requires therapy is meningitis, |
| | 2) | Organisms were not seen on the stain of the culture, |
| | 3) | The type of infection is bacterial, |
| | 4) | The patient does not have a head injury defect, and |
| | 5) | The age of the patient is between 15 years and 55 years |
| THEN: | | The organisms that might be causing the infection are diplococcus-pneumoniae and neisseria-meningitidis |

**Figure 20.1.** A typical rule from the MYCIN system. Rules are conditional statements that indicate what conclusions can be reached or actions taken if a specified set of conditions is found to be true. In this rule, MYCIN is able to conclude probable bacterial causes of infection if the five conditions in the premise are all found to be true for a specific patient. Not shown are the measures of uncertainty that are also associated with inference in the MYCIN system.

# HELP

- Integrated hospital information system developed at LDS Hospital in Salt Lake City.
- HELP has the ability to generate alerts when abnormalities in the patient record are noted
- Grounded the development of Arden Syntax

# LANGUAGES:
# Arden syntax

- AIM → structuring and sharing knowledge

- STANDARD LANGUAGE →

  1994 – American Society for Testing Materials (ASTM)

  now – American National Standard Association (ANSA)

- USE→
  - Implementation of medical knowledge bases
  - Alarms and alerts generation
  - Diagnosis interpretation
  - Clinical studies screening
  - Message delivery managment

# ARDEN SYNTAX: medical logic modules

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DB managment

MAINTENANCE

File identification

LIBRARY

File content description

Real guideline

KNOWLEDGE

Decision rules and actions

- Three modules structure
- ASCII files (textual description)

```
maintenance:
    title: ______________________;;   (some brief description)
    filename: ______________;;   (a unique name for the MLM)
    version: 1.00;;   (always start with 1.00)
    institution: ____________________;;   (your affiliation)
    author: ______________________;;   (your name)
    specialist: ;;   (always blank to start)
    date: _______________;;   (today's date, like 1993-10-31)
    validation: testing;;   (start with testing)
library:
    purpose:   (why would you use the MLM)
        ______________________________________________
        ______________________________________________;;
    explanation:   (how does the MLM work)
        ______________________________________________
        ______________________________________________
        ______________________________________________
        ______________________________________________;;
    keywords:   (words or phrases that describe the MLM)
        ____________; ____________; ____________;;
knowledge:
    type: data-driven;;   (always data-driven)
    data:   (define the event used in the evoke slot, and read data for the logic slot)
        ______________________________________________
        ______________________________________________
        ______________________________________________
        ______________________________________________
        ______________________________________________;;
    evoke: _______________;;   (what event should trigger this MLM)
    logic:   (create the logic necessary to carry out the task and conclude true when
        you want to write a message)
        ______________________________________________
        ______________________________________________
        ______________________________________________
        ______________________________________________
        ______________________________________________;;
    action:   (write a message, combining narrative text and calculated values)
        ______________________________________________
        ______________________________________________
        ______________________________________________;;
end:
```

# ARDEN SYNTAX: example

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```
maintenance:
     title: Alert on low hematocrit;;
     filename: low_hematocrit;;
     version: 1.00;;
     institution: CPMC;;
     author: George Hripcsak, M.D. (hripcsa@cucis.columbia.edu);;
     specialist: ;;
     date: 1993-10-31;;
     validation: testing;;

library:
     purpose: Warn provider of new or worsening anemia.;;
     explanation: Whenever a blood count result is obtained, the
          hematocrit is checked to see whether it is below 30 or
          at least 5 points below the previous value.;;
     keywords: anemia; hematocrit;;

knowledge:
     type: data-driven;;
     data:
          blood_count_storage := event
               {'complete blood count'};
          hematocrit := read last
               {'hematocrit'};
          previous_hct := read last (
               {'hematocrit'}
               where it occurred before the
               time of hematocrit);;
     evoke: blood_count_storage;;
     logic:
          if hematocrit is not number then
               conclude false;
          elseif hematocrit <= previous_hct - 5
            or hematocrit < 30 then
               conclude true;
          endif;;
     action:
          write "The patient's hematocrit ("|| hematocrit ||") is
               low or falling rapidly.";;

end:
```

ALERT ON LOW HEMATOCRIT

# EVOLUTION OVER TIME

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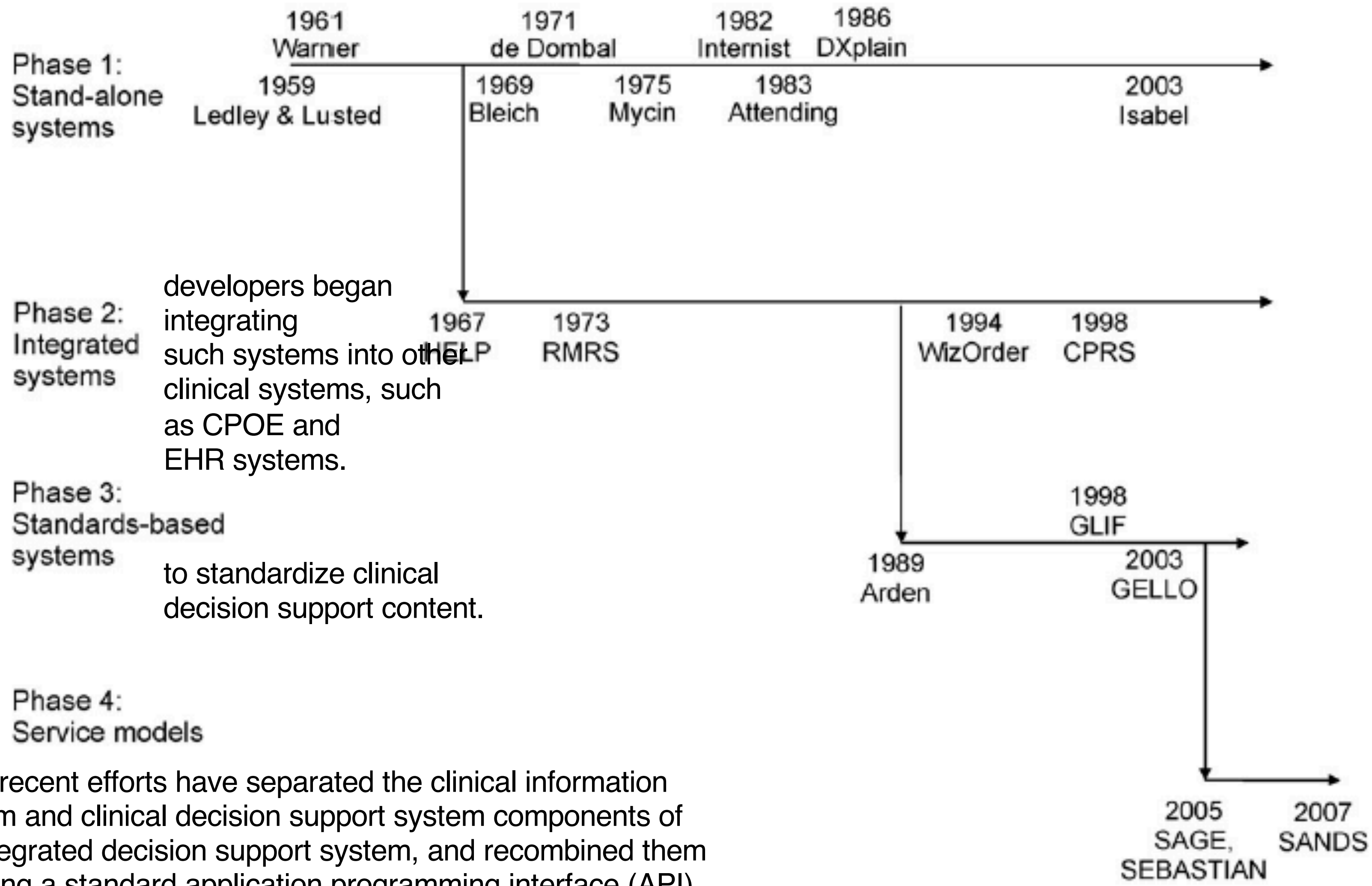


developers began integrating such systems into other clinical systems, such as CPOE and EHR systems.

to standardize clinical decision support content.

More recent efforts have separated the clinical information system and clinical decision support system components of an integrated decision support system, and recombined them by using a standard application programming interface (API).

**Fig. 1 – A schematic drawing of the four-phase model for clinical decision support.**

Wright and Sittig, Int J Med Info, 2008

# Lessons learnt from history

- Demonstrated the feasibility of encoding medical knowledge so that it could be processed by computers.
- Helped to clarify both the strengths and limitations of alternative knowledge-representation approaches.
- Evolution had four influences:
  - the emergence of personal devices, the World Wide Web, and easy-to-use interfaces, and mobile devices;
  - The need of transparency and integration with the work practices of groups that are asked to adopt new technologies;
  - the growing amount of information that practitioners need to practice medicine well and to avoid errors
  - the increasing fiscal pressure to practice costeffective, evidence-based medicine, which leads practitioners to consider carefully the clinical utility and reliability of tests, procedures, and therapies—especially when the latter are expensive or risky.

# CHARACTERIZATION FRAMEWORK

Five dimensions:

1. the system’s intended function
2. the mode by which advice is offered
3. the consultation style
4. theunderlying decision-making process
5. the factors related to human–computer interaction.

# SYSTEM INTENDED FUNCTION

- What is true →
  - what is the correct diagnosis based on a fixed set of data that are already available
  - May lead to the user the task of deciding what data to gather or requires a fixed set of data for all patients
  - Does not need the cost/benefit analysis

- What to do →
  - How to manage the patient (e.g., what kind of treatment, if any?)
  - Requires cost/benefit analysis

- Usually the systems mix the two functions

# THE MODE FOR GIVING ADVICE



| Passive (total control of the user) | Active (partial control of the user) |
| --- | --- |
| • the practitioner must recognize when advice would be useful and then must make an explicit effort to access the computer program;<br>• the decision-support system waits for the user to come to it.<br>• The clinician can accept or reject the advice | • provide decision support as a byproduct of monitoring or of data-management activities;<br>• such systems do not wait for physicians or other health workers specifically to ask for assistance<br>• The clinician can accept or reject the advice |

# STYLE OF COMMUNICATION

## Consulting model

- the program serves as an advisor, accepting patient-specific data, possibly asking questions, and generating advices and hypothesis

## Critiquing model

- the clinician has a preconceived idea of what is happening with a patient or what management plan would be appropriate.
- The computer then acts as a sounding board for the user's own ideas, expressing agreement or suggesting reasoned alternatives.

# THE UNDERLYING DECISION-MAKING PROCESS

- Logical rules based on experience
- Statistical approach
- Knowledge-based system → a program that symbolically encodes concepts derived from experts in a field—in a knowledge base— and that uses that knowledge base to provide the kind of problem analysis and advice that the expert might provide.

# HUMAN COMPUTER INTERACTION

- Efficacy is based also on user interfaces
- Decrease error probability
- Boost the adoption

# BUILDING WORKFLOW



### Acquisition and Validation of Patient Data

- How are data acquired?
- Is there data entry?
- Data representation? Standard languages?

### Modeling of Medical Knowledge

- How to model the domain? Medical Ontologies?
- Evolution of Medical Knowledge
- New knowledge creation/acquisition
- Representation of and Reasoning About Medical Knowledge

### Validation of system performance

- What is correctness?
- Is accuracy enough?

### Integration in clinical practice

- How to include the CDSS in the practice?
- How does it learn from experience?

# TELEMEDICINE AND DSS IN INTENSIVE CARE UNITS

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## Intensive Care Unit Telemedicine in the Era of Big Data, Artificial Intelligence, and Computer Clinical Decision Support Systems

Ryan D. Kindle, MD[a,b,1], Omar Badawi, PharmD, MPH, FCCM[a,c,d,2],
Leo Anthony Celi, MD, MS, MPH[a,b,*,1],
Shawn Sturland, MBChB, FANZCA, FCICM[a,e,1]

### KEY POINTS

- Telemedicine intensive care units (tele-ICUs) cover more than 11% of ICU beds in the United States and produce enormous quantities of data, which can be used to create machine learning algorithms.
- Tele-ICU systems including clinical decision support systems have been shown to improve adherence to ICU best practices.
- Machine learning algorithms exist for sepsis detection, sepsis management, mechanical ventilation, false-alarm reduction, and ICU outcomes; validation using external data sets is important.
- Translating ICU machine learning algorithms to the tele-ICU requires the ability to generalize and adapt to a tele-ICU work flow that manages larger populations.

# APPLICATIONS



**Table 1**
**Recent studies of machine learning applicable to critical care**

| | |
|---|---|
| Sepsis | • Numerous studies evaluating a variety of ML methods to predict sepsis 3–12 h before onset[37–42]<br>• Nonblinded randomized controlled trial of a proprietary ML algorithm (vs EMR severe sepsis alert) showed shorter ICU and hospital LOS and lower in-hospital mortality[43]<br>• Retrospective study of ICU complications before and after implementation of real-time predictive analytics monitoring display associated with decrease in sepsis incidence[44]<br>• Reinforcement learning model developed to assess optimal treatment of patients with septic shock (vasopressors vs IV fluids) predicted higher-value treatments than clinicians[45]<br>• Switching-state autoregressive model predicted vasopressor administration and successful vasopressor weaning[46] |
| Mechanical Ventilation | • Random forest algorithm showed significant agreement with clinical experts in detecting ventilator asynchrony[51]<br>• Multiple ML algorithms identified ventilator dyssynchrony, but the best-performing model differed by type of event[52]<br>• Gradient-boosted decision trees algorithm predicted need for prolonged mechanical ventilation (AUROC, 0.820) and tracheostomy (AUROC, 0.830) at time of ICU admission[53]<br>• Support vector machine algorithm trained using heart rate variability and patient-specific calibration data discriminated between light and deep sedation with 75% accuracy[54] |

# APPLICATIONS

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| | |
|---|---|
| False-alarm Reduction | • Random forest model trained on human annotated alerts discriminated between true and false alarms for peripheral oximetry, blood pressure, and respiratory rate[55]<br>• Multiple ML algorithms were used by teams competing to classify true and false arrhythmia alarms[56] |
| ICU Outcomes | • Gradient-boosting decision tree model developed using a single-center 14,962-patient cohort to predict the risk of ICU readmission was superior to other risk assessments (AUROC, 0.76 vs 0.58–0.65); validation in MIMIC-III had comparable results (AUROC, 0.71 vs 0.57–0.58)[57]<br>• Random forest model developed using a single-center 6376-patient cohort to predict hospital-acquired pressure injury had an AUROC of 0.79 for stage 1 and stage 2+ injuries[58]<br>• Recurrent neural network models developed using a single-center 9269-cardiac surgery patient cohort to predict mortality, renal replacement therapy, and postoperative bleeding requiring surgery outperformed other predictors in all outcomes (AUROCs of 0.95 vs 0.71, 0.96 vs 0.72, and 0.87 vs 0.53 respectively). Validation in MIMIC-III had comparable results[59]<br>• Unstructured text data added to ML models from MIMIC-III improved prediction of death or prolonged ICU stay. Gradient-boosted machines slightly outperformed random forests, elastic net regression, and logistic regression[60]<br>• Gradient-boosted decision tree model developed using a 53-center 237,173-patient ICU cohort predicted in-hospital mortality well (AUROC, 0.951 in training subset and 0.943 in validation subset)[61] |

# BARRIERS AND ACCEPTANCE



- Tele-ICU provides:
  - improved workflow
  - improved monitoring
  - rapid availability
  - specialty expertise
- Barriers:
  - Unrealistic expectations
  - Poor communication
  - Black-box decision
- Tele-ICU systems perceived to be “appropriate, responsive, consistent, and integrated with bedside workflows” were associated with decreased mortality after being deployed.
- Transparency of the decisions/suggestions is a requirement