

Connected Health Summer School

Artimino, Tuscany, Italy 26 -30 June 2017



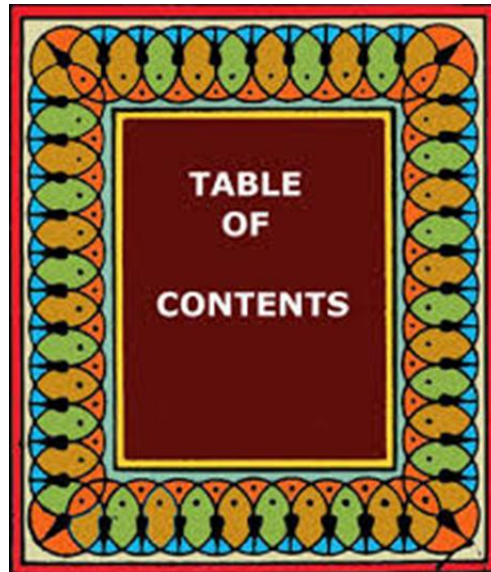
# Intelligent Medical Platform

June 25<sup>th</sup>, 2017

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Kyung Hee University, Korea



경희대학교  
KYUNG HEE UNIVERSITY



- Introduction to UC Lab., KHU, Korea
  - Preliminary Works - Smart CDSS
  - Video for Knowledge Construction
  - IMP(Intelligent Medical Platform)
  - Benefits & Lessons
  - Video for IMP Concept
- Appendix



[Professor Sungyoung Lee]



[Ubiquitous Computing Lab, **since 1993**]



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**Authored/coauthored more than 500 technical articles (190 of which are published in archival journals)**

**Current Members (25)**  
2 Post Doctorate Researchers  
14 PhD Students  
6 MS Students  
3 Undergraduate Students

## Major Projects



**2006- 2014**



**2014- 2018**

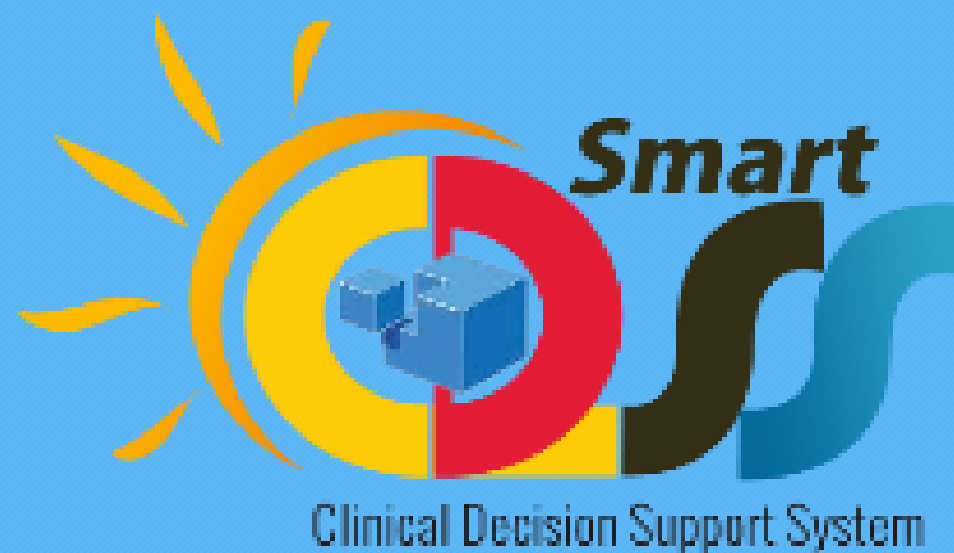


INTELLIGENT MEDICAL  
PLATFORM

**2017-2023**

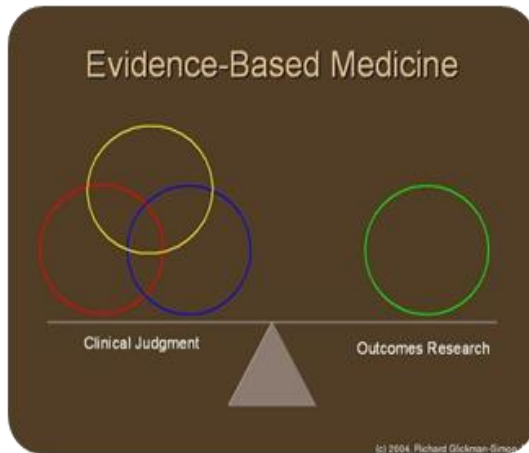
<b>Machine Learning</b>	Context Aware Computing	Ontology Engineering and Matching
Interoperability	Clinical Decision Support System (CDSS)	Knowledge Authoring Tool Development
<b>Big Data</b>	Activity and Emotion Recognition	uHealthcare
Security and Privacy	<b>User Experience</b>	Cloud Computing

# Smart CDSS

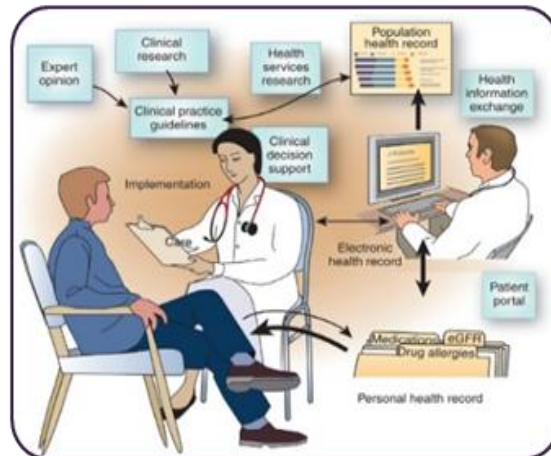




# What is CDSS (Clinical Decision Support Systems) & Why CDSS?



Decision Making



Clinical Practice Guidelines

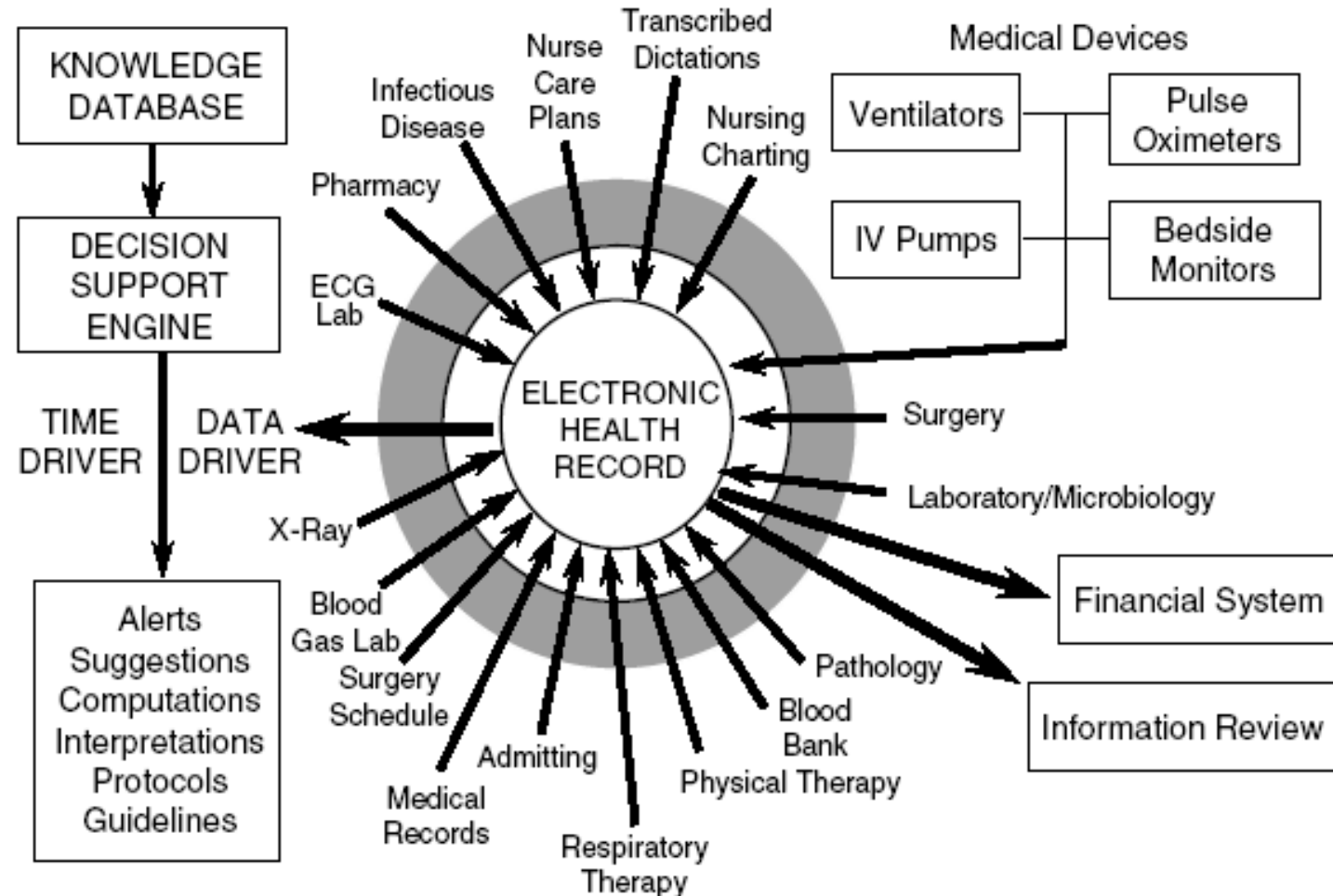


Efficiency of healthcare delivery

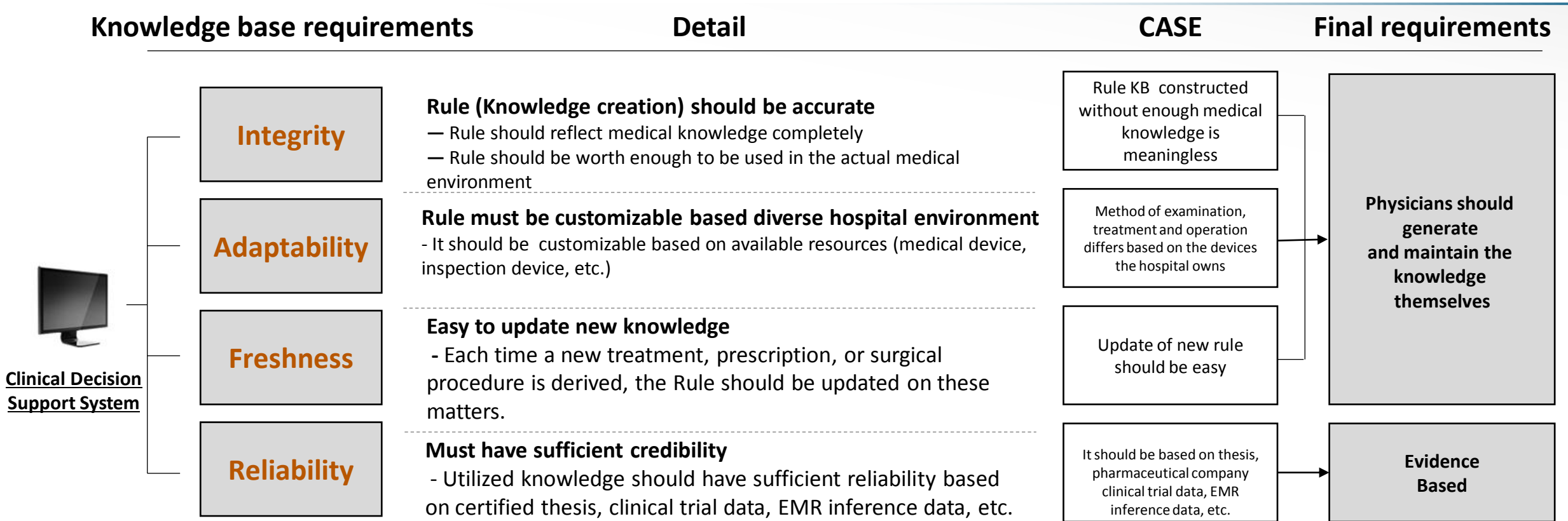


Patient Safety

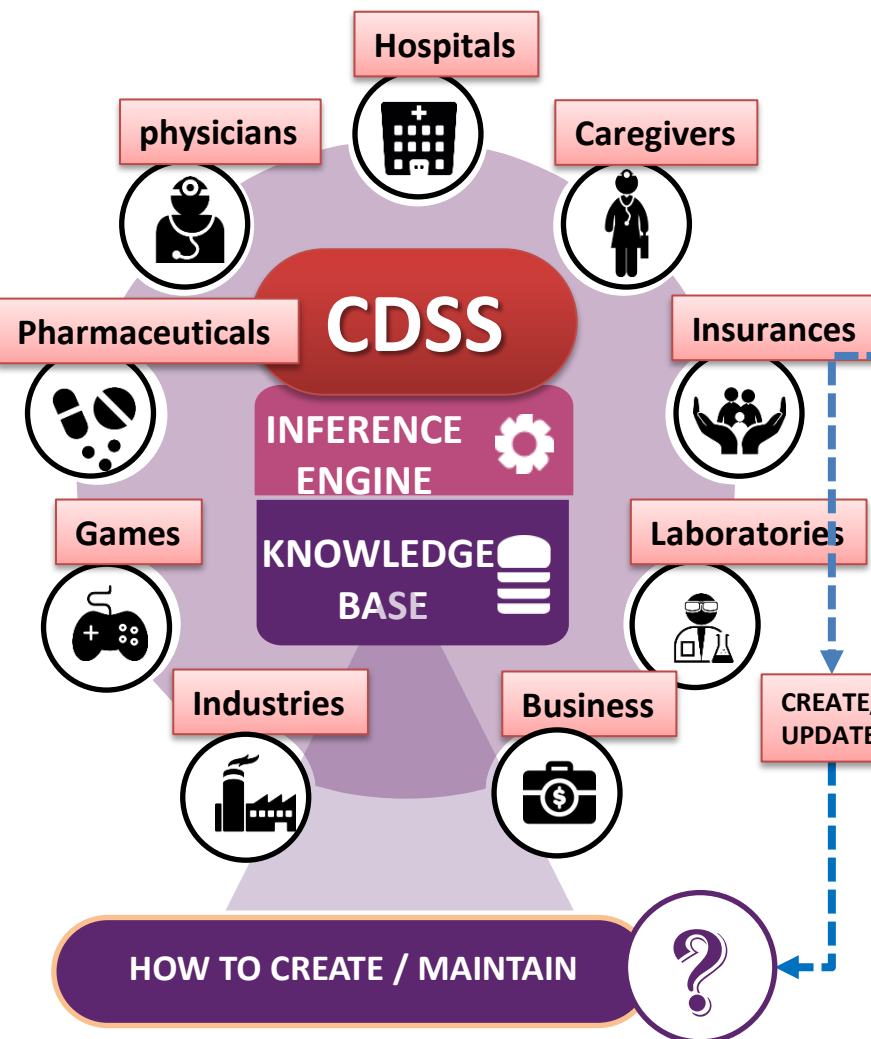
# CDSS Architecture in General



## Requirements of Knowledge Construction

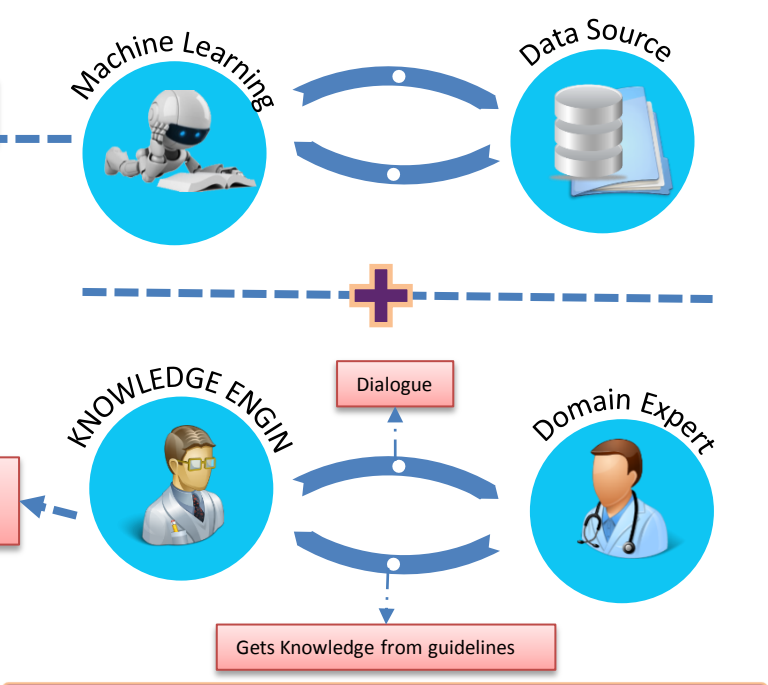






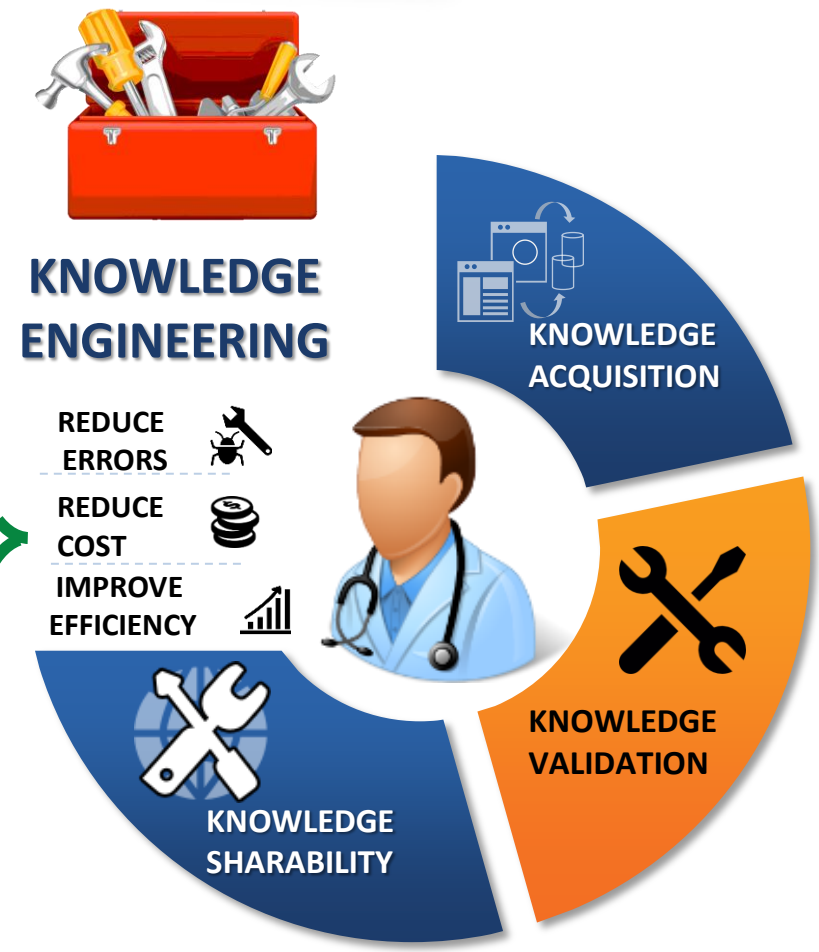
**Limitations (Data Driven)**

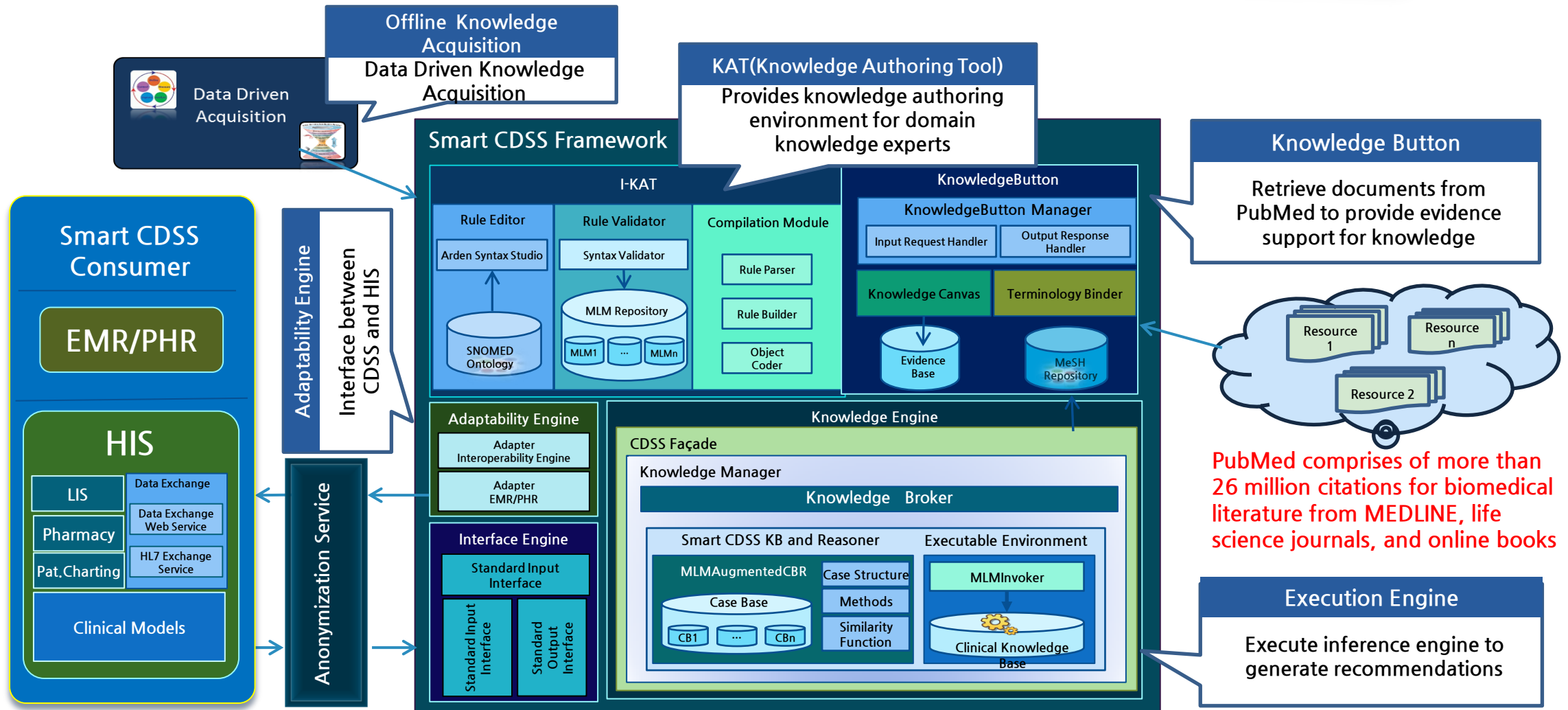
- Low level of Knowledge accuracy
- Hard to know the reason for decision making (Black Box)



**Limitations (Expert Driven)**

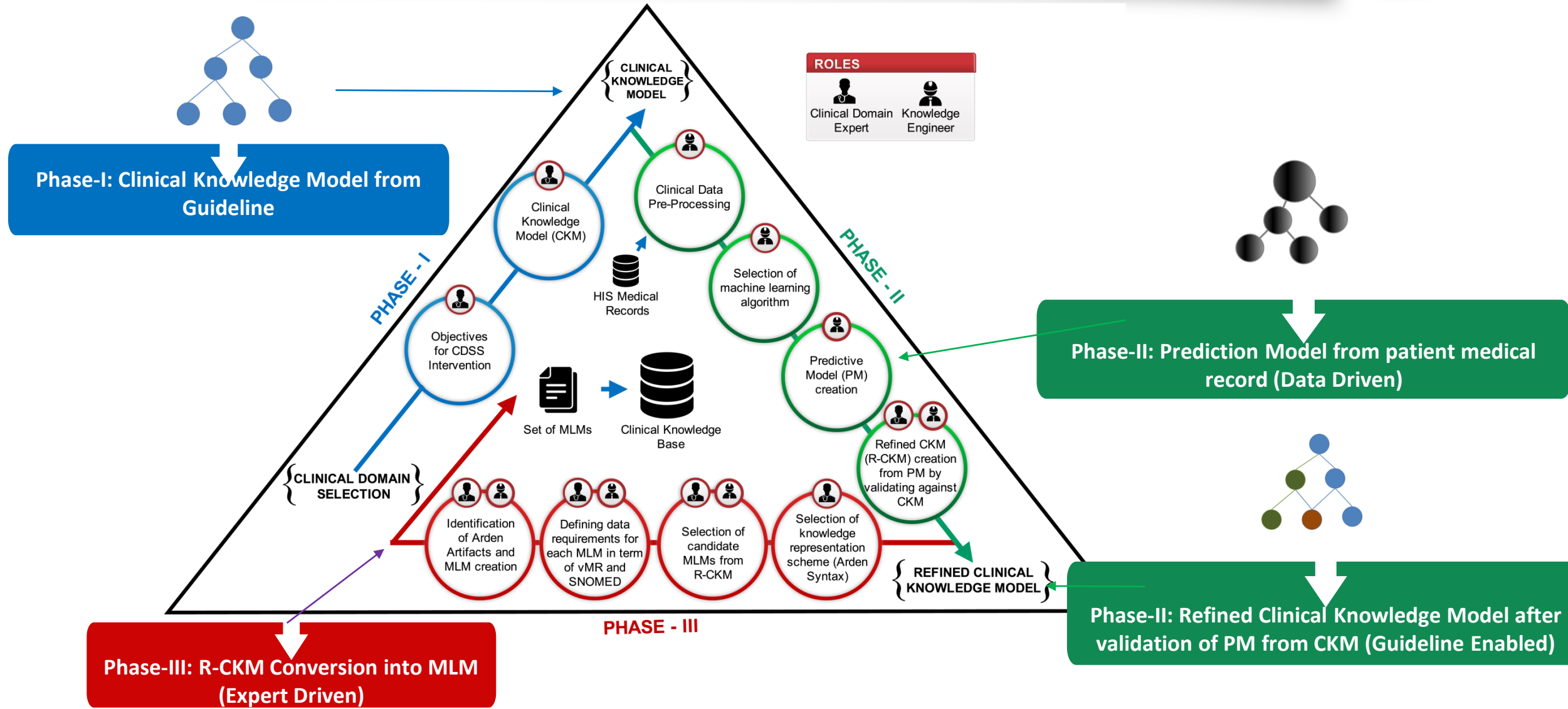
- Difficult to validation & Verification
- Hard to manage Knowledge base by domain expert





PubMed comprises of more than 26 million citations for biomedical literature from MEDLINE, life science journals, and online books

# Case Study: Knowledge Acquisition-3 Phase Model



# Case Study: Knowledge Acquisition Pathway



## Mind Maps

### (Domain Experts Tree Model)

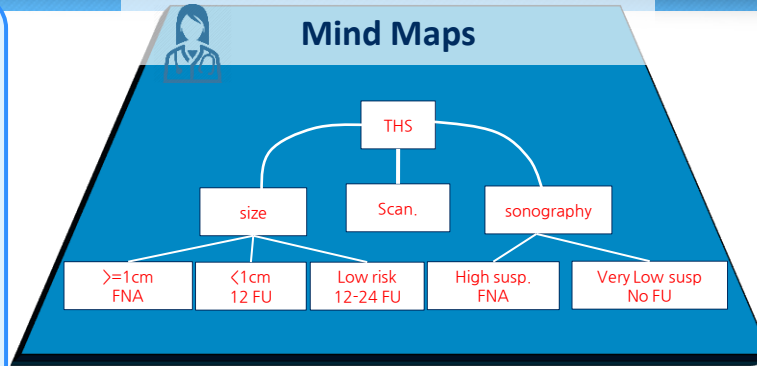
- Consulting guidelines, Clinical Trails, and others
- Incorporating local practices and context

### Advantages

- Easy representation (Most domain expert adopt)
- Provide detailed narratives

### Limitations

- High abstraction (not explicit knowledge)
- Chance of redundancy & ambiguity



## Knowledge-base

### (Medical Logic Module: MLM)

- Combining PRs into coherent logics
- Represent concepts in standard format

### Advantages

- Sharable and executable representation
- Concrete representation (explicit knowledge with detailed meta-data support)

### Limitations

- Complex compared to PR

```

maintenance:
  title: Thyroid Treatment by Physician
  author: Author System V1.0
  version: Version 1.0
  lastupdate: 2020/01/01
  author: Dr. Physician
  specialist: Dr. Physician
  date: 12/12/2019
  validation: testing

Library:
  purpose: Experimental testing
  explanation: Experimental testing
  keywords: Qual Center

Knowledge:
  type: decision-tree
  data:
    ProcedureEventList = object (ProcedureEvent);
    ProcedureEventList = read in ProcedureEvent;
    ProcedureEventList = select ProcedureEvent FROM client Where ProcedureEvent.procedureCode IN ('39507000');
    RecommendationList = object (Recommendation);
    RecommendationList = read in ProcedureEvent;
  evoker: null_event;
  logic:
    ProcedureEvent.isInitial = EXTRACT ATTRIBUTE NAMES ProcedureEventList;
    ProcedureEvent.isAttribute (ProcedureEventList) FROM ProcedureEventList;
    IF (ProcedureEvent.procedureCode = '39507000' And ProcedureEvent.procedureMethod = '363870007');
      THEN
        noPart = new ProcedureEvent with ('39507000');
        rec = new Recommendation with recPart;
        recommendationList = recommendationList.rec;
    action:
      WRITE recommendationList.procedureMethod;
      at: initial_client;
  end;
  
```

## Clinical Knowledge Model

### (Decision Tree)

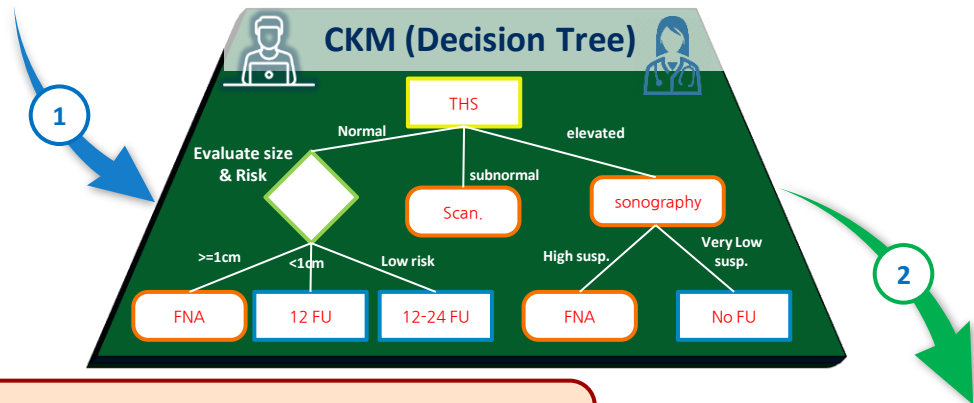
- Separating actions, conditions, and recommendations
- Representation in formal decision tree

### Advantages

- Concrete representation (explicit knowledge)
- Remove redundancy & ambiguity (reduce error chance)
- Provide detailed narratives

### Limitations

- Adoption needs to follow formalism
- Non-executable by computer



## Knowledge-base

### (Production Rules: PR)

- CKM -> rules using top-down: left-right traversing
- Conversion of OR into ANDs in PR

### Advantages

- Concrete representation (explicit knowledge)
- Computer executable representation

### Limitations

- Non-sharable

## Knowledge-base (PR)

Rule	THS	Size	Risk	Sonog.	Recmd.
I-1	Normal	>=1cm	Na	Na	FNA
I-2	Normal	<1cm	NA	NA	12 FU
I-3	Normal	NA	Low	Na	12-24FU
2-4	Subnormal	NA	NA	NA	Scan
3-5	Elevated	NA	NA	High	FNA
3-6	Elevated	NA	NA	Very Low	No FU

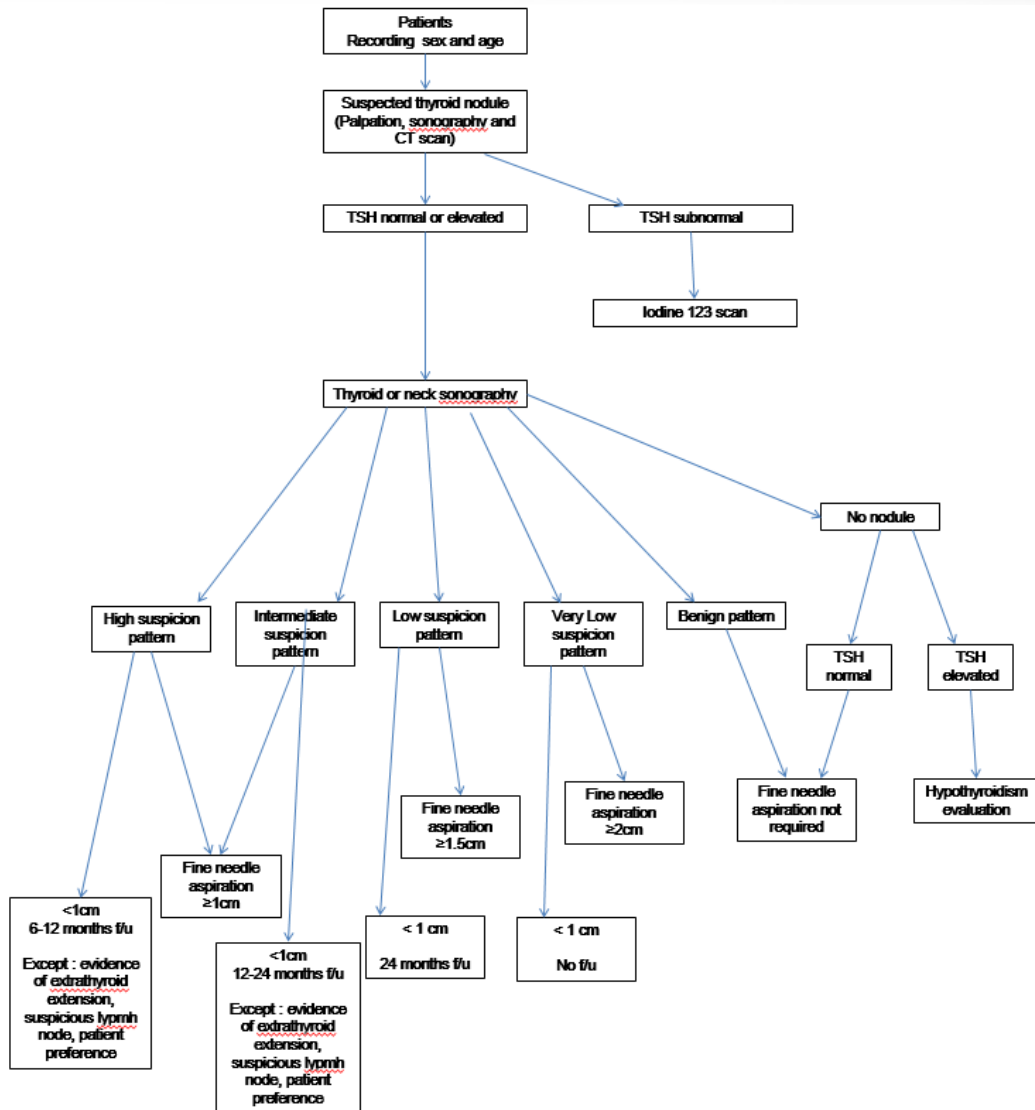
## MLMs

### KNOWLEDGE BASE



# Case Study: Knowledge Modeling for Thyroid Cancer

## Mind Maps Development Process - Example SNU Hospital



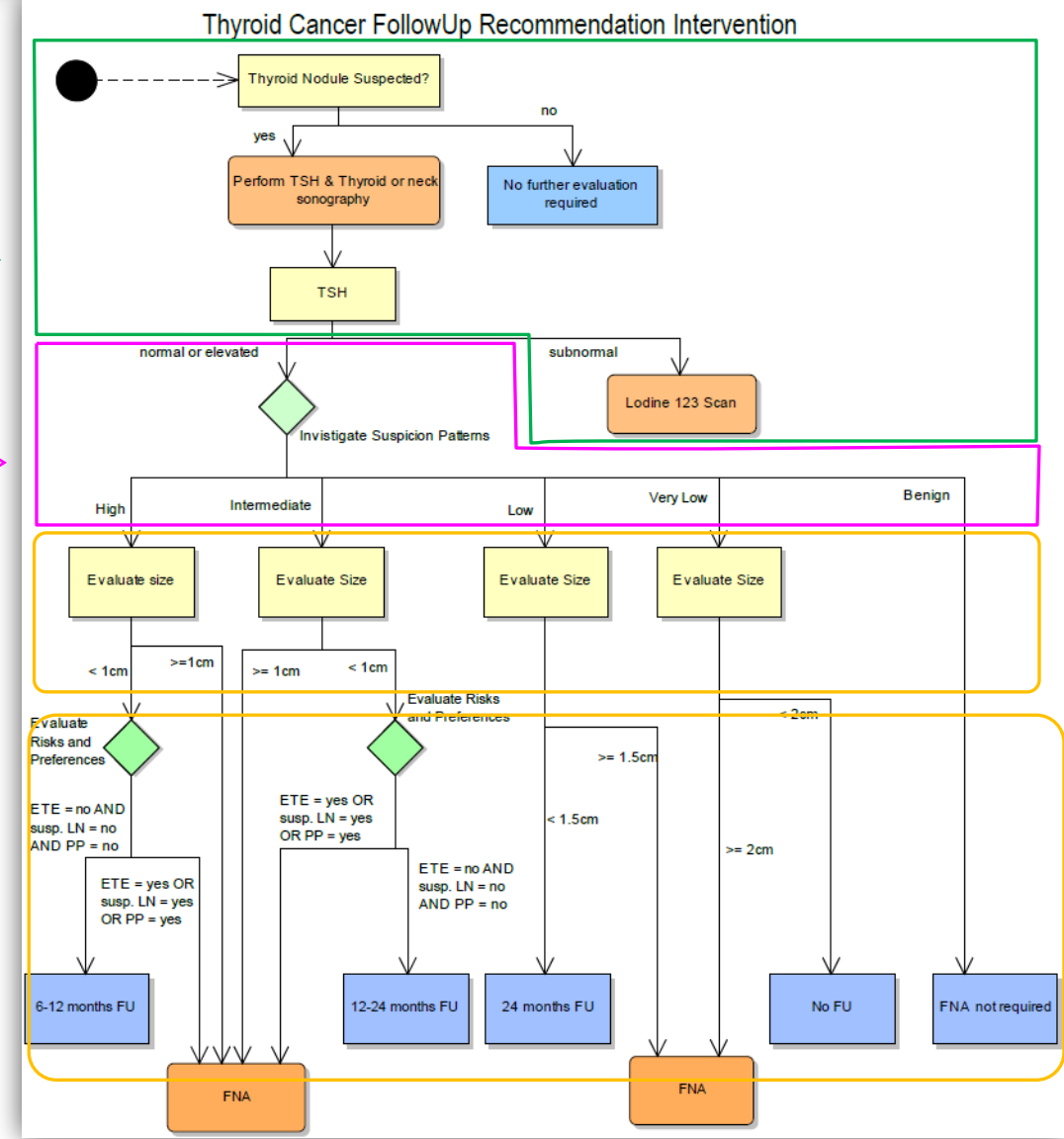
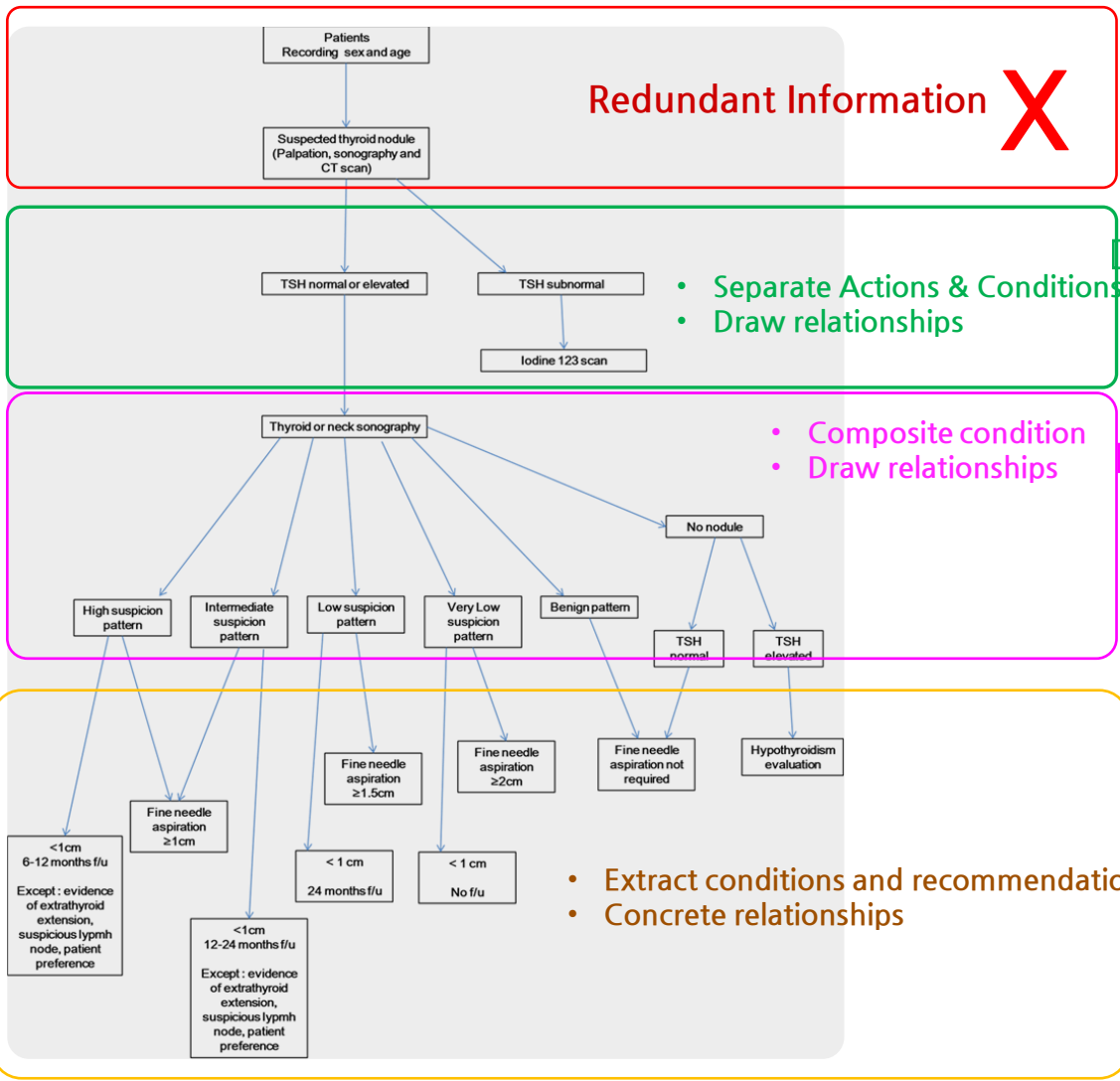
### Guideline based strategy

1. Patient initial observation for tumor presence
2. Ordering sonography
3. Evaluate sonography results and evaluate patients
4. Based on severity and size of the tumor, decision is made for further Surgery evaluation using FNA



# Case Study: Thyroid Cancer Follow Up Recommendation

## Expert Tree (Mind Maps) -> Formal Decision Tree (CKM-Clinical Knowledge Model)





# Case Study: Thyroid Cancer Follow Up Recommendation

## Formal Decision Tree (CKM-Clinical Knowledge Model) -> Rules (Production Rules)

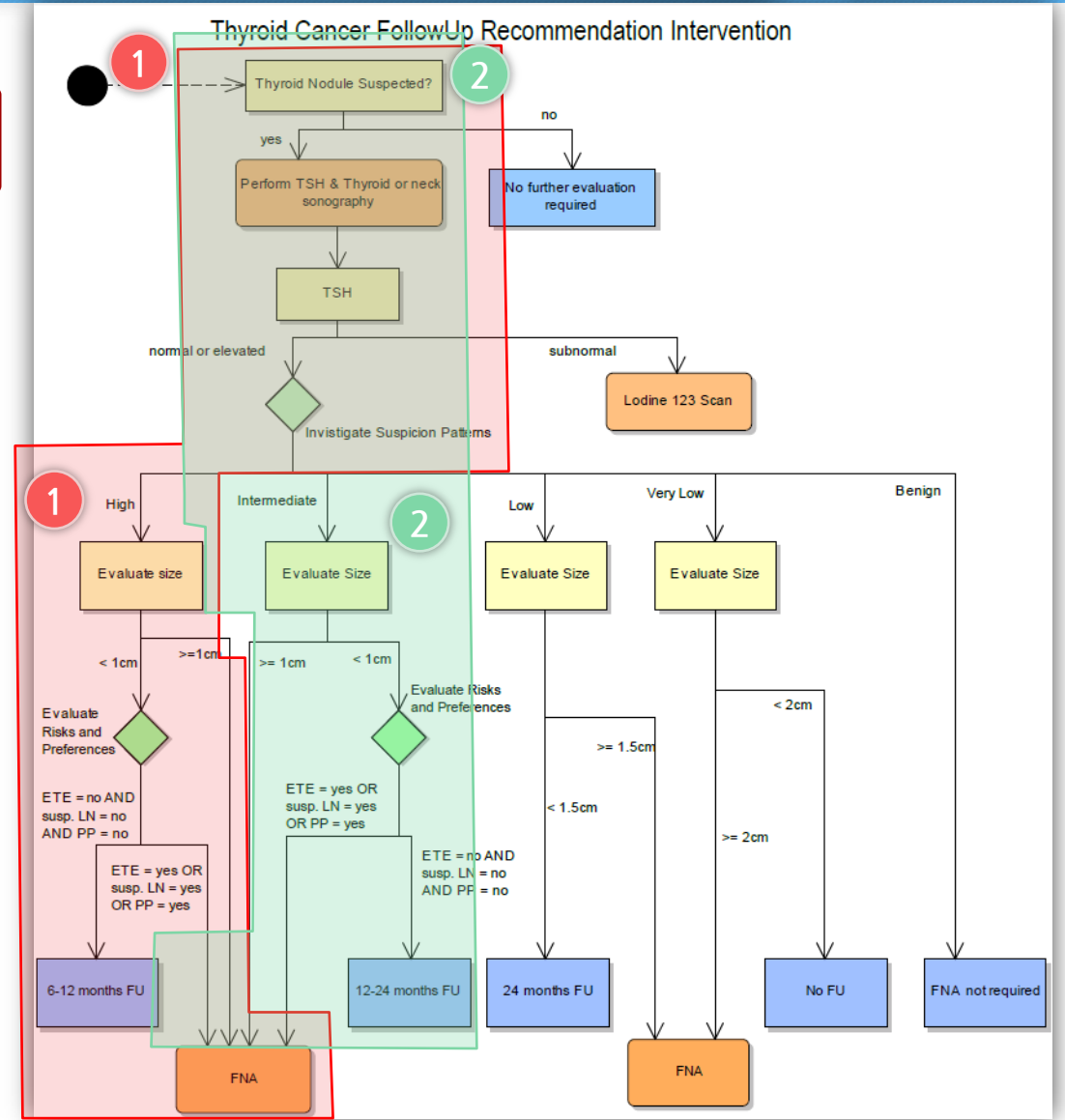


Rule#	Thyroid Nodule Expected	TSH	Suspicion Patterns	Size	ETE	susp. LN	PP	Treatment-Decision
1	yes	normal	High	<1cm	no	no	no	6-12 months follow up
2	yes	normal	High	<1cm	yes	no	no	FNA
3	yes	normal	High	<1cm	no	yes	no	FNA
4	yes	normal	High	<1cm	no	no	yes	FNA
5	yes	normal	High	<1cm	yes	yes	no	FNA
6	yes	normal	High	<1cm	yes	no	yes	FNA
7	yes	normal	High	<1cm	no	yes	yes	FNA
8	yes	normal	High	<1cm	yes	yes	yes	FNA
9	yes	normal	High	≥1cm	-	-	-	FNA
10	yes	elevated	High	<1cm	no	no	no	6-12 months follow up
11	yes	elevated	High	<1cm	yes	no	no	FNA
12	yes	elevated	High	<1cm	no	yes	no	FNA
13	yes	elevated	High	<1cm	no	no	yes	FNA
14	yes	elevated	High	<1cm	yes	yes	no	FNA
15	yes	elevated	High	<1cm	yes	no	yes	FNA

Traversing:  
• Top-Down

35	yes	elevated	Intermediate	<1cm	yes	yes	yes	FNA
36	yes	elevated	Intermediate	<1cm	no	no	no	12-24 months follow up
37	yes	normal	Low	<1.5cm	-	-	-	24 months follow up
38	yes	normal	Low	≥1.5cm	-	-	-	FNA
39	yes	elevated	Low	<1.5cm	-	-	-	24 months follow up
40	yes	elevated	Low	≥1.5cm	-	-	-	FNA
41	yes	normal	Very Low	≥2cm	-	-	-	FNA
42	yes	normal	Very Low	<2cm	-	-	-	No follow up
43	yes	elevated	Very Low	≥2cm	-	-	-	FNA
44	yes	elevated	Very Low	<2cm	-	-	-	No follow up
45	yes	normal	Benign	-	-	-	-	FNA not required

Traversing:  
• Left-Right



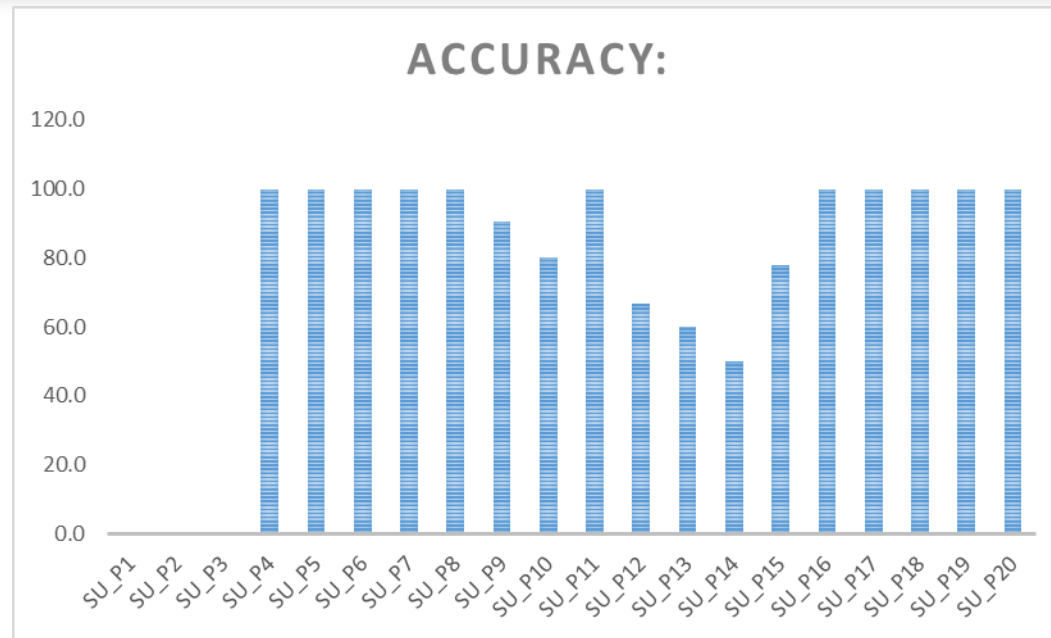
# Case Study: Results



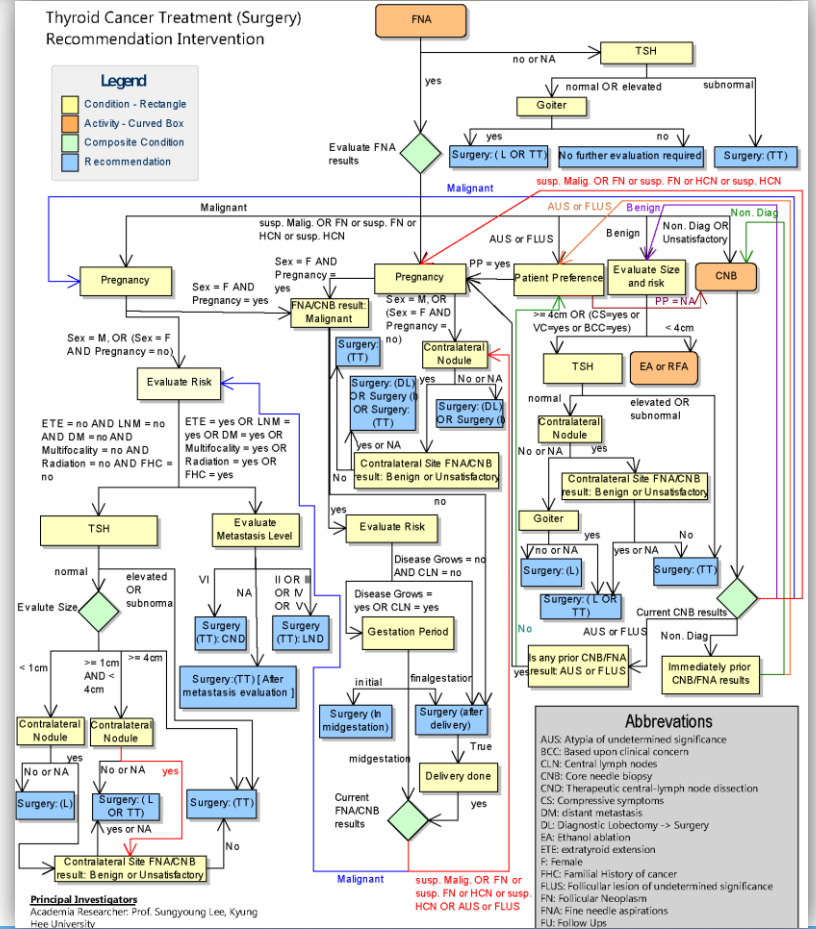
Surgery Paths	SU_P1	SU_P2	SU_P3	SU_P4	SU_P5	SU_P6	SU_P7	SU_P8	SU_P9	SU_P10	SU_P11	SU_P12	SU_P13	SU_P14	SU_P15	SU_P16	SU_P17	SU_P18	SU_P19	SU_P20	Total Patients
Patients:	2	3	1	15	4	8	3	1	43	55	1	3	10	2	123	1	1	9	2	5	292
Pat: S:	0	0	0	15	4	8	3	1	39	44	1	2	6	1	96	1	1	9	2	5	238
Pat: F:	2	3	1	0	0	0	0	0	4	11	0	1	4	1	27	0	0	0	0	0	54
Accuracy:	0.0	0.0	0.0	100.0	100.0	100.0	100.0	100.0	90.7	80.0	100.0	66.7	60.0	50.0	78.0	100.0	100.0	100.0	100.0	100.0	81.5

### Interpretation:

- Total Patients : 292
- Patient Distribution: 20 paths



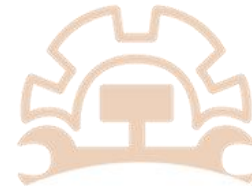
**System Accuracy: 81.5%**  
**Overall KB rules: 3034**



## HEAD AND NECK CANCER DATA INTEGRATION



INTEGRATION OF  
**5100 PATIENTS**  
RECORDS of SKMCH WITH  
SMART CDSS




PRIMITIVE SHAREABLE RULES  
(MLM) CREATION



NCCN based


Oral Cavity + Salivary Gland

TREATMENT INTERVENTION IS HANDLED BY SMART CDSS



EVERY WEEK


on average  
**125 PATIENTS**  
records are enabled for  
decision support in  
SKMCH



WHAT WE **ACHIEVED**  
IN THE **LAST 4 YEARS**

PERFORMANCE OF PHYSICIANS WERE ENHANCED  
**26 TIMES**  
IN CREATION OF RULES

The error rates RECORDED  
**1 per MLM** while for other tools  
it was **11 per MLM** creation



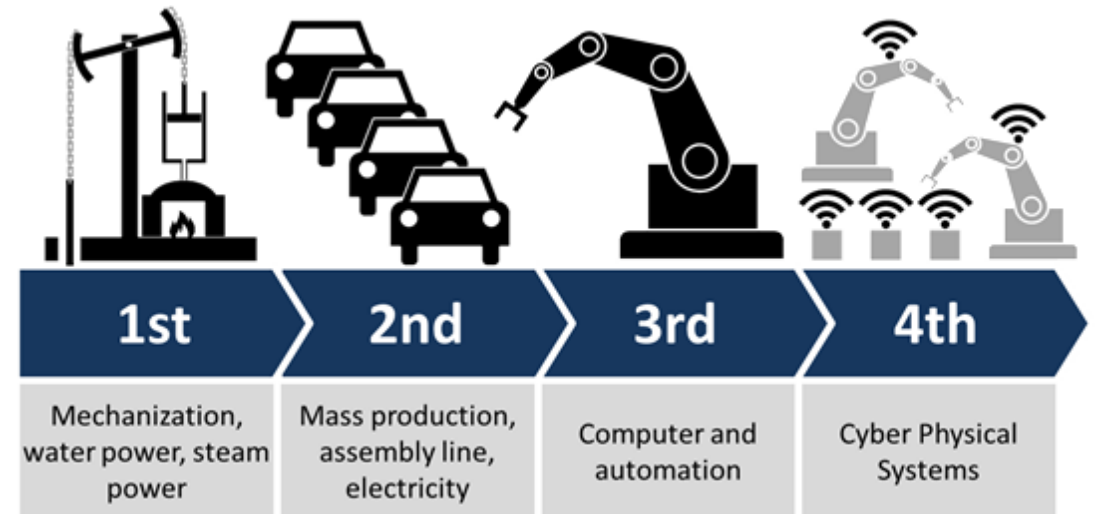
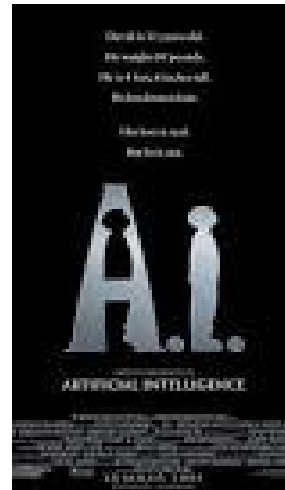
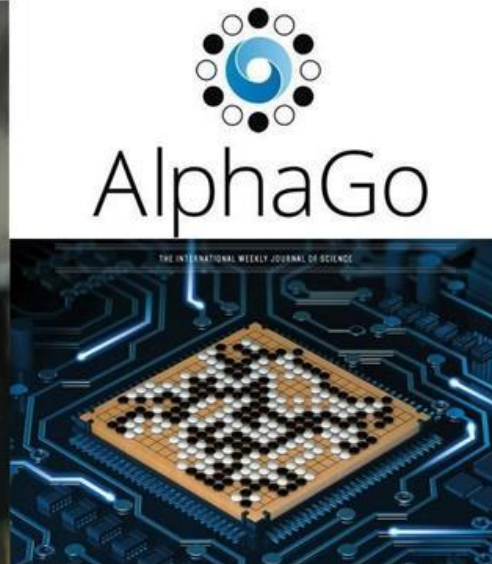
# Intelligent Medical Platform





## New Waves

- ✓ Artificial Intelligence Society
- ✓ 4th Industrial Revolution
- > **Increased Productivity by Super Connectivity and Super Intelligence**



## AI in Medical Service Systems – AI Doctor

### Korea



Physician's prescription and **diagnosis support system** using **voice recognition** so called AI 'NUGU'

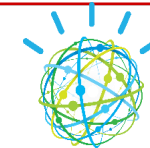
### International



Intelligent diagnosis system using 1.6 million patient's medical data in NHS, UK



Medical **big data cloud infrastructure** with patient's gene and clinical information



Next generation AI assistance system which has a reasoning ability



AI based Diagnosis system for lung disease, pneumonia and breast cancer using chest x-ray image



Conducting Hanover project where AI can offer the best effective medication by analyzing state of tumor



## Healthcare Systems

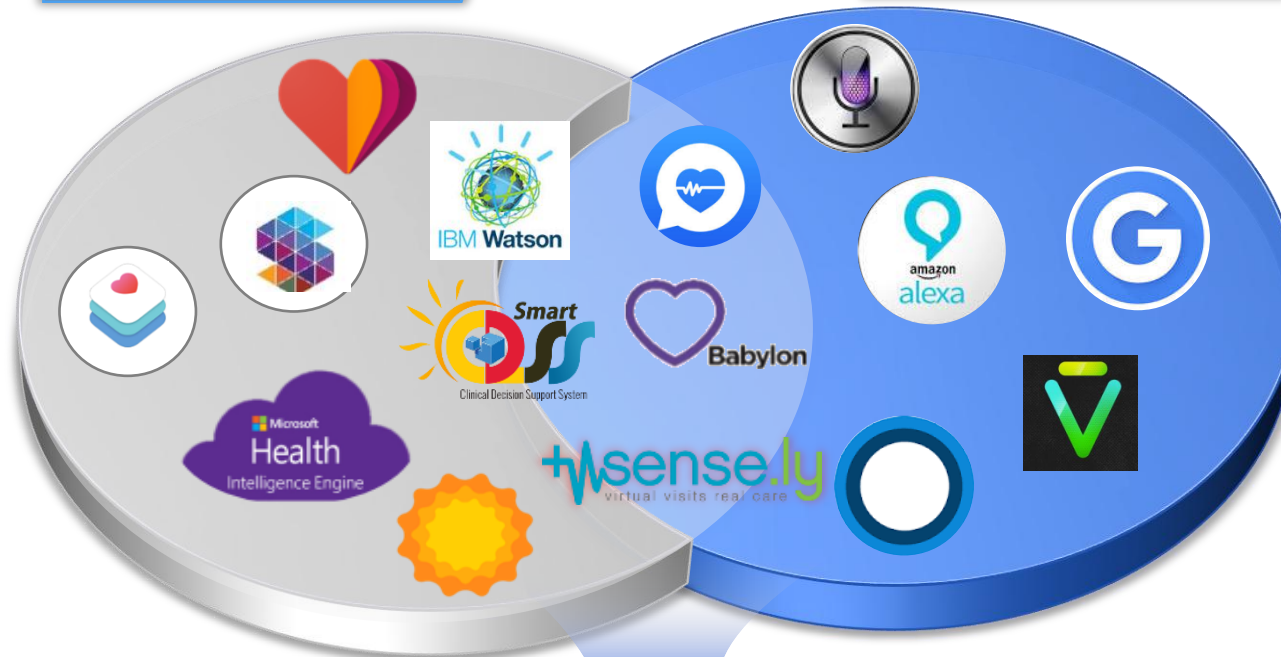
## Personal Assistants

### Strength

- Actionable Knowledge
- Empowering the expert user
- Evidence support for domain experts

### Weakness

- Non-Interactive
- Rigid Knowledge Structures
- Lack Context-awareness



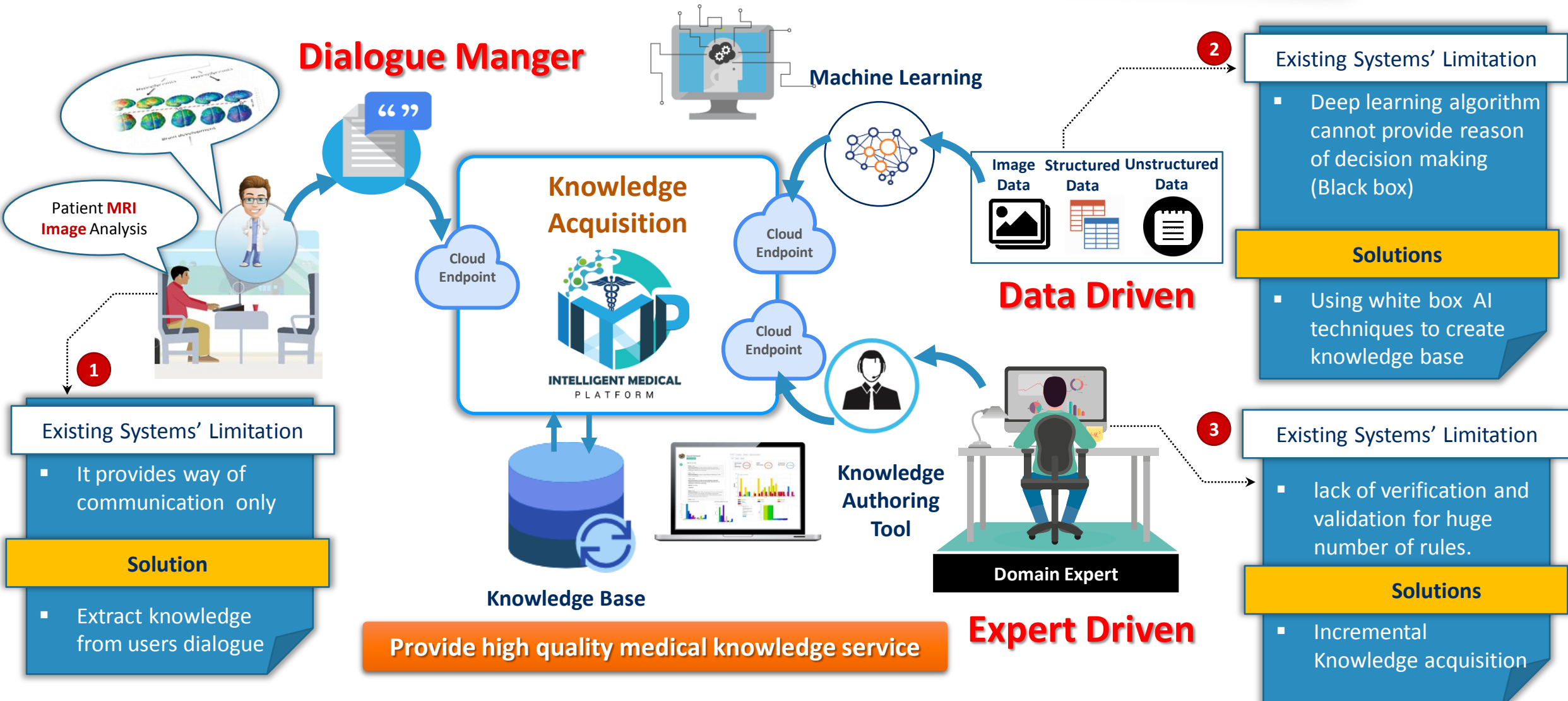
### Strength

- Highly Interactive
- Natural User Interfaces
- User Engagement

### Weakness

- No Actionable Knowledge
- No Concept of appraised evidence support
- Limited Visual Understanding

Existing Medical Systems



**Existing Systems' Limitation**

- It provides way of communication only

**Solution**

- Extract knowledge from users dialogue

**Existing Systems' Limitation**

- Deep learning algorithm cannot provide reason of decision making (Black box)

**Solutions**

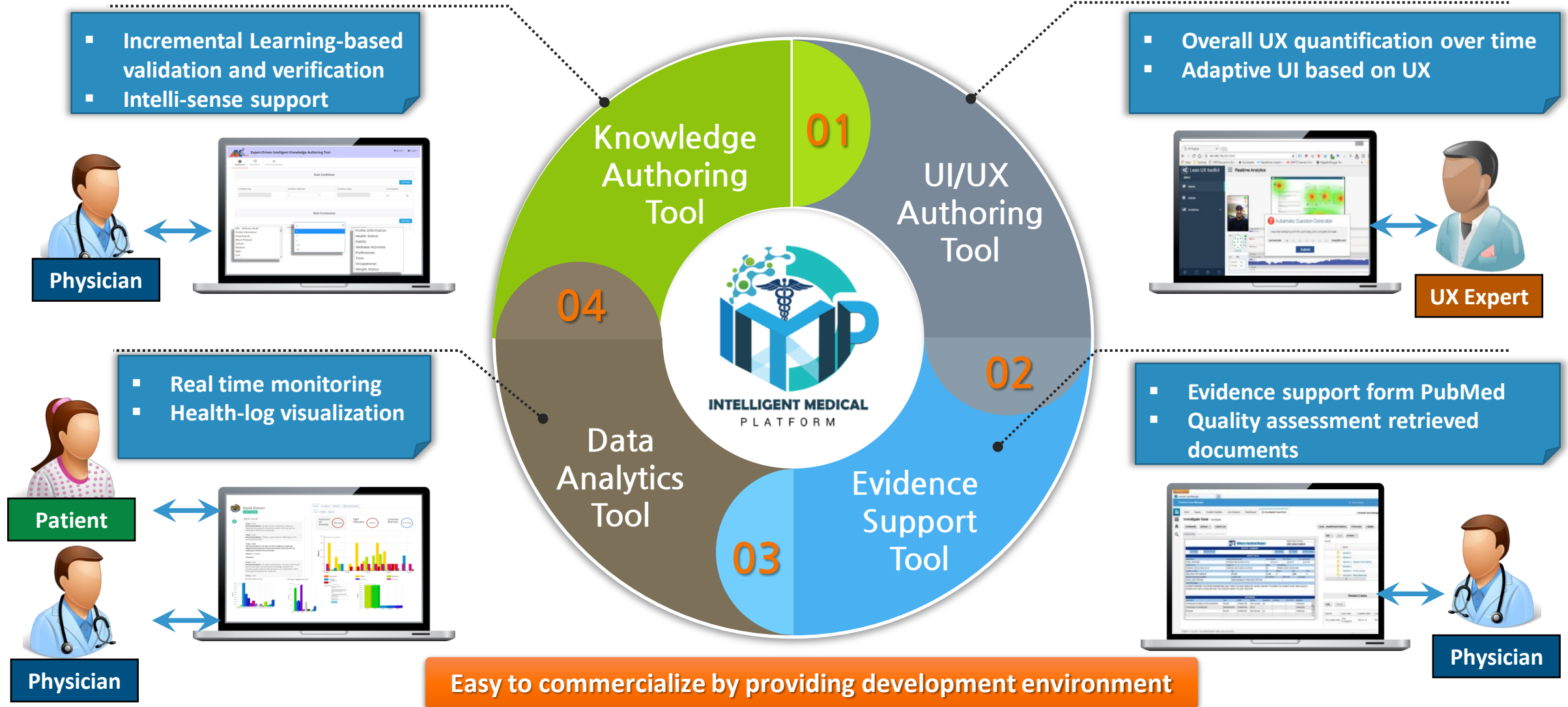
- Using white box AI techniques to create knowledge base

**Existing Systems' Limitation**

- lack of verification and validation for huge number of rules.

**Solutions**

- Incremental Knowledge acquisition





Credible



Secure



Personalized



Reliable



Accurate



Transparent

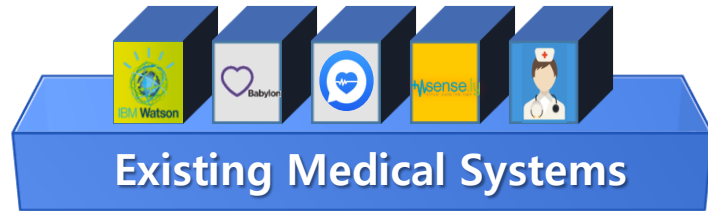


Context Aware



Easy to use





## Limitations

## Solutions

▶ **Restricted Method of Knowledge Acquisition**

**Data Driven and Human Driven Knowledge Acquisition with Dialogue**

▶ **Difficult to Knowledge Construction & Maintenance**

**Knowledge Authoring Tools**

▶ **Minimum level of Evidence Support**

**Evidence Supporting Tools (for PubMed)**

▶ **Poor User's Interaction**

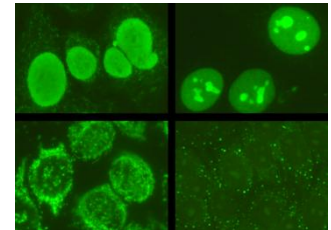
**Dialogue & UI/UX Tools**

▶ **Lack of Interoperability in Heterogeneous EMR/HIS**

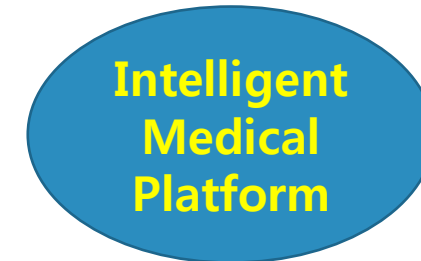
**Standard based Mapping and Interoperability Methods**



Clinical Decision Support Systems



Clinical diagnosis



Patient education



Intelligent communications

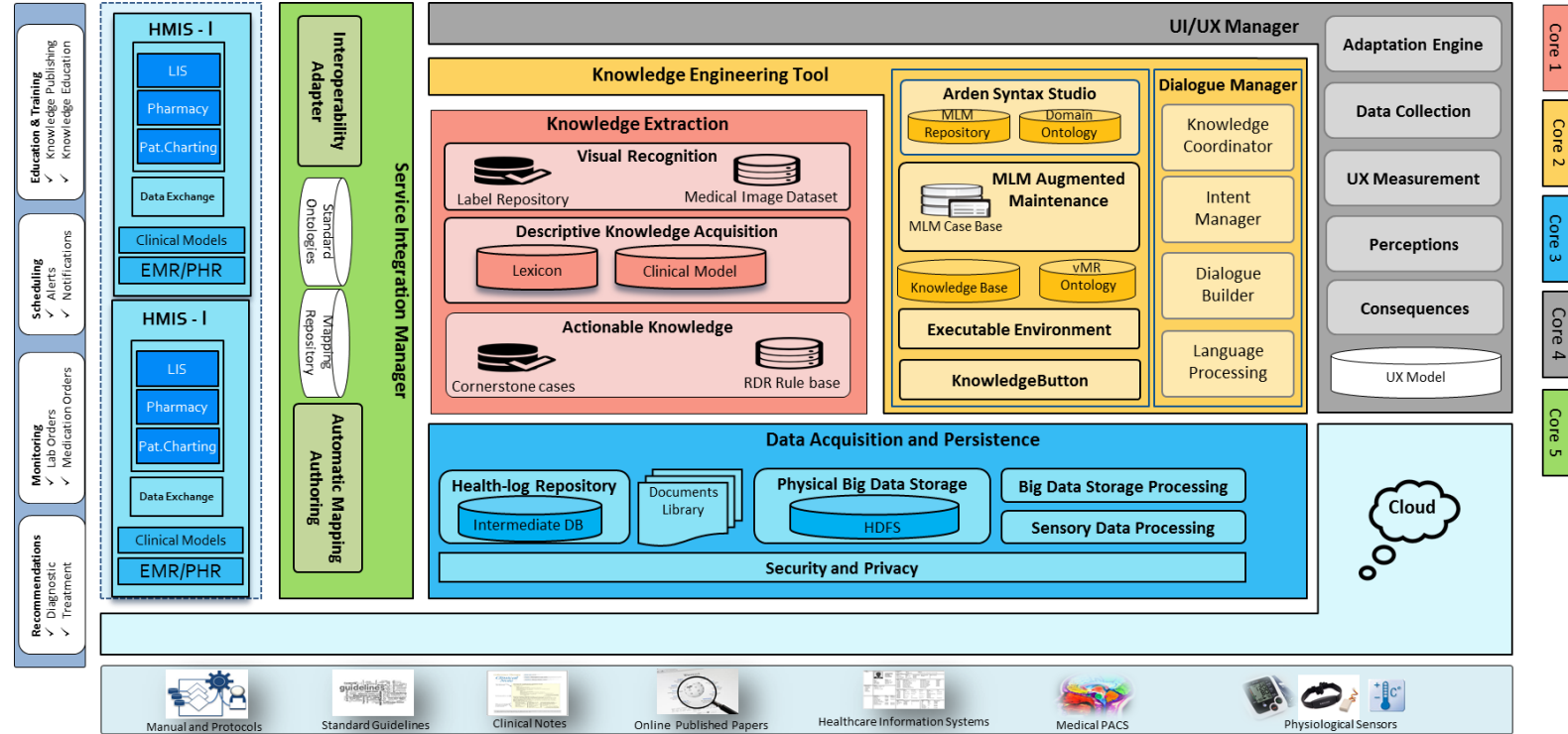
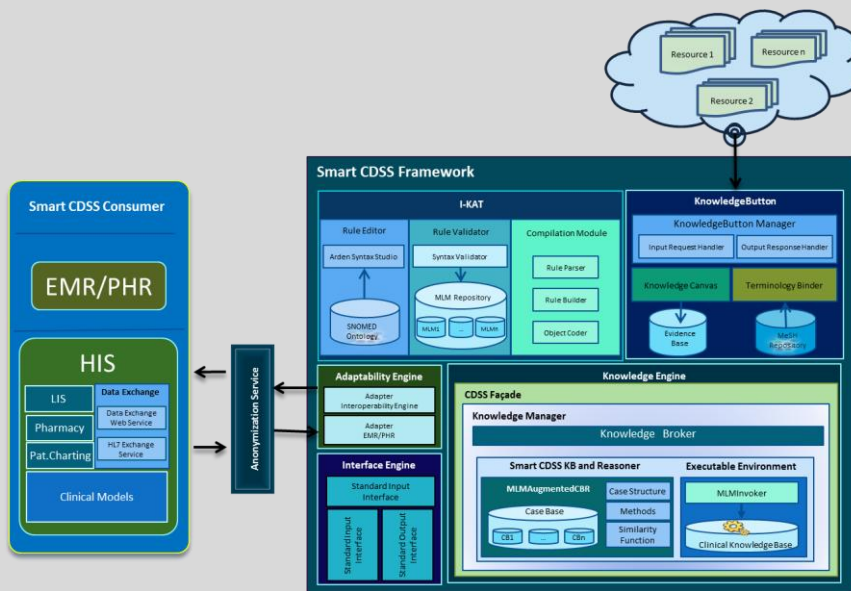
# Proposed IMP: AS-IS vs TO-BE



## AS IS: Smart CDSS



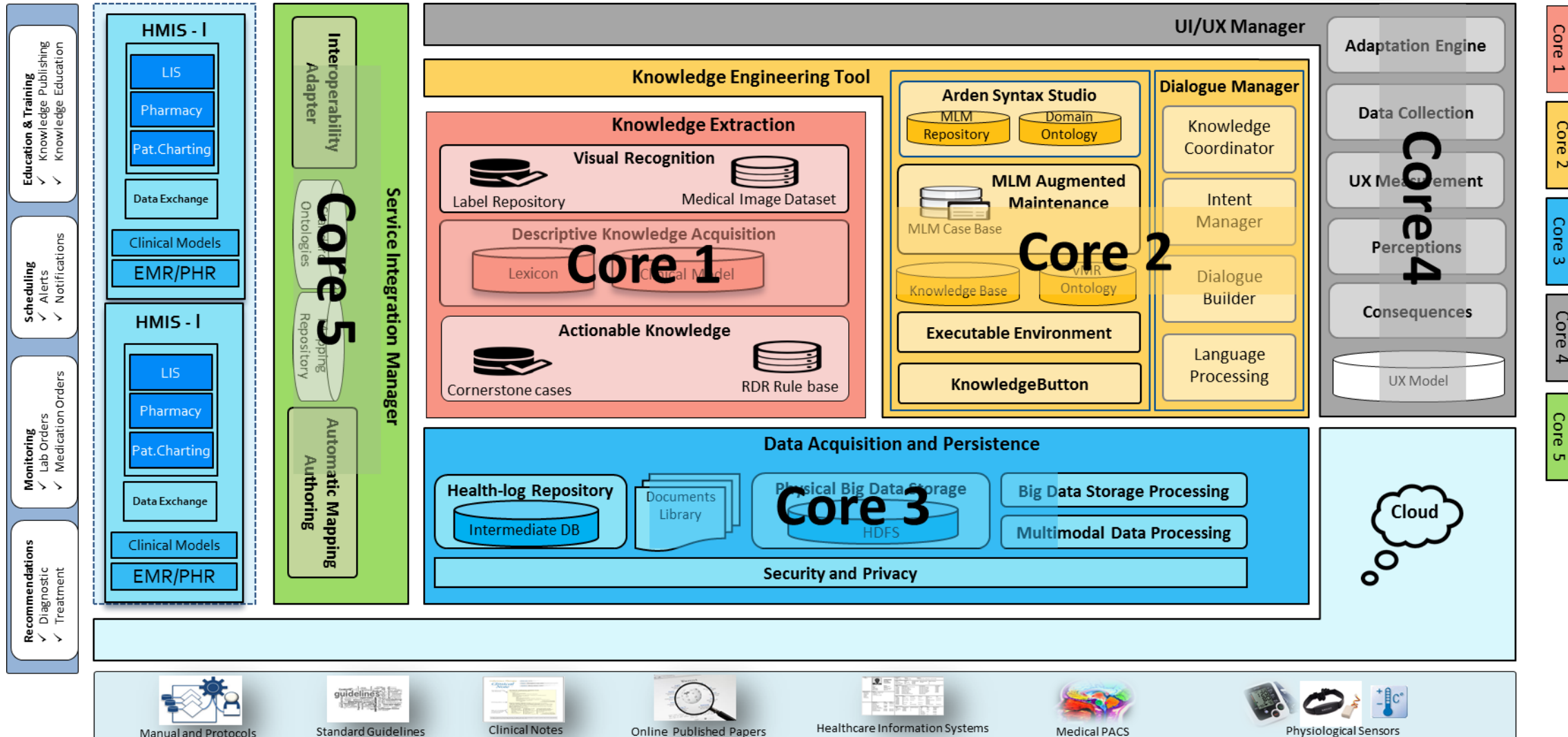
## TO BE: Intelligent Medical Platform (IMP)



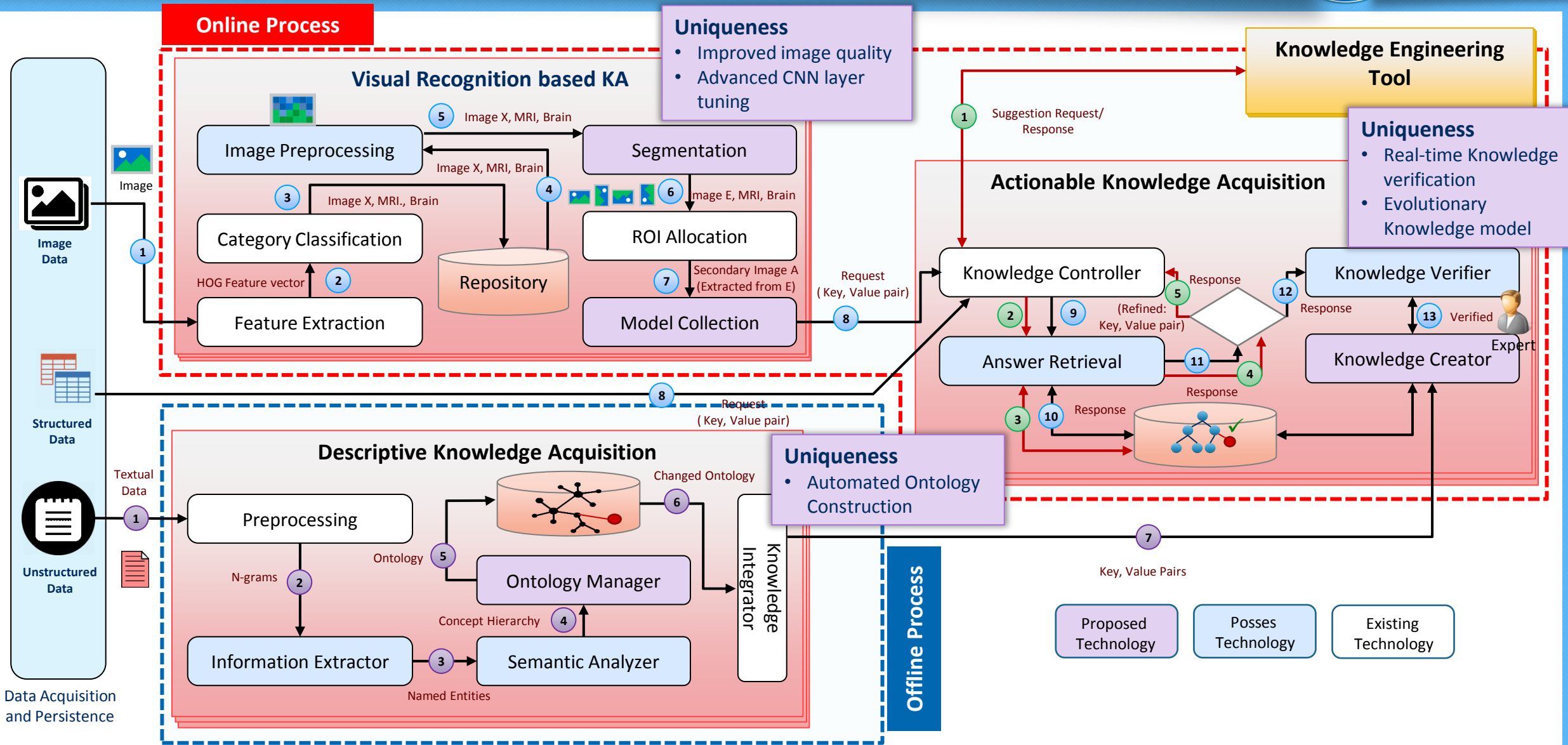
Core 1  
Core 2  
Core 3  
Core 4  
Core 5



# Proposed IMP (Intelligent Medical Platform) Architecture

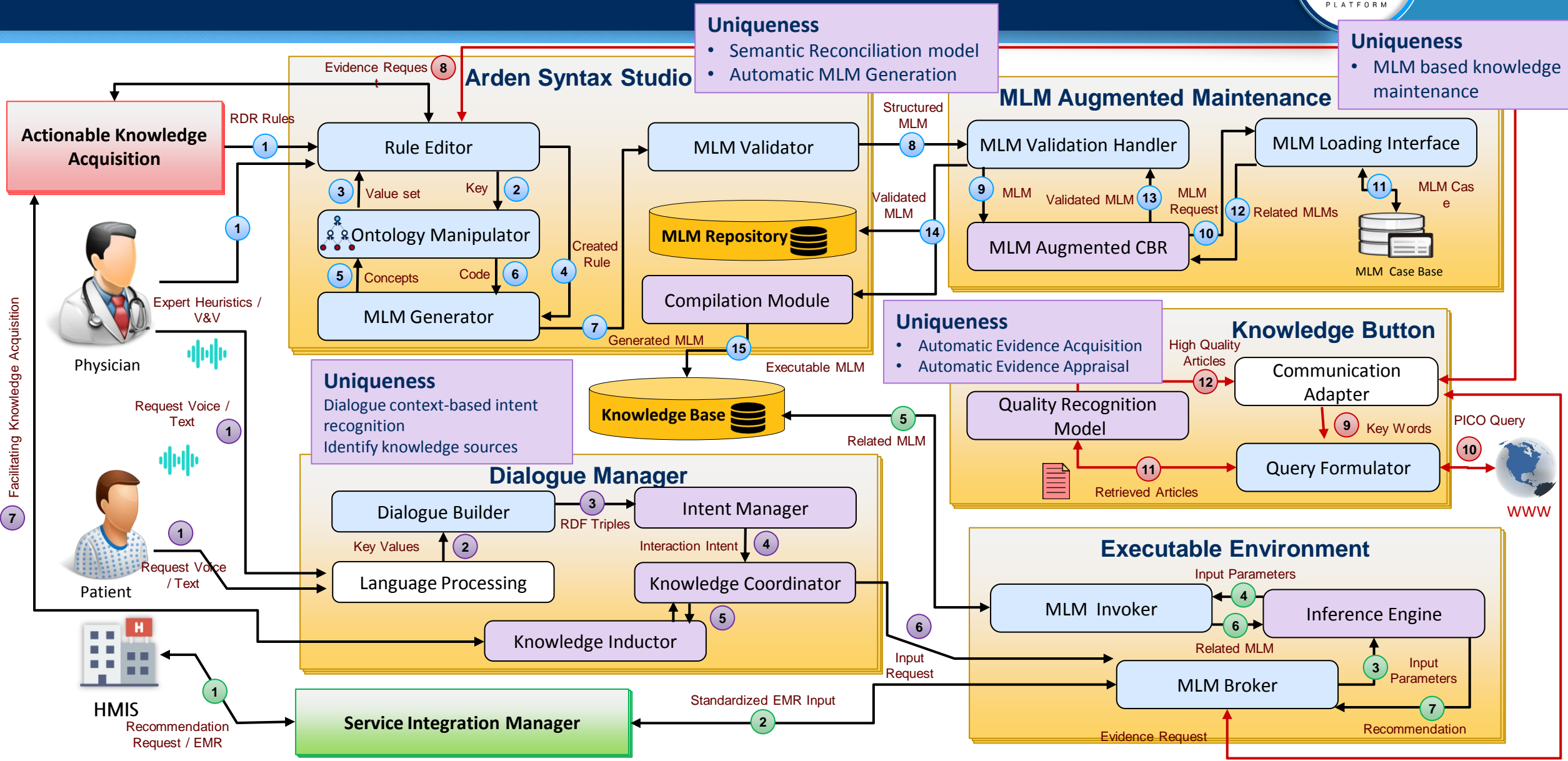


# Core 1: Knowledge Acquisition and Inference



# Core 2: Knowledge Engineering Tool

Proposed Technology      Posses Technology      Existing Technology

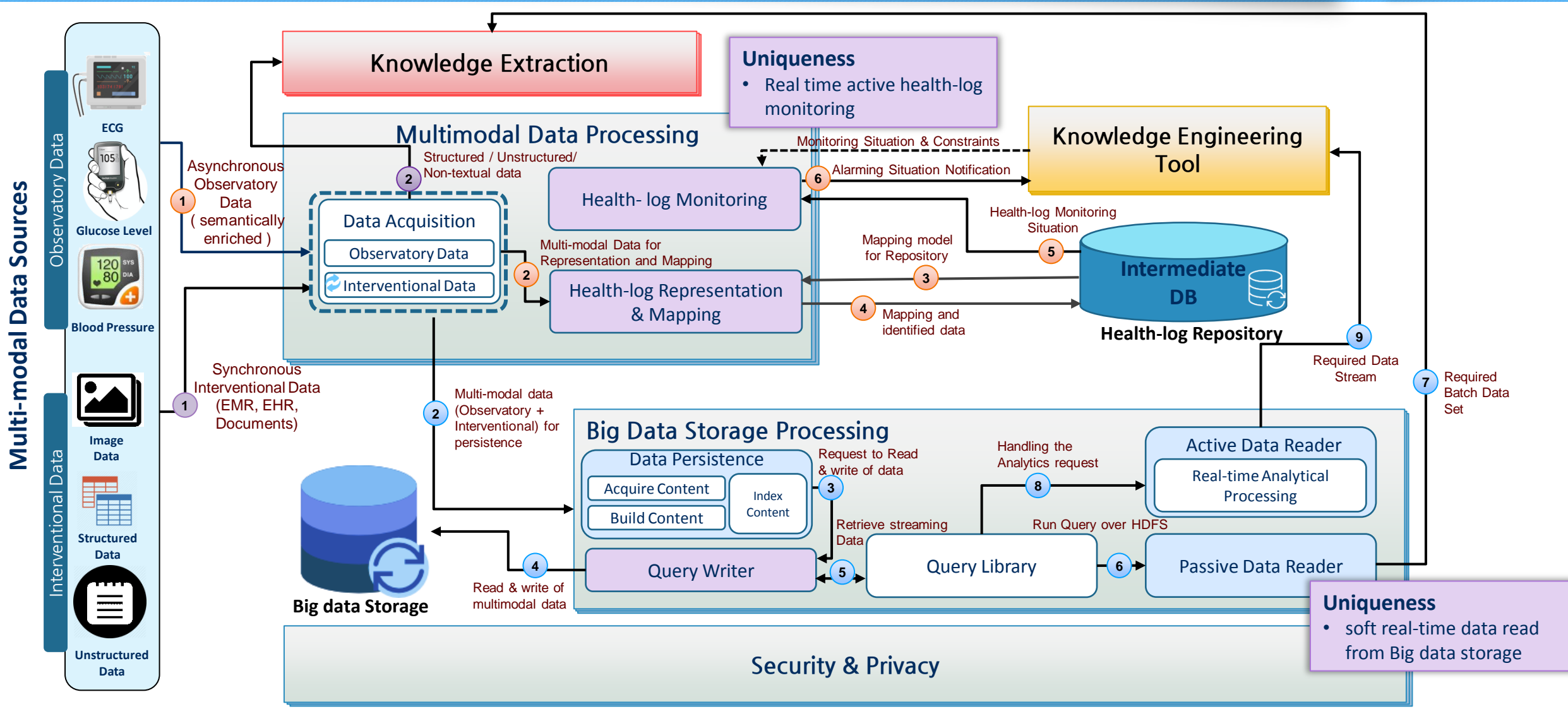


# Core 3: Big Data Processing and Storage

Proposed Technology

Posses Technology

Existing Technology

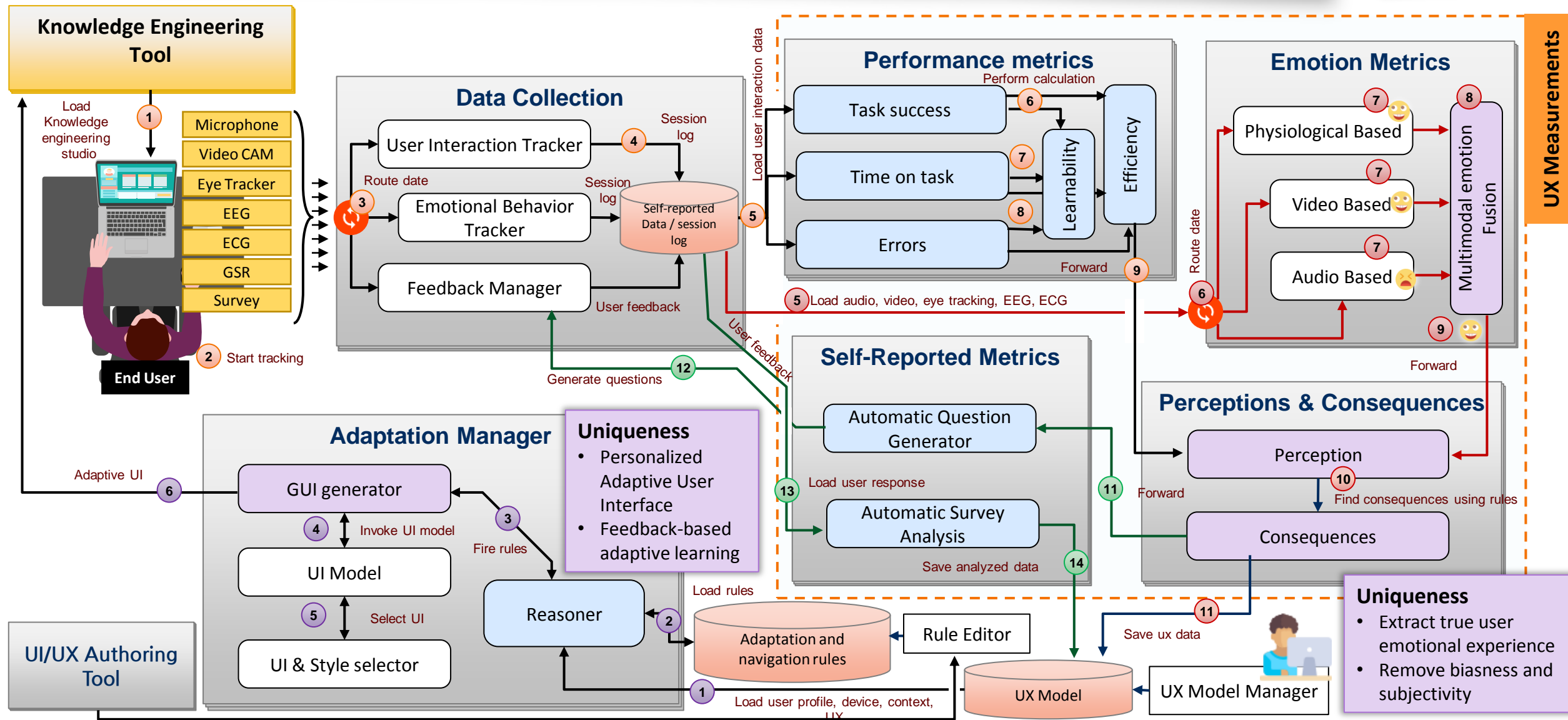


# Core 4: UI/UX Evaluation and Management

Proposed Technology

Poses Technology

Existing Technology



**Uniqueness**

- Extract true user emotional experience
- Remove biasness and subjectivity



# Core 5: Medical Service Integration

Proposed Technology	Poses Technology	Existing Technology
---------------------	------------------	---------------------

**HMIS**

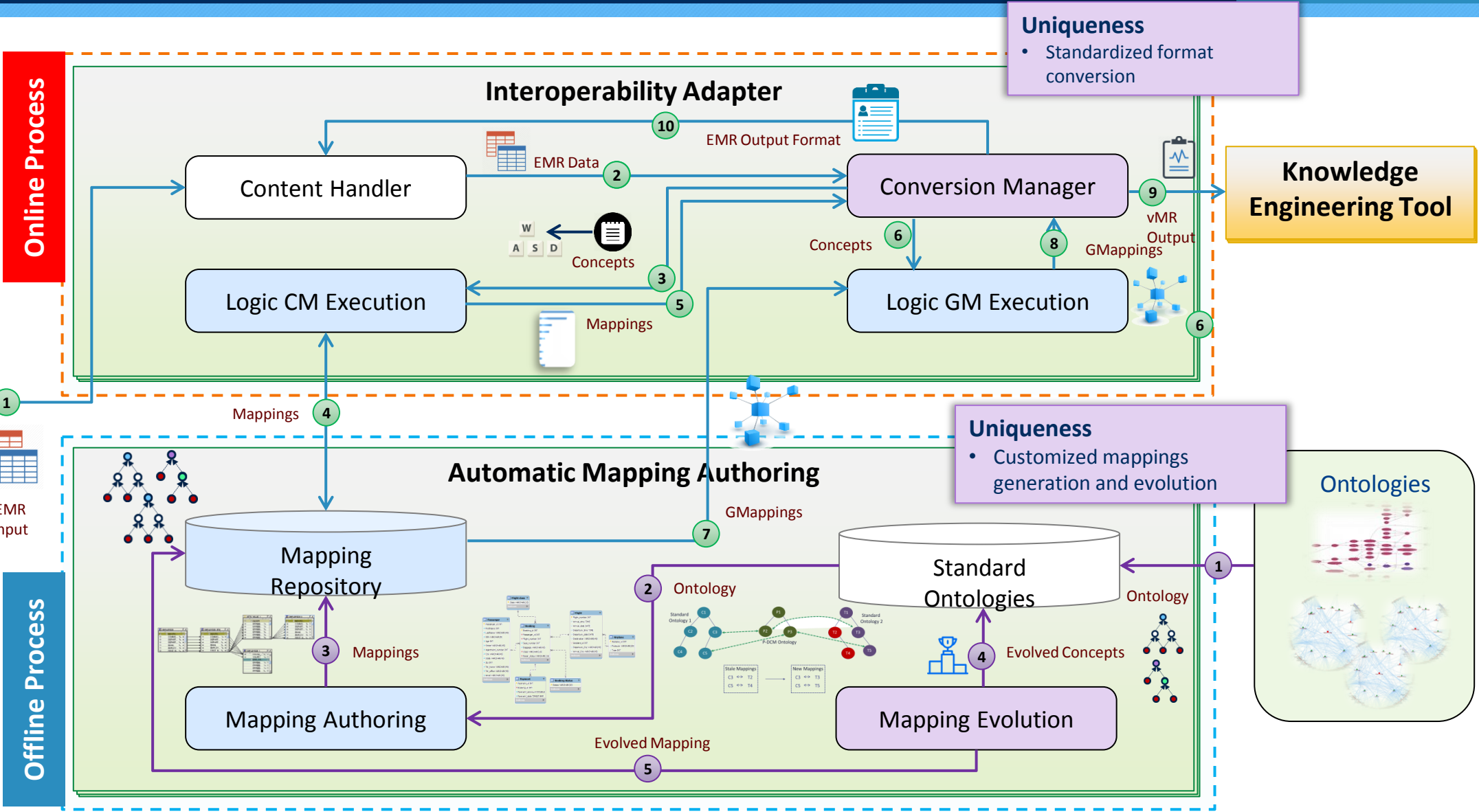
- LIS
- Pharmacy
- Pat. Charting

**Data Exchange**

- Data Exchange WS
- HL7 Exchange Service

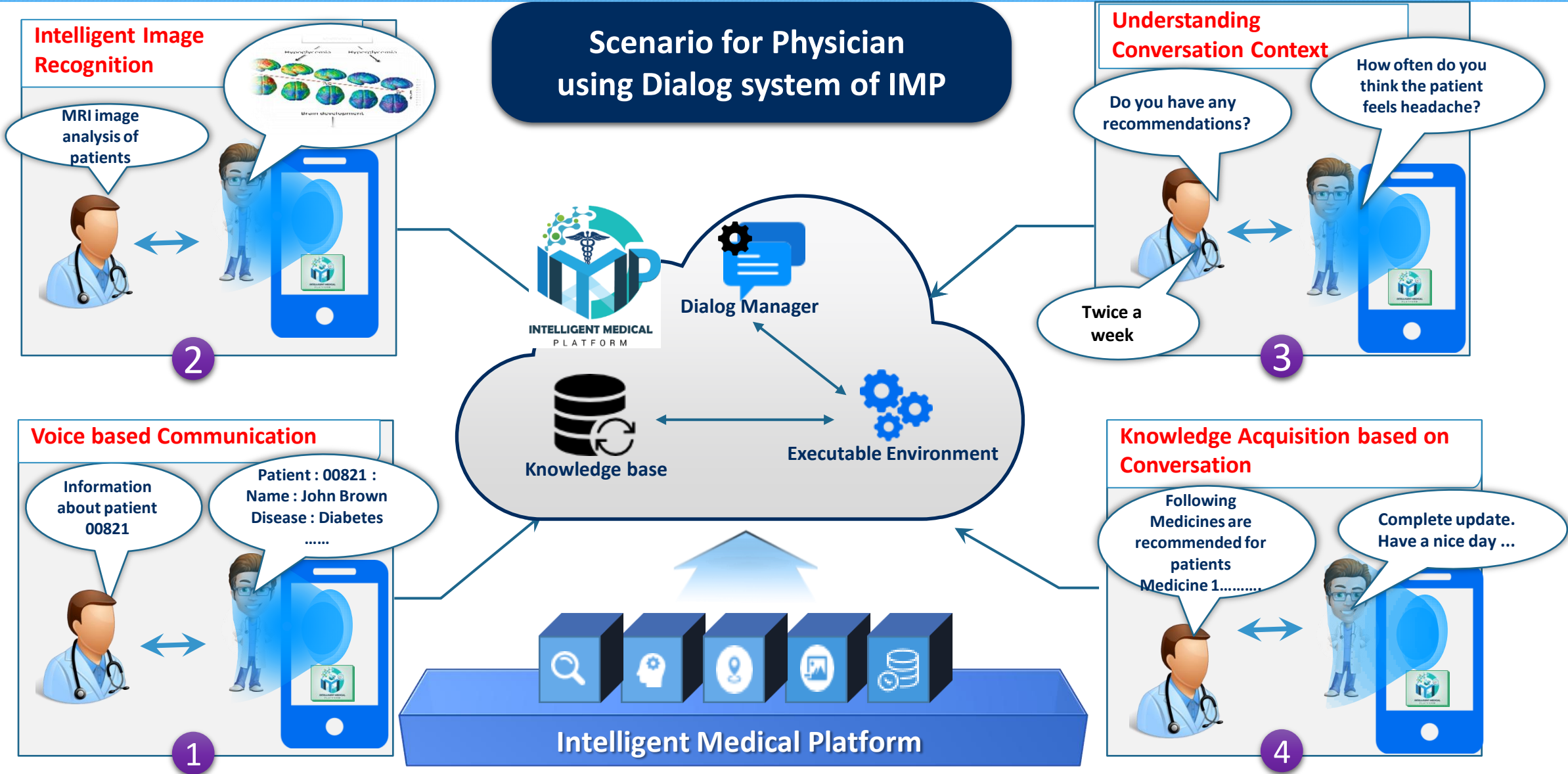
**Clinical Models**

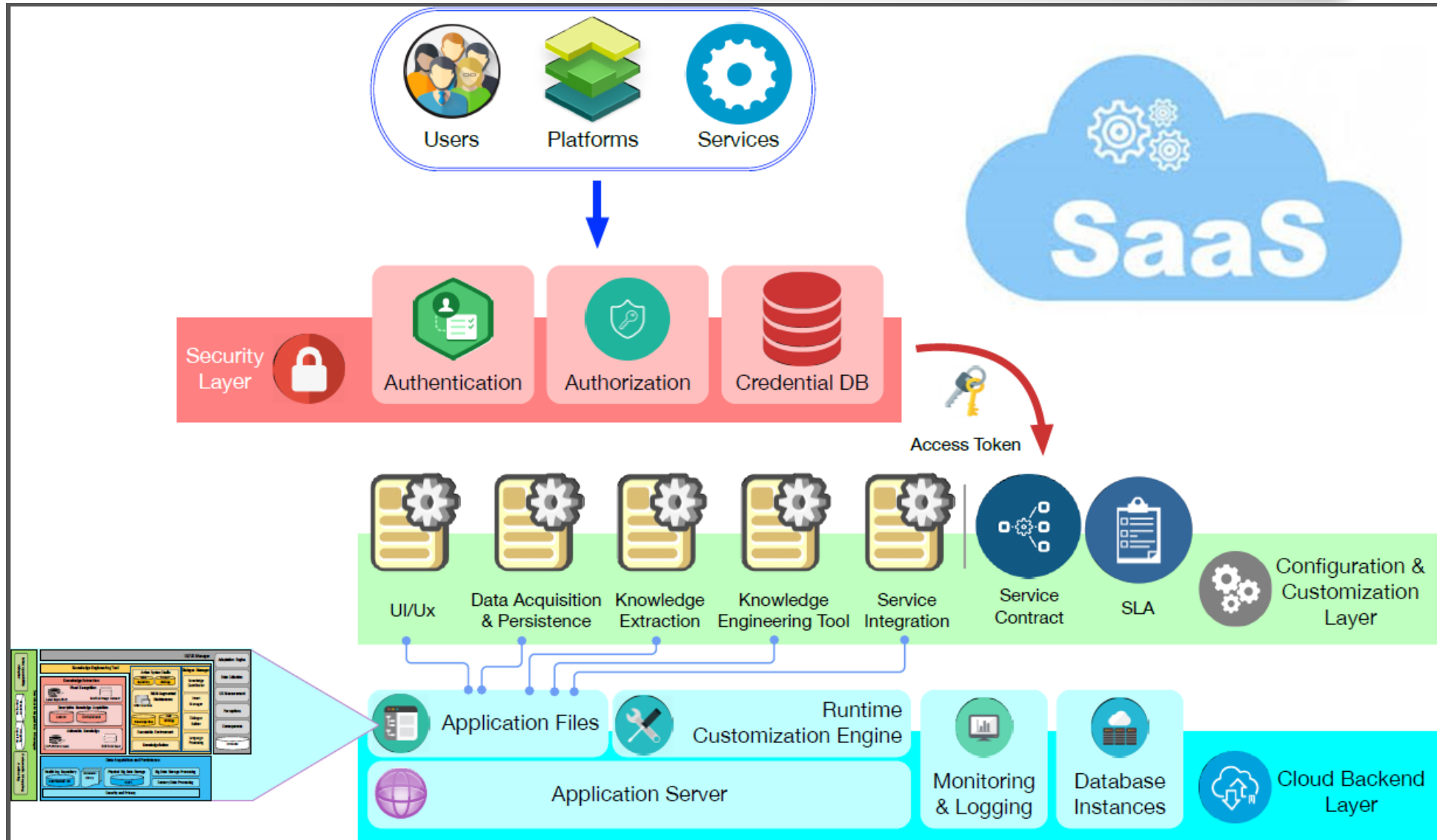
**EMR/PHR**



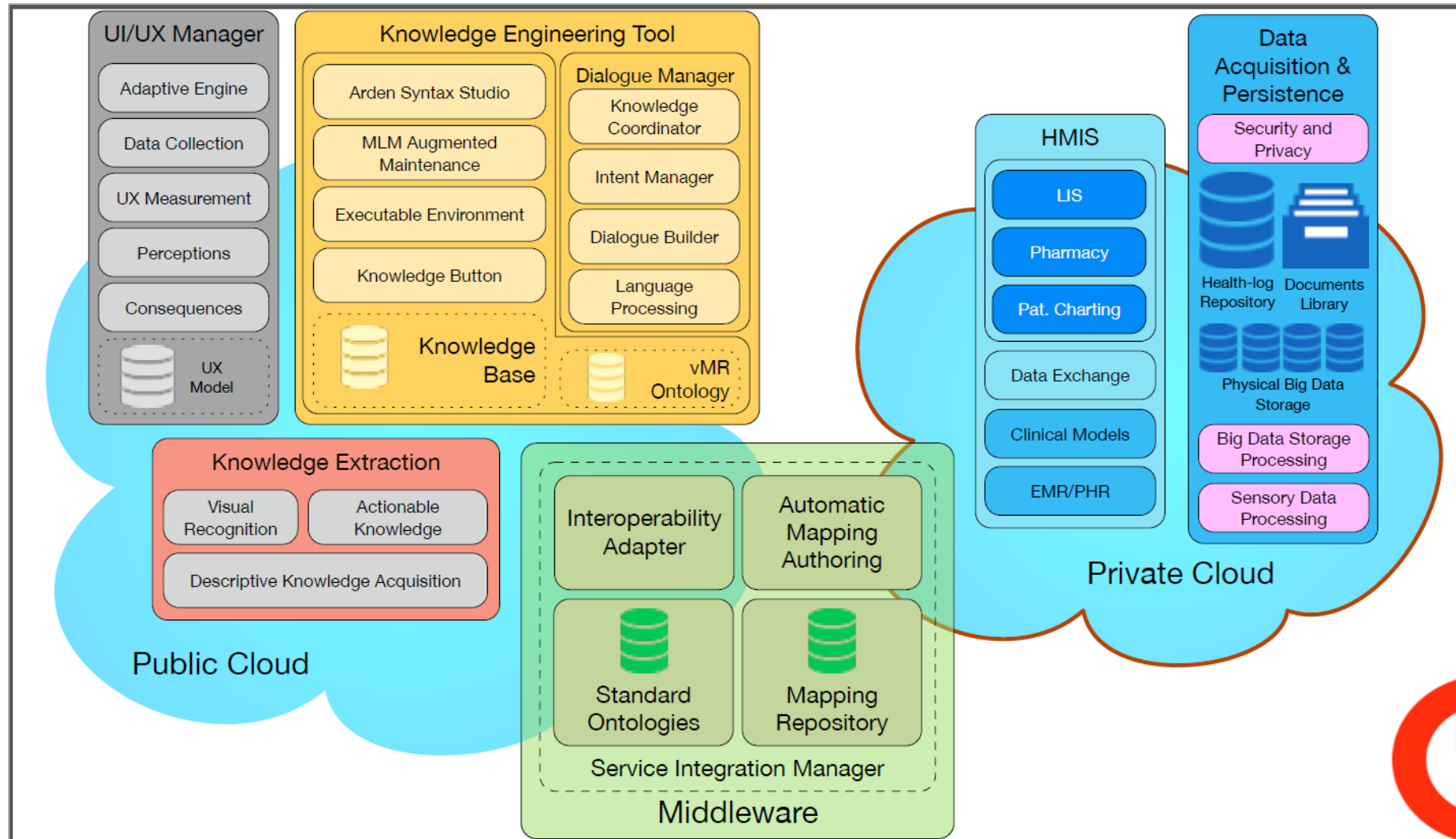


## Scenario for Physician using Dialog system of IMP







# Deployment over Cloud





-  **Research Initiative for Intelligent Medical Systems and Services**
-  **Promote Collaboration in ICT Medical Convergence**



-  **Triggering Business Innovation with IMP**
-  **Construct Business Ecosystem using Open Source Code**



-  **Construct High Quality of Medical Knowledge Base**
-  **Obtain and Share Clinical Data**
-  **Achieve Medical Innovation by means of Reducing Medical Errors and Cost**
-  **HIS Integration by Standardization**

## Considering factors for New Generation of Intelligent Medical Platform

- **Incremental Knowledge Learning (Expert Driven + Data Driven)**
- **Engineering Tool Support**
- **Dialog-based User Interaction**
- **Cloud Services such as SaaS**
- **Interoperability in Heterogeneous Resources**
- **Holistic Approach**
- **Ethical Issues**



# Appendix

## Proposed IMP






vs

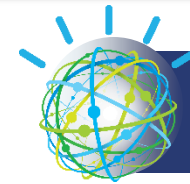
## IBM Watson

### Intelligent Medical Platform









#### Small Data & Human Knowledge Base

-  The system use fine-grained knowledge to provide customized services
-  Knowledge creation from small and big data with human intervention
-  Enriched knowledge technology to make highly accurate knowledge bases for small data
-  Combining data and human knowledge, ideal for both generalized and specialized cases
-  It also enables knowledge fusion and learning through Dialogue between humans and systems.



### IBM Watson

#### Big data Foundation







-  The 4th industry revolution turned to the IoT environment
-  Knowledge creation is primarily based on data-driven approaches only
-  Data-driven and statistical approaches prone to accuracy and performance degradation
-  Generalized knowledge creation, rare cases cannot be considered
-  High verification cost in knowledge acquisition and maintenance
-  Limited knowledge description results in low level satisfaction

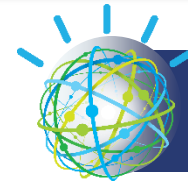
## Knowledge-Based Construction Methods

### Intelligent Medical Platform









### Evolutionary Knowledge Learning

-  Learning with the small and big data
-  Learned Knowledge can be described with example
-  Learned knowledge uses automatic tagging of data, securing high quality data and improving utilization of big data.
-  Difficult to make real-time correction of knowledge
-  Incremental learning based knowledge evolution
-  Automatic verification of knowledge acquisition process



### IBM Watson

### Deep Learning Knowledge

-  Large size data is required
-  Cannot explain reason for learned knowledge
-  Manual data labelling
-  Error in data acquisition results in low accuracy
-  Unable to extract new knowledge from existing data
-  Knowledge re-learning cannot guarantee the retention of previous knowledge



# Thanks

Sungyoung Lee, Kyung Hee University, Korea

URL: <http://uclab.khu.ac.kr>



경희대학교  
KYUNG HEE UNIVERSITY