KYUNG HEE UNIVERSITY

Department of Computer Science & Engineering

Ubiquitous Computing Lab

Hybrid Knowledge Modeling for Case Selection and Adaptation in CDSS

Ph.D. Defense Presentation

May 11th, 2022

Syed Imran Ali

Dept. of Computer Science and Engineering

Kyung Hee University

Advisor : Professor Sungyoung Lee

Co-Advisor : Professor TaeChoong Chung

Ubiquitous Computing Laboratory

Kyung Hee University, Korea

Presentation Agenda

HYBRID KNOWLEDGE MODELING

INTRODUCTION
- Background
- Motivation
- Problem Statement
- Taxonomy
- Related Work

PROPOSED IDEA
- Solution 1: Active Case Partitioning
- Solution 2: Case Selection
- Solution 3: Case Adaptation

EXPERIMENTATION & RESULTS
- Experimental Design
- System-centric Experimentation
- User-centric Experimentation

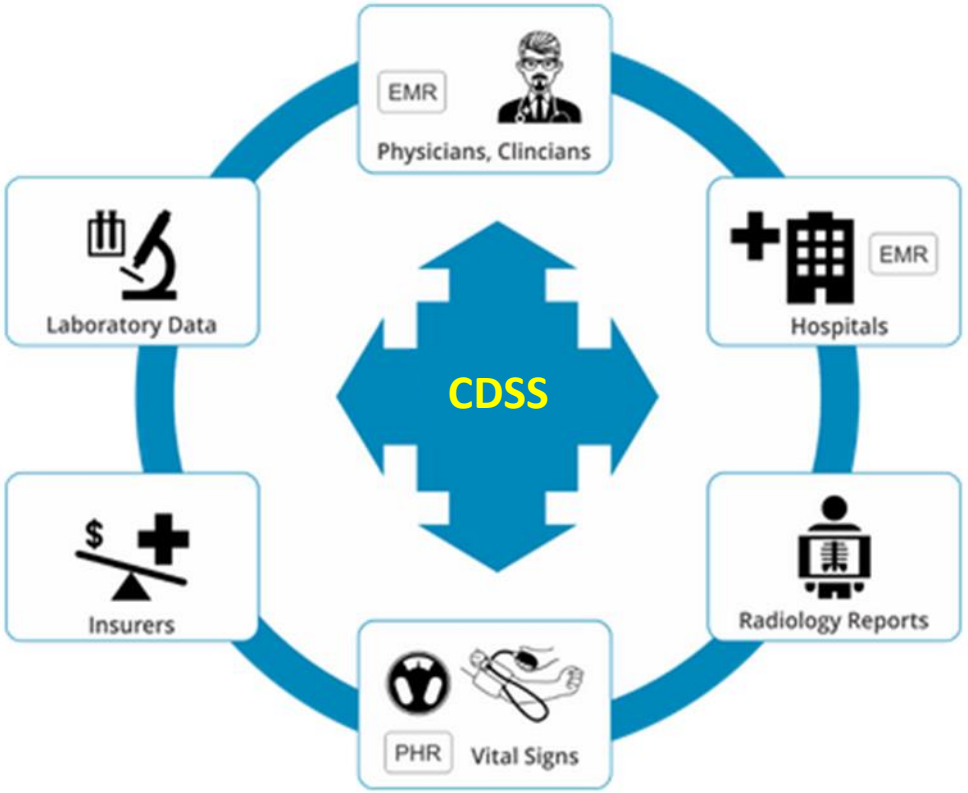
CONCLUSION

Background

- **Clinical Decision Support Systems (CDSS)** are specialized software solutions that ingest data to provide a wide array of services for cognitive-intensive complex decision making e.g. *disease diagnosis and treatment.*[1,2,3]

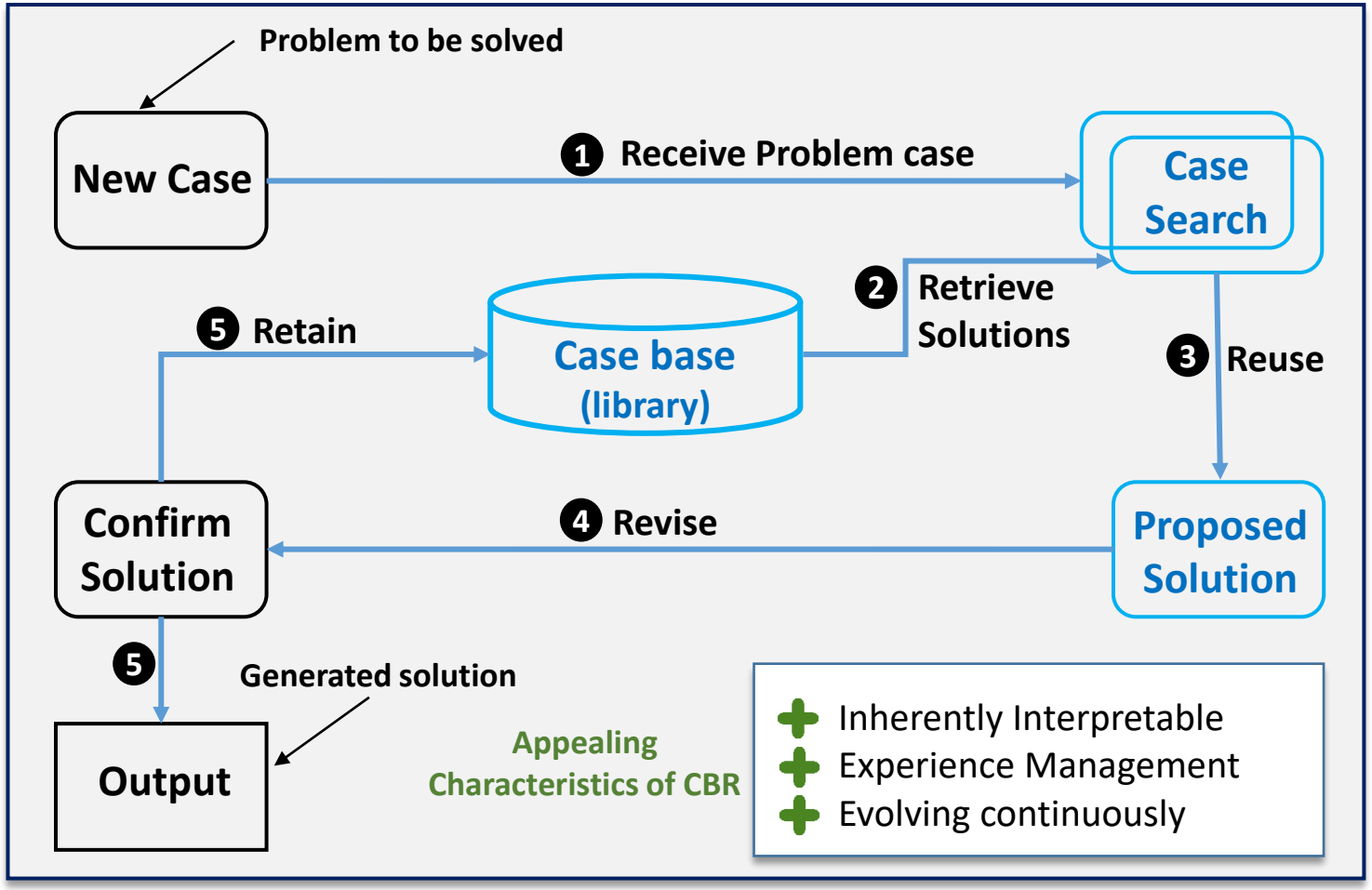
- CDSS increasingly leverage **data-driven** approaches for decision modeling along with **expert-driven** approaches for compliance with the domain processes.[4,5,6]

- **Hybrid knowledge modeling** play an important role in generating accurate and domain relevant recommendations for **complex scenarios** such as medication recommendation.[4,6,7]



Case-based Reasoning in CDSS

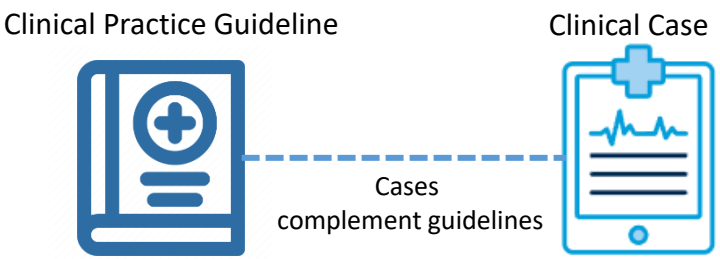
- **New Case:** Receive a test case comprised of problem component.
- **Case Search:** Search all the cases and retrieve a pre-defined set of nearest cases.
- **Proposed Solution**: Combine solution component of the retrieved cases e.g. majority vote or averaging.
- **Confirm Solution**: Domain expert finally accepts the generated solution or update the generated solution.
- **Knowledge base** contains past cases and newly retained cases.



Khan, M. J., Hayat, H., & Awan, I. (2019). Hybrid case-base maintenance approach for modeling large scale case-based reasoning systems. Human-centric Computing and Information Sciences, 9(1), 1-25.

Motivation

- Align consensus-based **domain knowledge** and experience-based routine **clinical practice** for multi-factor recommendations.



- Provide recommendation for **complex cases** with inherent **data scarcity** issues.

- Provide **transparency** and knowledge-based **interpretability** for the domain expert in recommendation generation.

- Reducing cognitive-load on the physician with **intuitive** and **reliable** decision support approach.

Problem Statement

Clinical Practice Guidelines provide a **general framework** to guide clinicians but lack **operational details i.e.** cover the partial scope of the recommendation. How to incorporate **expert-model** in case-based reasoning for **domain compliant** complex **recommendation** generation e.g. medication prescription? [8,9,18,19]

Overall Goal

Design a hybrid knowledge modeling approach for both medication and dosage selection that can leverage both partial domain knowledge as well as routine clinical practice of clinicians.

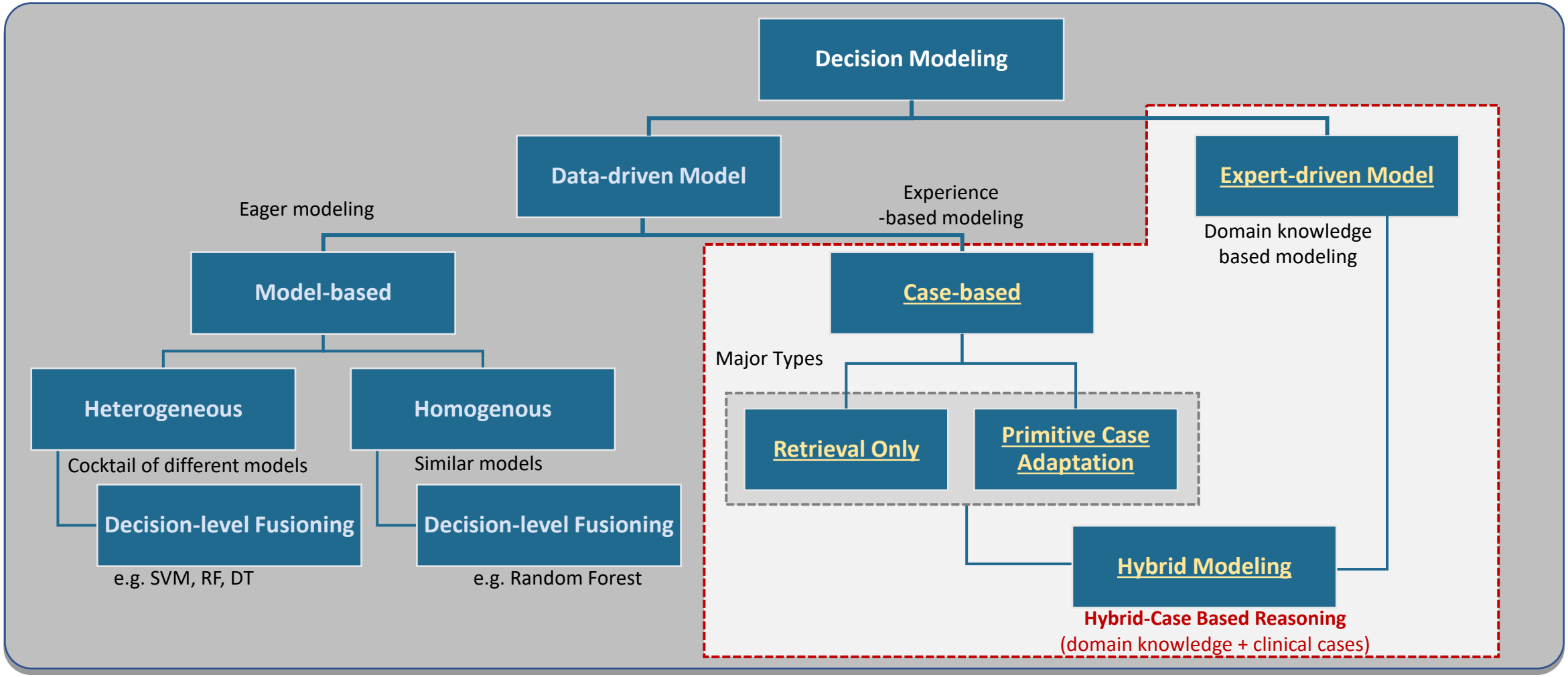
Objectives

1. Leverage partial domain knowledge for active partitioning of clinical case base.
2. Select highly relevant subset of clinical reference cases from a general pool of the candidate cases.
3. Synthesize domain model with selected cases for multi-factor recommendation generation.

Challenges

1. How to identify **distinct neighborhoods** within a single clinical case base?
2. How to identify relevant high prospect clinical cases for **effective solution selection**?
3. How to provide **fine-grained solution** recommendations from a partial domain model?

Taxonomy of Decision Modeling Approaches in CDSS



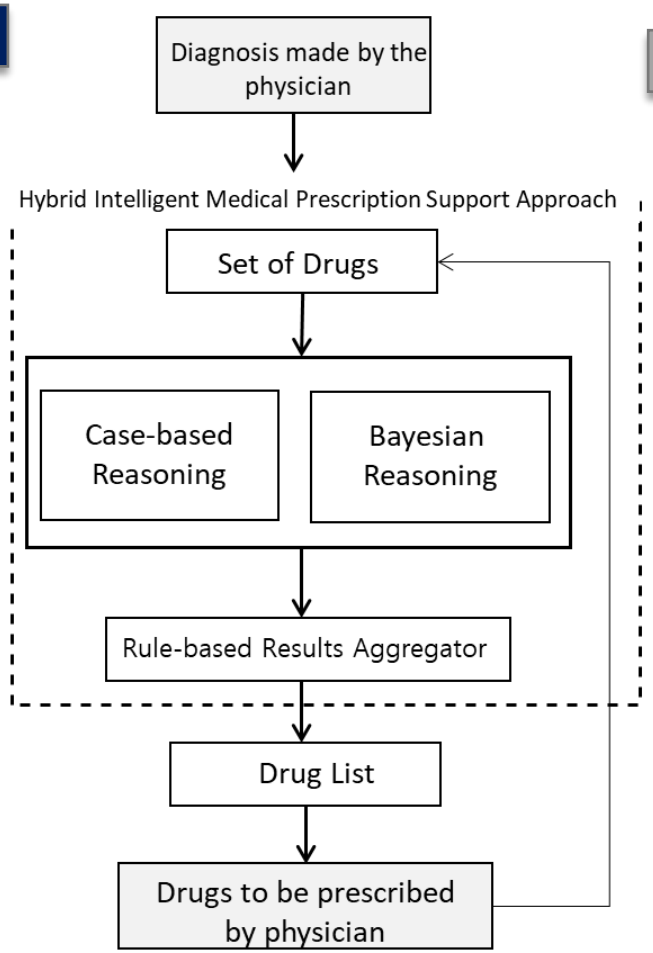
- [10] Artificial Intelligence: A Modern Approach, 4th US ed. by Stuart Russell and Peter Norvig. 2021
- [11] Alazzam, Malik Bader, et al. "Nursing care systematization with case-based reasoning and artificial intelligence." *Journal of Healthcare Engineering* 2022 (2022).

Related Work

Reference	Domain	Modeling	Guideline Incorporation	Capture Clinical Practice	Feedback	Medication Selection	Medication Dosing
[7] S.L. Ting, 2011	General treatment	Case-based	No	Yes	No	Yes	No
[16] Branden, 2011	Lung cancer treatment	Case-based	No	Yes	No	Yes	Yes (single)
[20] Khussainova, 2015	Brain cancer treatment	Case-based	No	Yes	No	No	No
[17] Teodorović, 2013	Thyroid Cancer treatment	Case-based	No	Yes	No	Yes	Yes (single)
[12] Shemeikka, 2015	Kidney patients treatment	Expert Model	Yes	No	No	Yes	No
[13] Hellden, 2015	General treatment	Expert Model	Yes	No	No	Yes	No
[14] Awdishu, 2016	Kidney patients treatment	Expert Model	Yes	No	No	Yes	Manual
[15] Pirnejad, 2019	Kidney patients treatment	Expert Model	Yes	No	No	Yes	Manual
[8] Niazkhani, 2020	Kidney patients treatment	Expert Model	Yes	No	No	Yes	Manual
Proposed	Kidney patients treatment	Hybrid: Case-based	Yes	Yes	Yes	Yes	Yes (multiple)

Comparison with Case-based Approach

As-Is

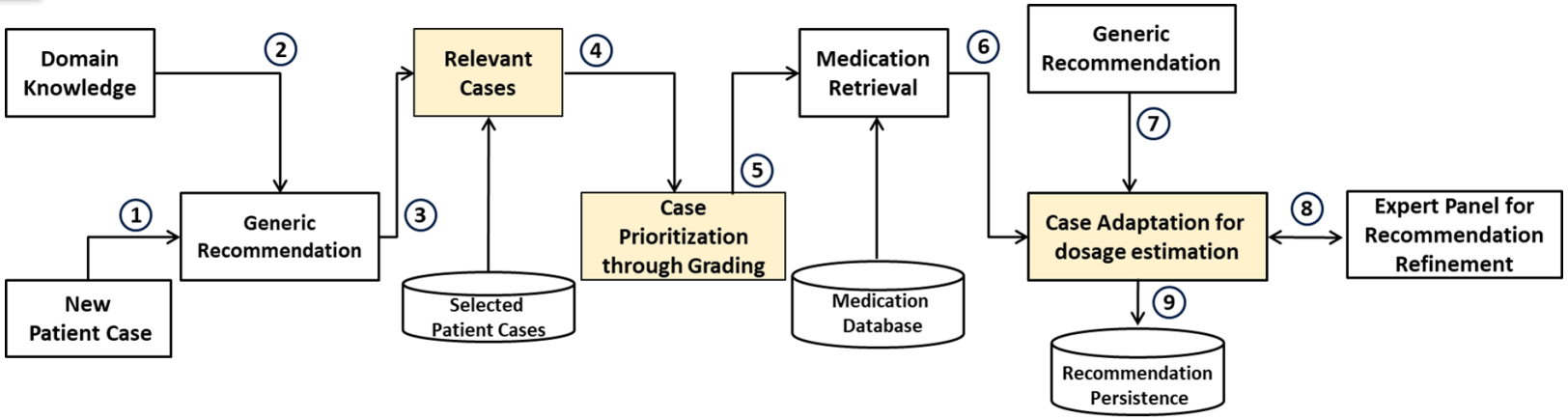


S.L. Ting, 2011: Hybrid Knowledge-based approach to Support Medical Prescription (**HKSMP**)

VS

To-Be

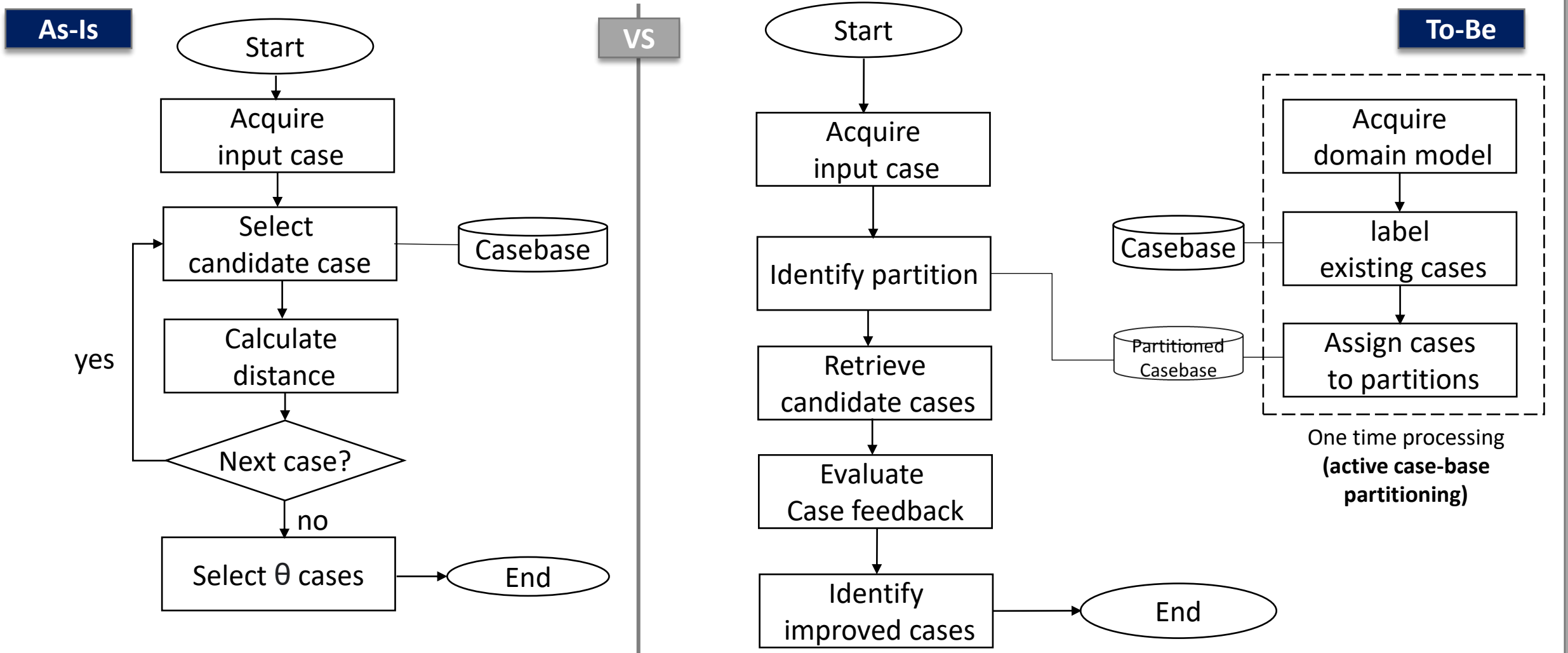
Hybrid Case-based Reasoning (H-CBR)



Summarized Comparison

Characteristics	HKSMP	H-CBR
Domain Knowledge	No	Yes
Capture Clinical Practice	Yes	Yes
Multi-level Selection	No	Yes
Medication Selection	Yes	Yes
Medication Dosing	No	Yes

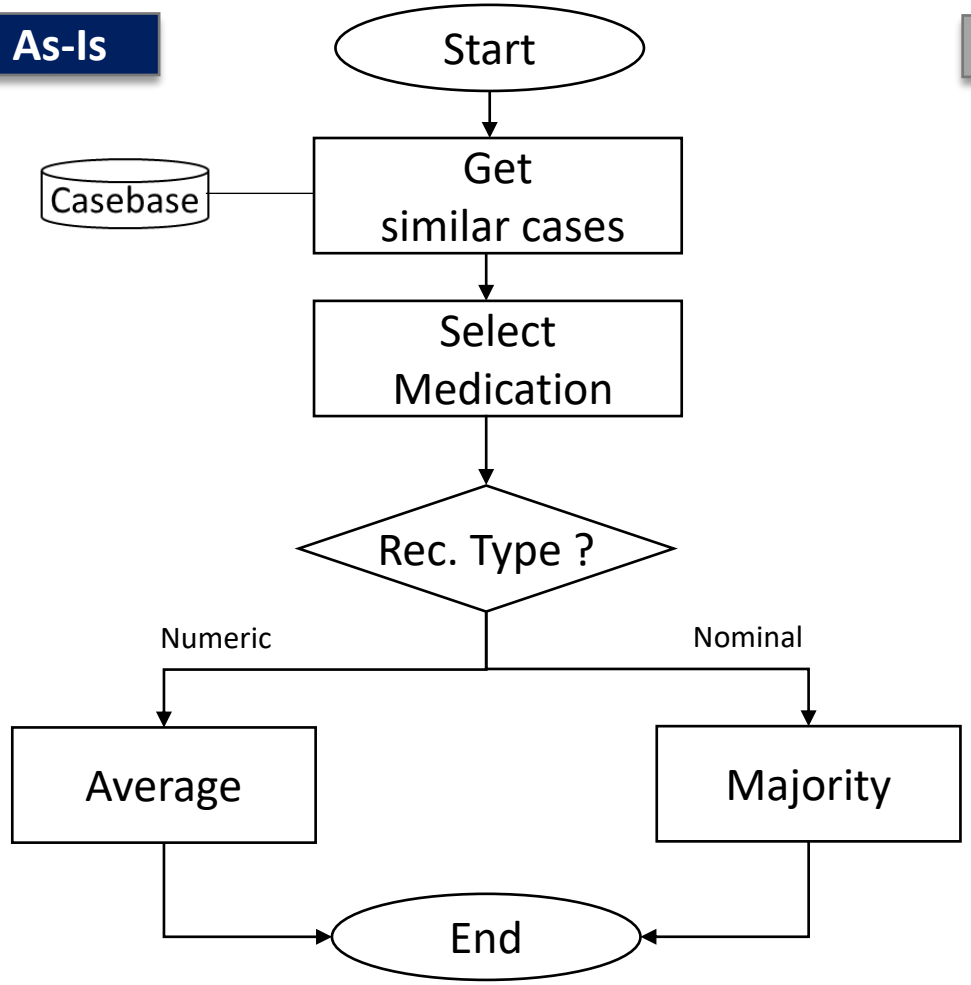
Comparison with Case Partition and Selection Process



S.L. Ting, 2011: Hybrid Knowledge-based approach to Support Medical Prescription (**HKSMP**)

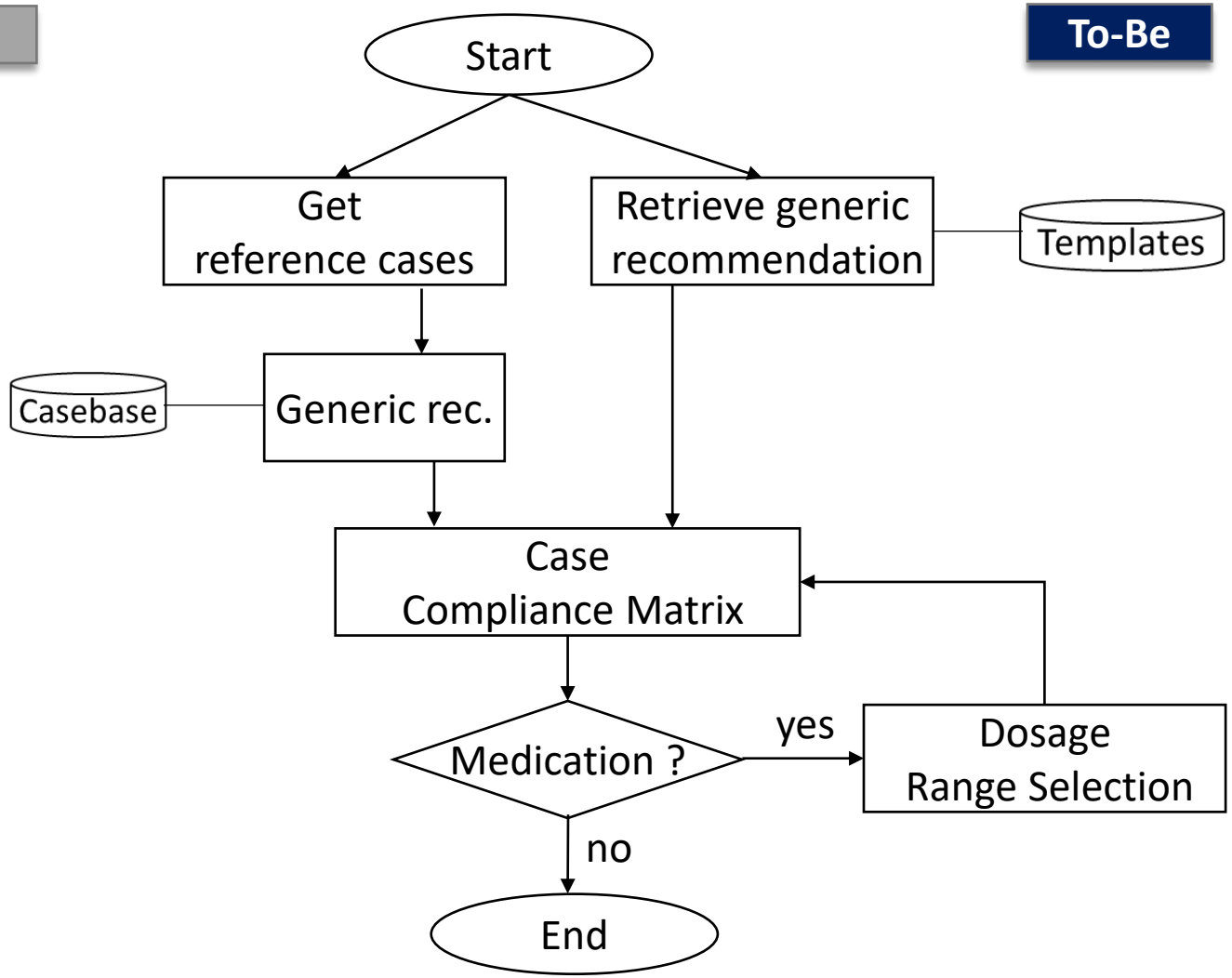
Comparison with Case Adaptation Process

As-Is



VS

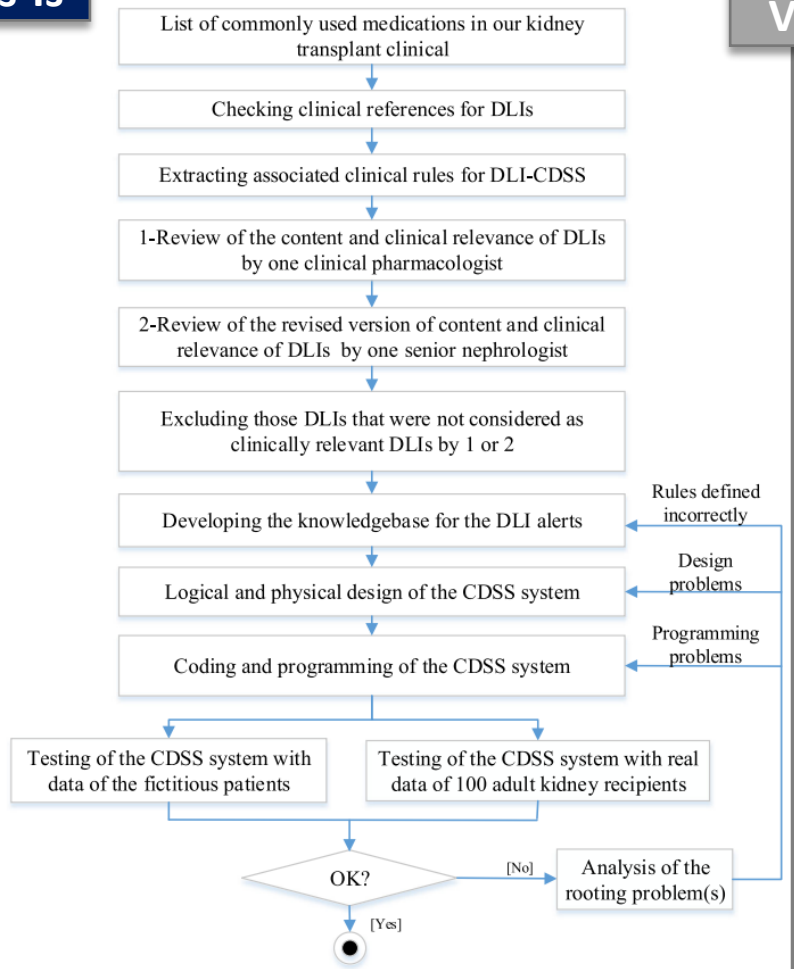
To-Be



Teodorović et al. "Combining case-based reasoning with Bee Colony Optimization for dose planning in well differentiated thyroid cancer treatment." Expert Systems with Applications 40.6 (2013): 2147-2155.

Comparison with Expert-model based Approach

As-Is

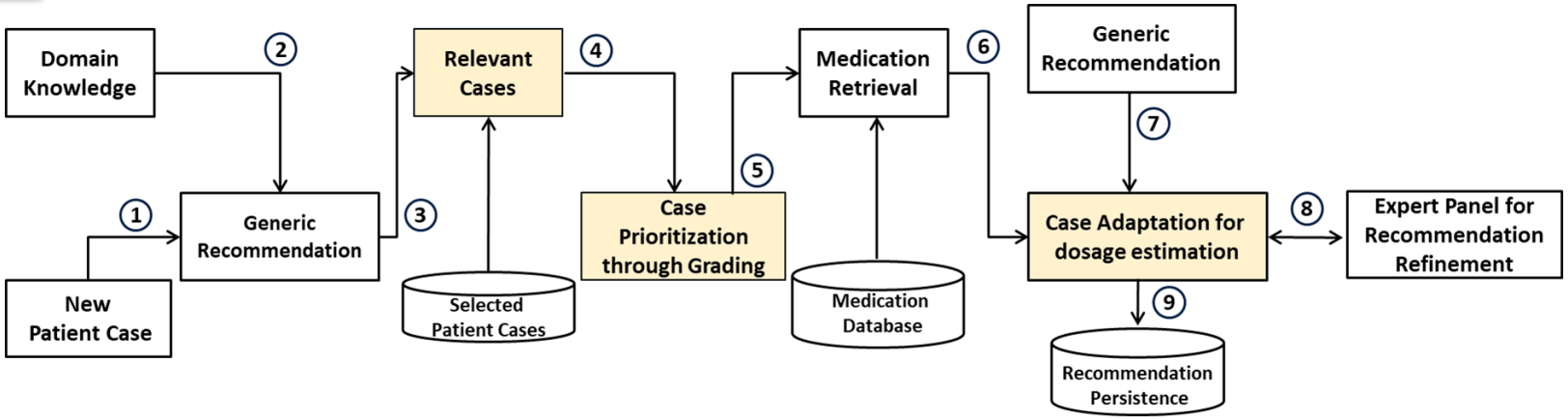


Niazkhani, 2020: Domain knowledge-based Medication Selection (**DKMS**)

VS

To-Be

Hybrid Case-based Reasoning (H-CBR)



Summarized Comparison

Characteristics	DKMS	H-CBR
Domain Knowledge	Yes	Yes
Capture Clinical Practice	No	Yes
Multi-level Selection	No	Yes
Medication Selection	Yes	Yes
Medication Dosing	Manual	Automated

Challenges and Solutions

Challenges	Solutions	Benefits
Ch-1 Distinct neighborhood identification	Sol-1 Leverage **domain knowledge** to actively partition the case base in an a priori manner.	Case insufficiency detection
Ch-2 Unspecified utility of similar cases	Sol-2 Leverage **case outcome** information from the **feedback** for reference solutions selection.	Quantify efficacy of similar cases
Ch-3 Partial domain model	Sol-3 Leverage **domain knowledge** with **reference cases** for multi-factor recommendation generation	Fine-grained Recommendation

Research Map

Domain Model

Clinical Cases

Proposed Solutions

Solution 1
Active Case base Partitioning

Problem: User define **neighborhood threshold** value results in **fixed size** case base partitions. Appropriate neighborhood size selection is based on **trial and error** approach.

Solution 2
Case Selection

Problem: Similar candidate cases are selected primarily based on their **proximity** to the test case while **outcome information** is not accounted for case selection.

Solution 3
Case Adaptation

Problem: Domain knowledge is generally **insufficient** for generating recommendations for **complex tasks** such as medication **dosage selection**

Recommendation

Outcomes

+ Variable neighborhood size
+ Quantify efficacy of similar cases
+ Fine-grained recommendation

Challenges

C1: Fixed size neighborhood

C2: Similar cases treated equally

C3: Partial domain knowledge

Challenge 1

Existing Approach

-- Trial and error approach for neigh borhood size selection

-- Pick top K nearest cases at the inference time (lazy-modeling)

Challenge 2

Existing Approach

-- Select all cases within a selected neighborhood

-- Assign weight to case dimensions based on domain experts

Challenge 3

Existing Approach

-- Primitive dosage estimation for a single medicine

-- Manual dosage selection by domain expert (physician)

Outcomes

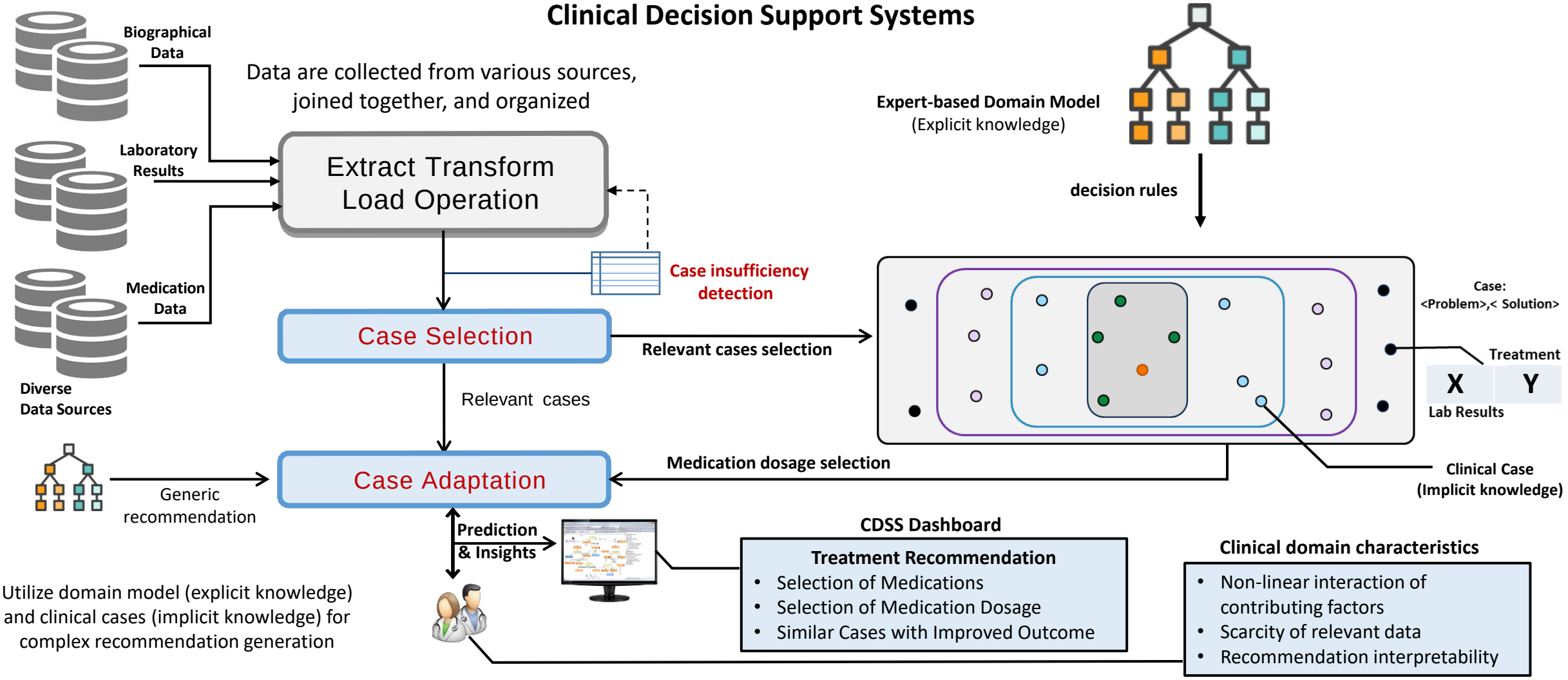
-- Case uncertainty

-- Similar case may be unrelated

-- Generic recommendation

Research At A Glance

Clinical Decision Support Systems



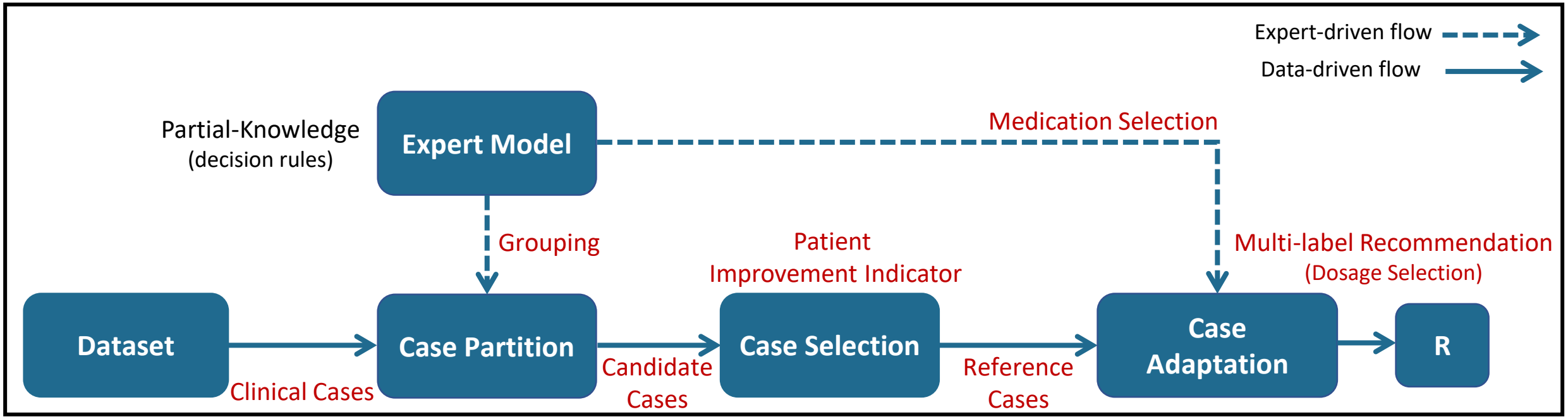
Utilize domain model (explicit knowledge) and clinical cases (implicit knowledge) for complex recommendation generation

Proposed Methodology

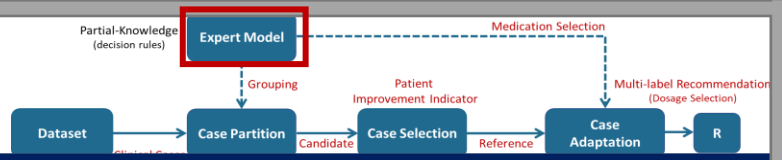
Hybrid Knowledge Modeling for Case-based Reasoning

Contributions:

- Active Casebase Partitioning
- Case Selection using Patient Improvement Indicator
- Case Adaptation using Hybrid Approach



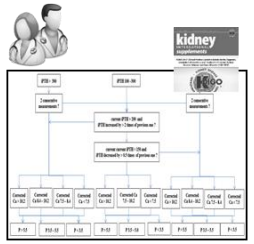
Ali, Syed Imran, et al. "Clinical Decision Support System Based on Hybrid Knowledge Modeling: A Case Study of Chronic Kidney Disease-Mineral and Bone Disorder Treatment." *International Journal of Environmental Research and Public Health* 19.1 (2021): 226.



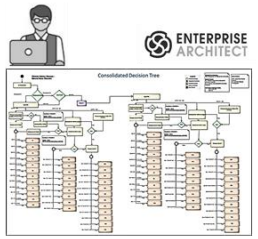
Expert-based Domain Model

Expert-model construction based on clinical practice guidelines (domain knowledge)

Multiple consultation sessions between Physicians and Knowledge Engineers



Mind Map creation based on domain knowledge for the clinical decision automation

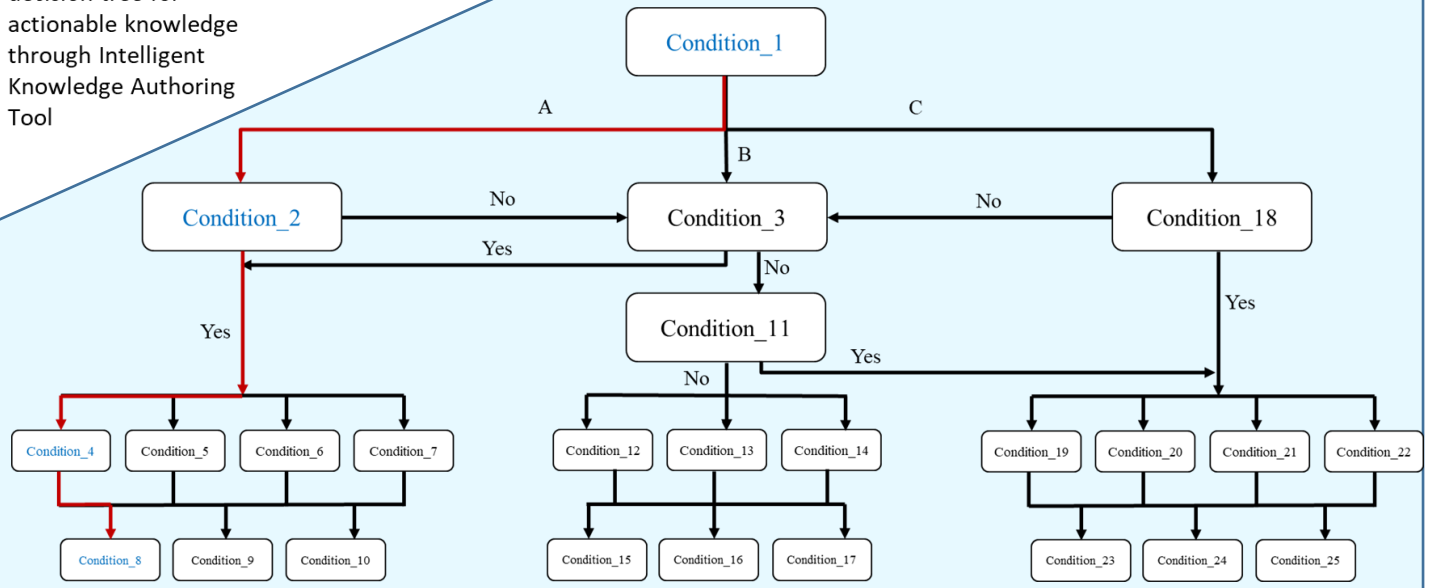


Iterative decision tree construction for formal knowledge modeling through Enterprise Architect

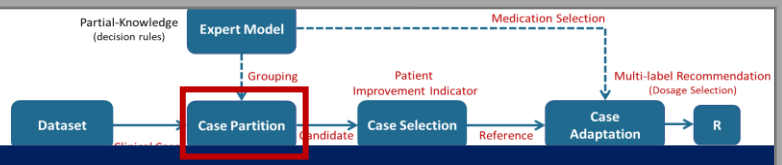
Creating production rules based on iterative decision tree for actionable knowledge through Intelligent Knowledge Authoring Tool

Once rules are validated, they are persisted in the Knowledge Base for recommendation generation

General representation of the expert model (Mind Map)

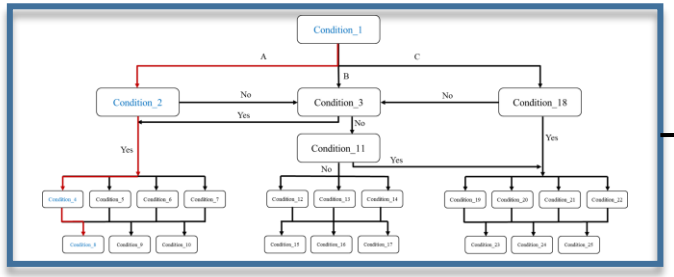


Sample Rule: $\boldsymbol{IF}: < ConditionSet: \{A, 2,4,8\} > \boldsymbol{THEN}: < Recommendation: \{T1\} >$



Active Case-base Partitioning

Expert Model



Sample Decision Rules

VascularCal	ValvularCal	PTH	PTH_(	PTH_(	PTH_(	PTH_C	CorrectedCa	Phosphate	RuleRecCode
Present	Absent	300-100	no	no	no	no	>10.2	>5.5	T13
Present	Absent	300-100	no	no	no	no	>10.2	3.5-5.5	T14
Present	Absent	300-100	no	no	no	no	>10.2	<3.5	T15
Present	Absent	300-100	no	no	no	no	8.4-10.2	>5.5	T16
Present	Absent	300-100	no	no	no	no	8.4-10.2	3.5-5.5	T17
Present	Absent	300-100	no	no	no	no	8.4-10.2	<3.5	T18
Present	Absent	300-100	no	no	no	no	7.5-8.4	>5.5	T16
Present	Absent	300-100	no	no	no	no	7.5-8.4	3.5-5.5	T17
Present	Absent	300-100	no	no	no	no	7.5-8.4	<3.5	T18
Present	Absent	300-100	no	no	no	no	<7.5	>5.5	T19
Present	Absent	300-100	no	no	no	no	<7.5	3.5-5.5	T20
Present	Absent	300-100	no	no	no	no	<7.5	<3.5	T21
Present	Absent	<100	no	no	no	no	>10.2	>5.5	T13
Present	Absent	<100	no	no	no	no	>10.2	3.5-5.5	T14
Present	Absent	<100	no	no	no	no	>10.2	<3.5	T15

rule: Reasoning (case)

Dataset

Patient Clinical Cases

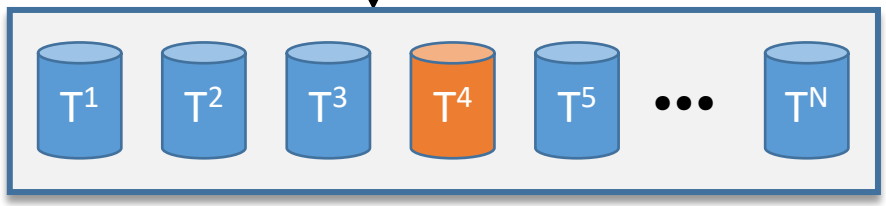
Active Case Partitioning

KB

Knowledge Base

Similar cases are placed in same neighborhood

Cases assigned to multiple variable size neighborhoods



Easily identify a neighborhood with **insufficient number of cases** prior to test case processing

Algorithm 1: Active Case Partitioning

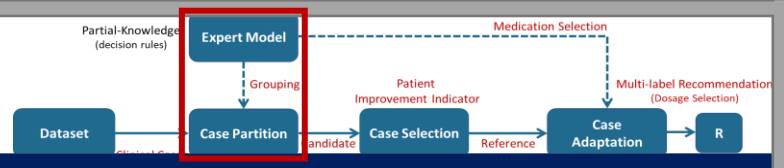
Input: Rules KB, Case Base CB

Output: Partition $P = \{T_1, T_2, T_3, \ldots, T_n\}$

Begin

1: ***foreach*** c *in* CB:
2: $\quad rule = \textbf{reasoning}(c)$
3: $\quad rec = rule[1].code$
4: $\quad P[rec] = c \quad //assign(c, rec)$
5: ***foreach*** pt *in* P:
6: $\quad$ ***if*** $pt.length \leq \emptyset$
7: $\quad\quad flag(pt)$
8: $return\ P$

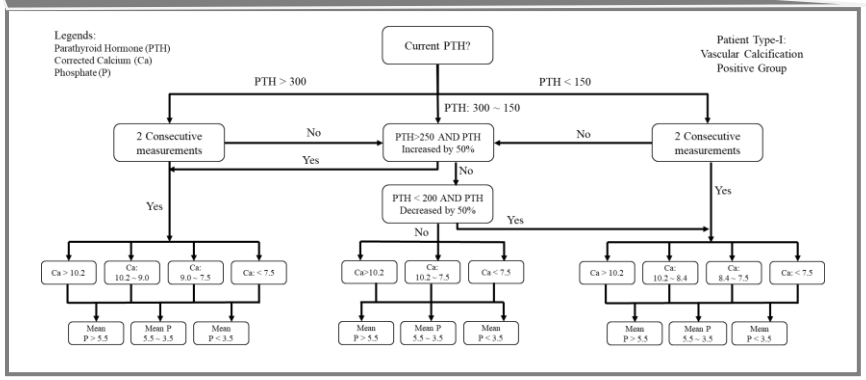
End



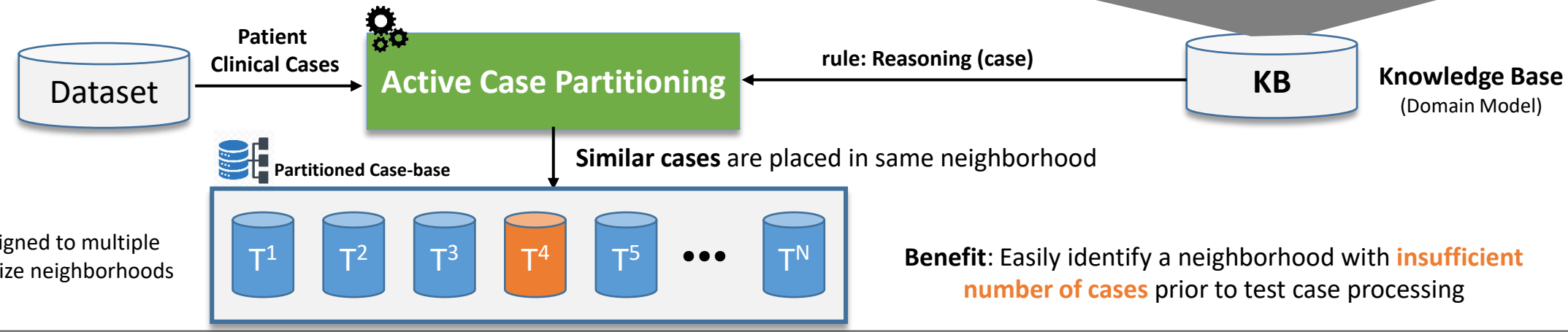
Active Case-base Partitioning based on Domain Model

Knowledge Engineering Process

Expert-model construction based on clinical practice guidelines (**domain knowledge**)

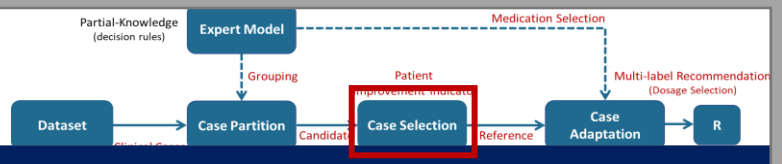


VascularCal	ValvularCal	PTH	PTH_	PTH_	PTH_	PTH_C	CorrectedCa	Phosphate	RuleRecCode
Present	Absent	300-100	no	no	no	no	>10.2	>5.5	T13
Present	Absent	300-100	no	no	no	no	>10.2	3.5-5.5	T14
Present	Absent	300-100	no	no	no	no	>10.2	<3.5	T15
Present	Absent	300-100	no	no	no	no	8.4-10.2	>5.5	T16
Present	Absent	300-100	no	no	no	no	8.4-10.2	3.5-5.5	T17
Present	Absent	300-100	no	no	no	no	8.4-10.2	<3.5	T18
Present	Absent	300-100	no	no	no	no	7.5-8.4	>5.5	T16
Present	Absent	300-100	no	no	no	no	7.5-8.4	3.5-5.5	T17
Present	Absent	300-100	no	no	no	no	7.5-8.4	<3.5	T18
Present	Absent	300-100	no	no	no	no	<7.5	>5.5	T19
Present	Absent	300-100	no	no	no	no	<7.5	3.5-5.5	T20

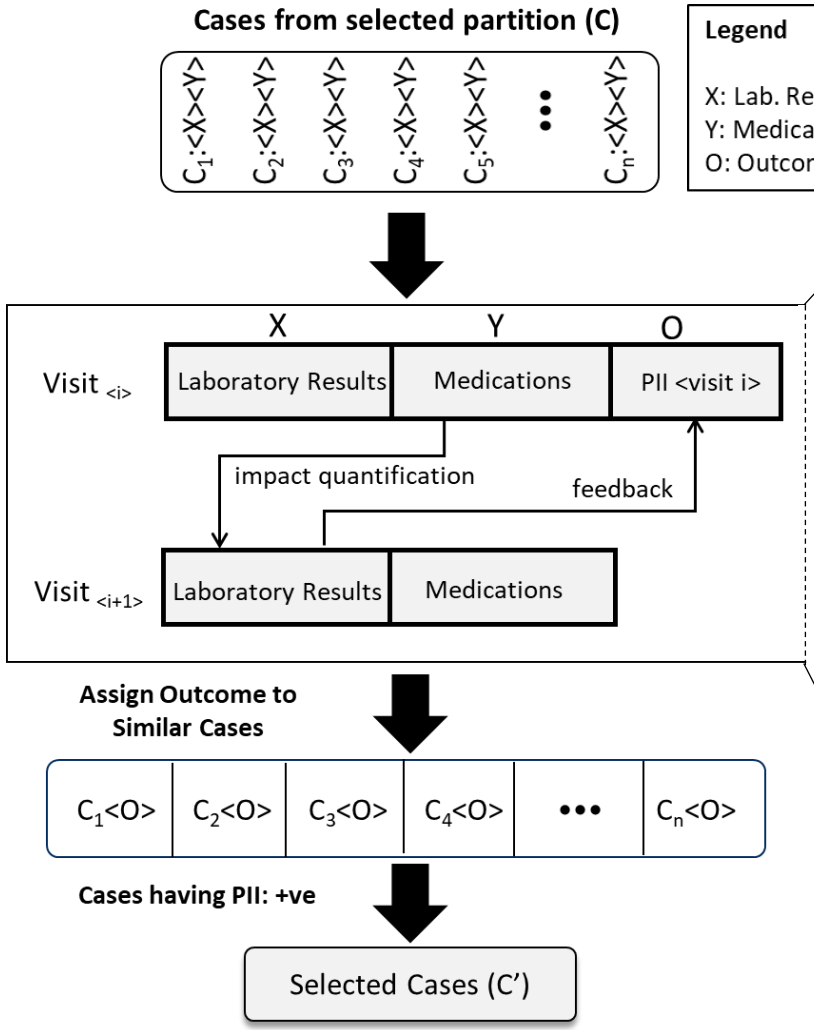


Cases assigned to multiple variable size neighborhoods

Benefit: Easily identify a neighborhood with **insufficient number of cases** prior to test case processing

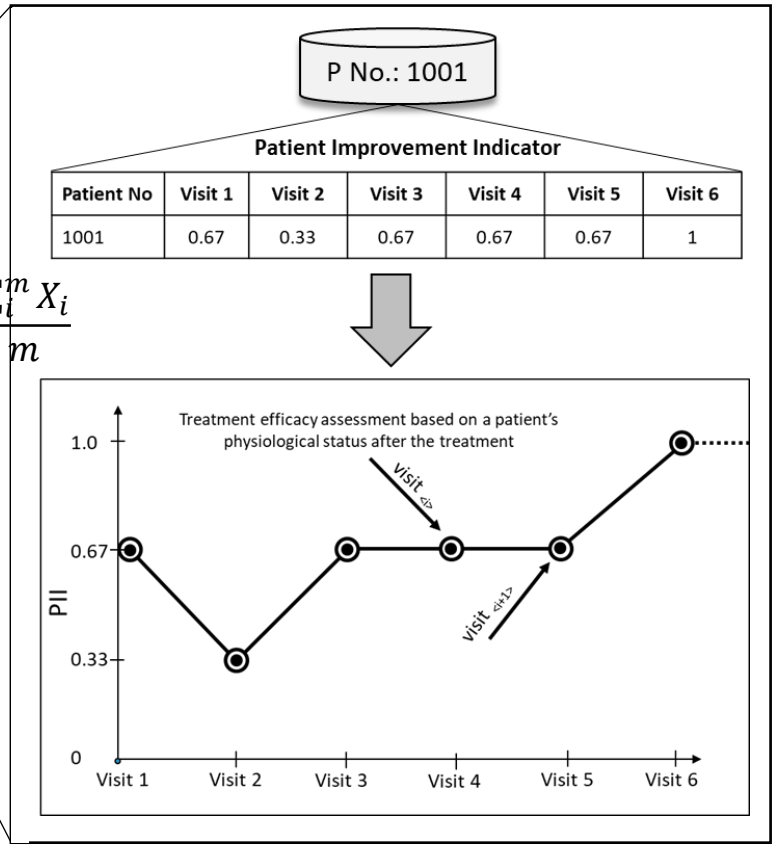


Case Selection based on Feedback



$$PII = \frac{\sum_i^m X_i}{m}$$

Example: Outcome score assignment



Patient No	Visit 1	Visit 2	Visit 3	Visit 4	Visit 5	Visit 6
1001	0.67	0.33	0.67	0.67	0.67	1

Algorithm 2: Case Selection

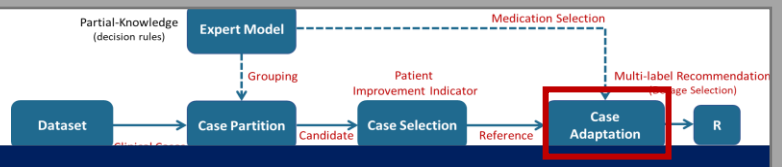
Input: Partitioned Cases C,

Output: Selected Cases C′

Begin

1: ***foreach*** c *in* C:
2: ***if*** $c_{outcome}$ $!= Null$:
3: $c_{outcome} \leftarrow fetch_{PII}(c)$
4: ***else***
5: ***foreach*** t *in* T:
6: $indicator = eval(c_t, Ref)$
7: $result += indicator$
8: $c_{out} = result \,/\, len(result)$
9: $c_{prev} \leftarrow fetch_{PII}(c)$
10: ***if*** $(c_{out} != 0)$ && $(c_{out} \geq c_{prev})$
11: $C_{selected} += c$
12: $return\ C_{selected}$

End

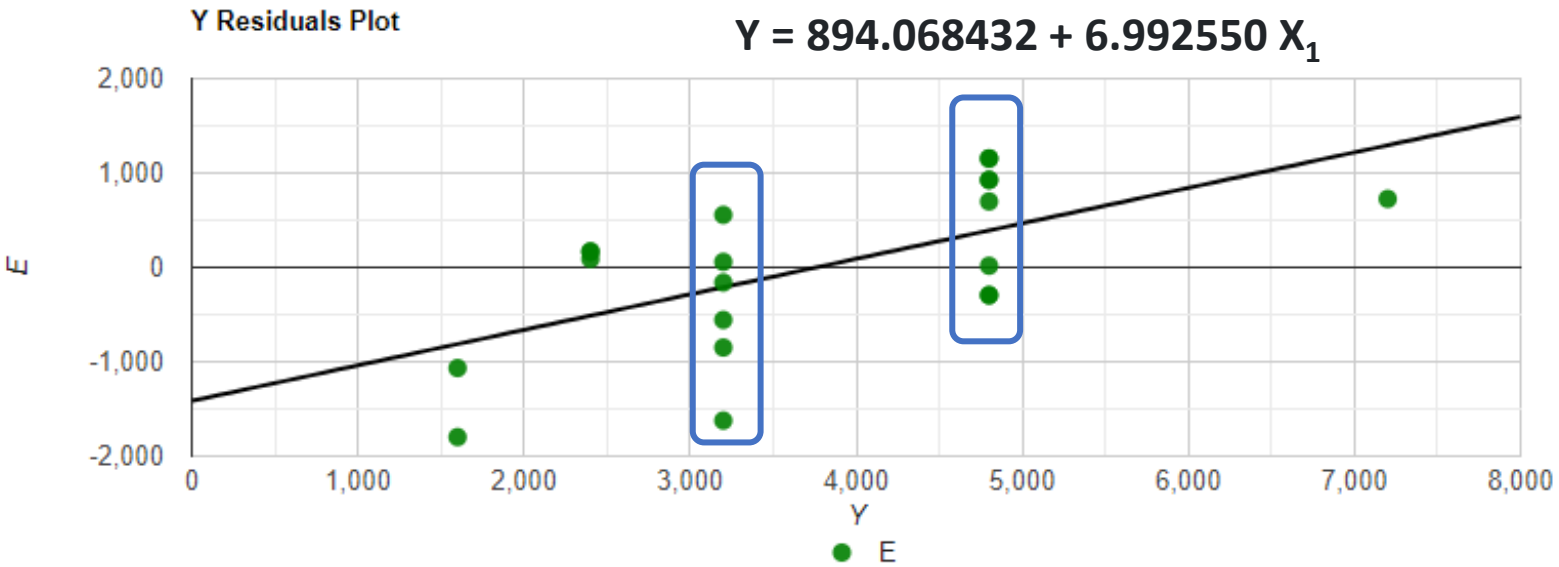


Case Adaptation

Point estimation through Multiple Linear Regression

R square (R2) equals 0.623822. It means that the predictors (Xi) explain 62.4% of the variance of Y.

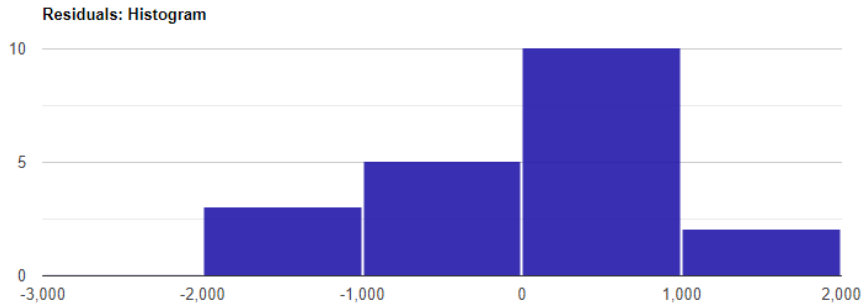
Y = 894.068432 + 6.992550 X_1

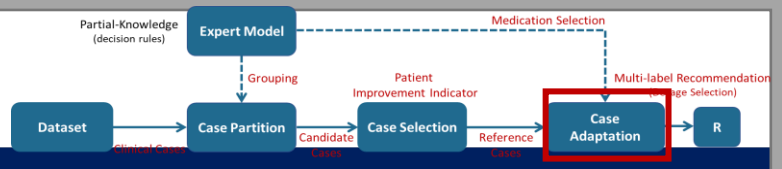


pid	visit	pth	albumi	calcium	phospha	correct	vascula	valvular	Cinacalc	Clacitr	Calcitr	Paricalcit	Alfacalcid	Calcium(	CalciumA	Sevelam	Lanthanu	Dialysa	rec
1447227	3	458.7	3.3	5.7	11.52	6.26	0	Absent	0	0	0	0	0	3000		4800	0	1.5	T19
1447227	4	600.7	3.6	6	15.8	6.32	0	Absent	0	0	0	0	0	3000		4800	0	1.5	T19
1447227	5	600.7	3.4	6.2	10.9	6.68	0	Absent	0	0	0	0	0	0		4800	0	1.5	T19
1447227	9	556.1	3.4	6.8	9.2	7.28	0	Absent	0	0	0	0	0	0		4800	0	1.5	T19
1447227	12	798	3.3	6.91	9.6	7.47	0	Absent	0	0	3	0	0	0		7200	0	1.5	T19
2251496	3	253.5	3.7	6.7	8.1	6.94	10	Present	0	0	0	0	0	1500		1600	0	1.25	T19
3380095	2	409.4	3.9	7.4	5.8	7.48	5	Absent	0	0	0	0	0	0		3200	0	1.25	T19
3380095	6	451.2	3.9	7.4	6.3	7.48	5	Absent	0	0	0	0	0	0		3200	0	1.25	T19
3618303	3	561.9	4.2	7.5	7.4	7.26	0	Absent	0	0	0	5	0	0		3200	0	1.25	T19
4194253	9	202.5	4	[illegible]	[illegible]	6.82	1	Present	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]		2400	0	1.25	T19
4194253	11	192	3.7	6.6	7.5	6.84	1	Present	0	0	0	0	0	1500		2400	0	1.25	T19
4194253	13	191	4.1	6.6	7.3	6.52	1	Present	0	0	0	0	0	1500		2400	0	1.25	T19
5032360	2	250.2	3.9	6.8	7.3	6.88	0	Absent	0	0	0	0	0	0		3200	0	1.75	T19
5358840	3	321.4	4	7	8.4	7	0	Absent	0	0	0	0	0	1500		3200	0	1.25	T19
5358840	5	352.7	4.1	7.1	5.6	7.02	0	Absent	0	0	0	0	0	1500		3200	0	1.25	T19
5358840	8	393.5	3.7	7.1	6.3	7.34	0	Absent	0	0	0	0	0	1500		4800	0	1.25	T19
5358840	9	393.5	4	6.6	6.9	6.6	0	Absent	0	0	0	0	0	1500		4800	0	1.25	T19
5358840	10	426	3.9	7.2	5.7	7.28	0	Absent	0	0	1.5	0	0	0		4800	0	1.25	T19
5358840	12	426	3.9	7	8	7.08	0	Absent	0	0	1.5	0	0	1500		4800	0	1.25	T19
7072931	1	358.1	4.3	7.2	8.4	6.96	0	Absent	0	0	0	0	0	0		1600	0	1.25	T19

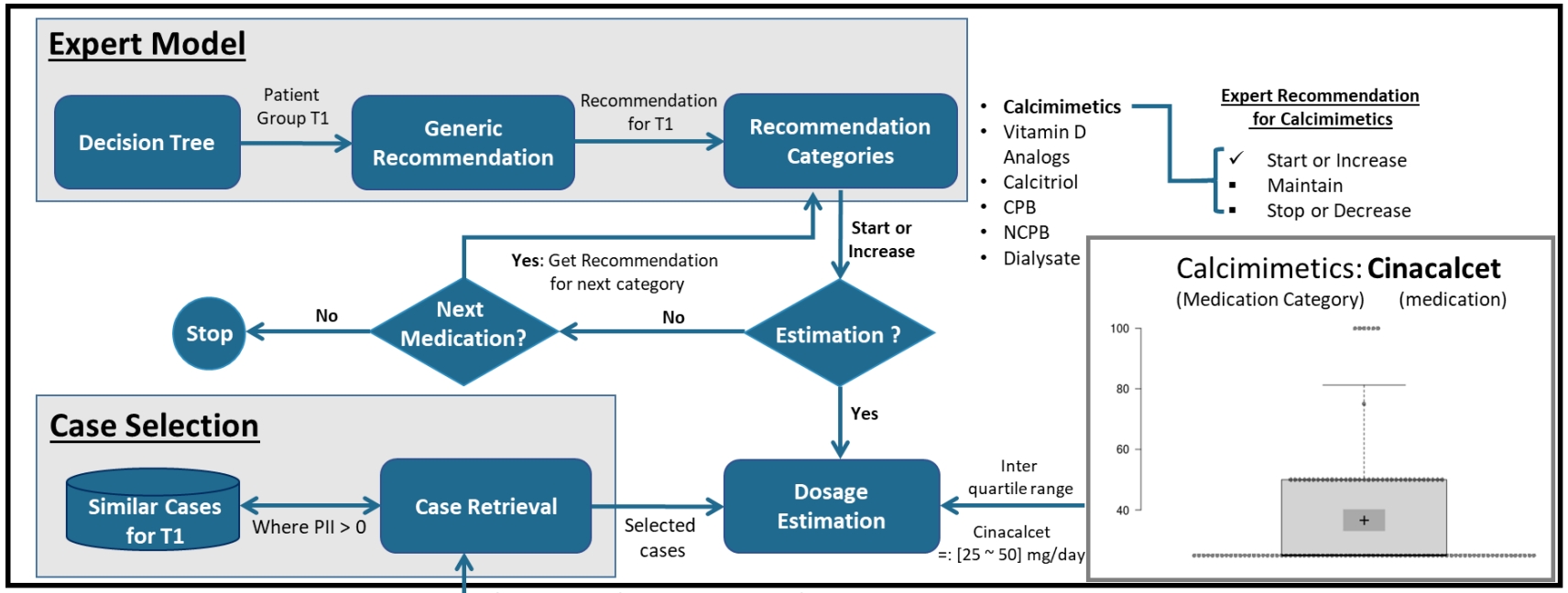
Reference Cases

Medication of Reference Cases





Case Adaptation using Hybrid Approach



Laboratory and imaging test results

MRN	Encounter No.	PTH	Albumin	Calcium	Phosphate	Vascular Calcification	Valvular Calcification	PII Value
1933623	10	103	3.7	8.9	6.9	4	Present	0.67
1933623	11	103	3.5	8.5	5.7	4	Present	0.33
1933623	12	103	3.7	8.5	6.5	4	Present	0.33
4855226	10	131	3.8	9.3	6.3	0	Absent	1.0
4855226	12	131	3.6	9.1	8.2	0	Absent	0.67
•••	•••	•••	•••	•••	•••	•••	•••	•••
1266498	2	145	3.9	10.2	9.1	4	Present	0.33

Medication for selected cases

Cincalcet (mg/day)	•••
25	•••
25	•••
25	•••
50	•••
50	•••
•••	•••
75	•••

Medications for Calcimimetics

Algorithm 3: Case Adaptation

Input: Domain Knowledge: DTcode,
Selected Case: C'

Output: Medication Dosage: R

Begin

$Rec_{gen} \leftarrow fetchRec(DTcode)$

foreach cat *in* Rec_{gen}:

  $action_{cat} \leftarrow process\ (cat)$

  if $action_{cat}$ == *Initiate or Increase*

    foreach m *in* C':

      $med_{dosage} \leftarrow fetch(C_m)$

      $med_{size} \leftarrow len(med_{dosage})$

      $m \leftarrow sort(med_{dosage})$

      $mid_{index} \leftarrow m(m, 0, \mathrm{med}_{\mathrm{size}})$

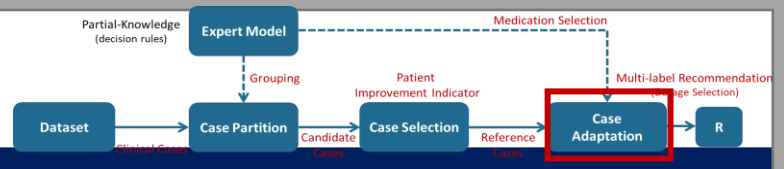
      $Range_L \leftarrow m[median(m, 0, mid_{index})$

      $Range_H \leftarrow m[mid_{index} + median(m, 0, mid_{index})]$

      $R.append(Range_L, Range_H)$

$Return\ R$

End



Case Adaptation: Dosage Estimation

Selected Generic Recommendation

Domain Model

Previous Cases

Reference Cases

Generate Generic Recommendation

Compare **previous** and **current** medications

Case Compliance Matrix

Cases/Factors	Factor 1	Factor 2	Factor 3	...	Factor N
Case 1	1	1	0	...	1
Case 2	1	0	0	...	1
Case 3	0	1	1	...	0
...	...	...	...	...	...
Case m	1	1	1	...	1

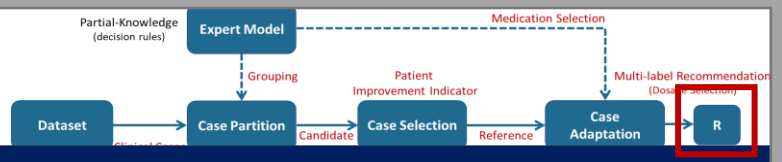
1: Matched **0**: Unmatched

Compare **previous** and **current** medications i.e. 1 or 0, and compute aggregations

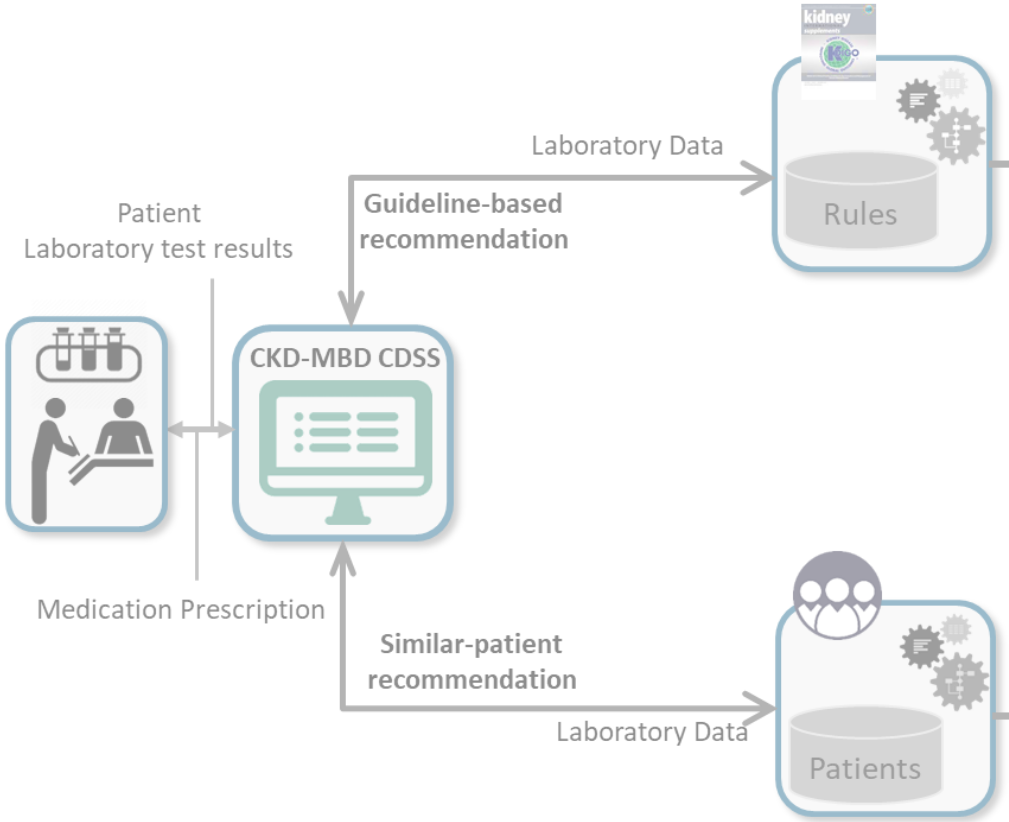
Compliance rate for each factor

Medication Dosage for each factor

Range selection using **interquartile range**



Multi-factor Recommendation



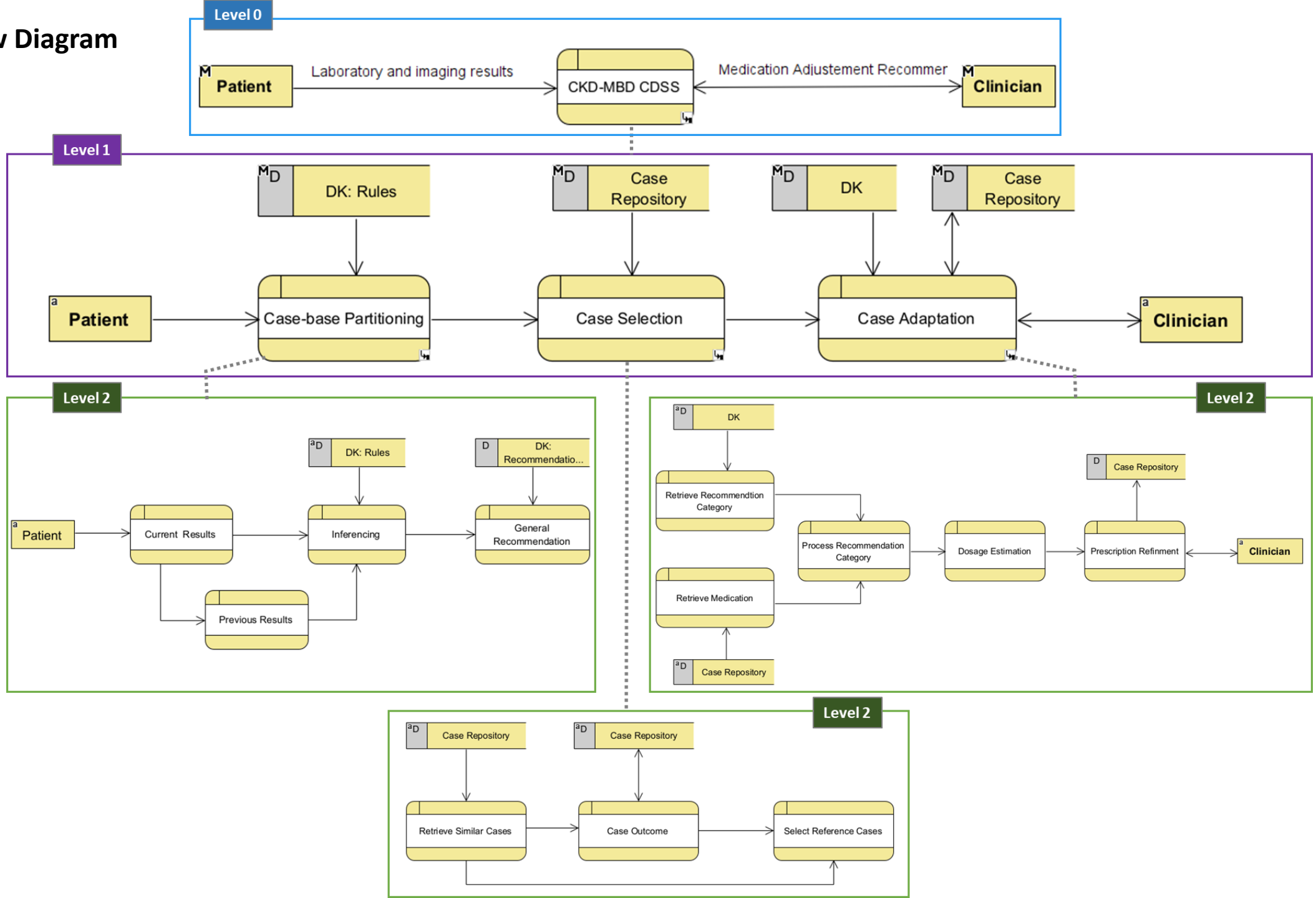
Generic Medication Prescription based on Guidelines

Calcimimetics	Dialysate Cal. Concentration
Start or Increase	Maintain
Calcium-based Phosphate Binder	**Non-Calcium-based Phosphate Binder**
Stop CPB	Start or Increase
Vitamin D receptor activators	**Calcitriol**
Stop Vitamin D & Analogs	Stop Calcitriol

Medication Dosage Prescription based on Similar Patients

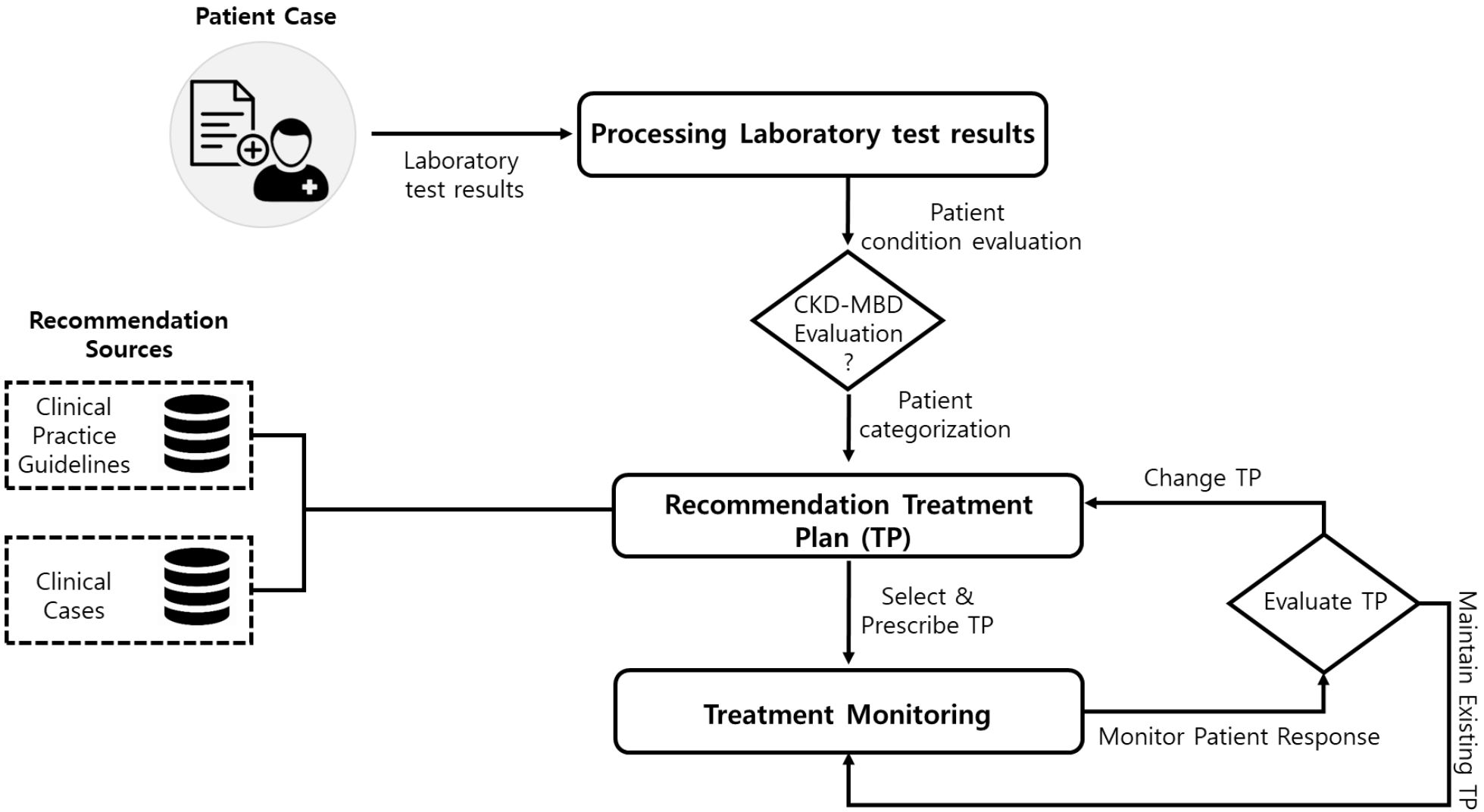
Cinacalcet (mg/day)	Calcitriol, po (ug/day)	Calcitriol, iv (ug/week)	Paricalcitol (ug/week)
25 - 50	0	2.5 - 5	0
Alfacalcidol (ug/day)	**Calcium Carbonate (mg/day)**	**Calcium Acetate (mg/day)**	**Lanthanum (mg/day)**
0	0	0	0
Sevelamer (mg/day)	**Dialysate Calcium Concentration (mmol/L)**		
800	1.25		

Data Flow Diagram

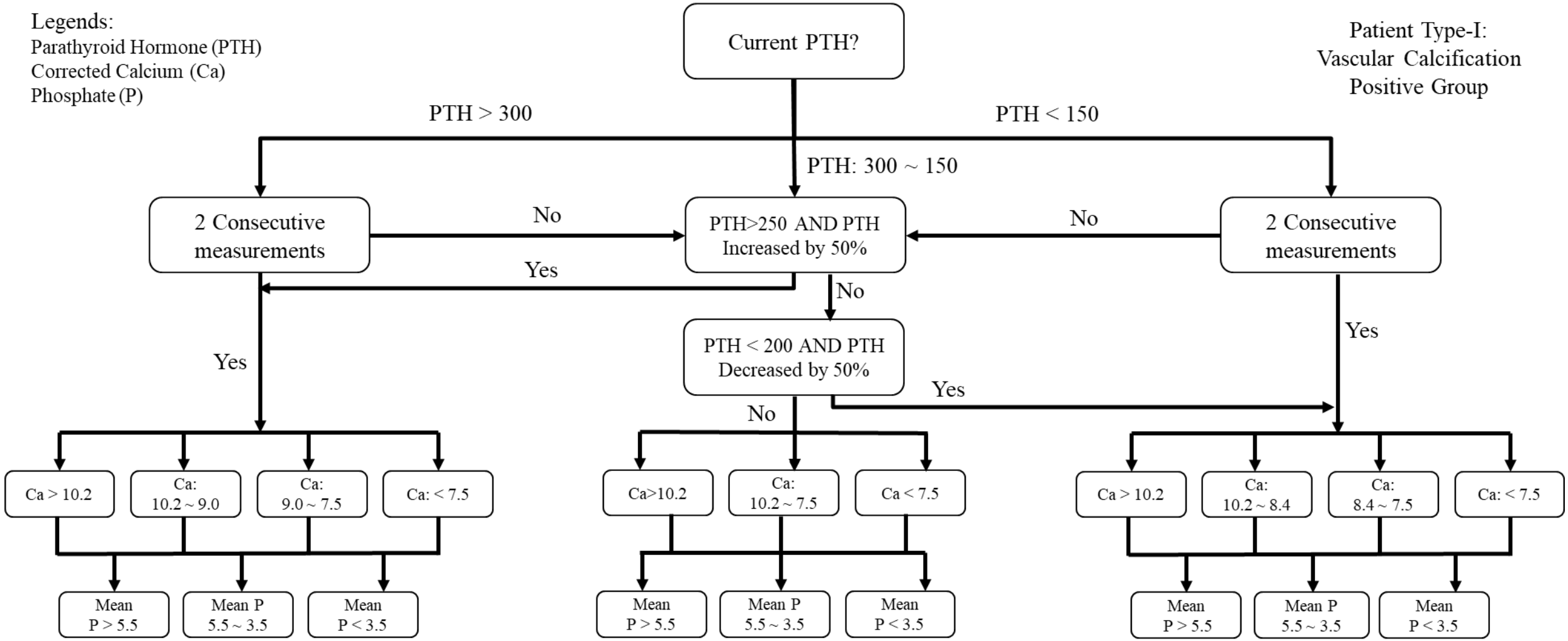


Case Study: CKD-MBD Treatment

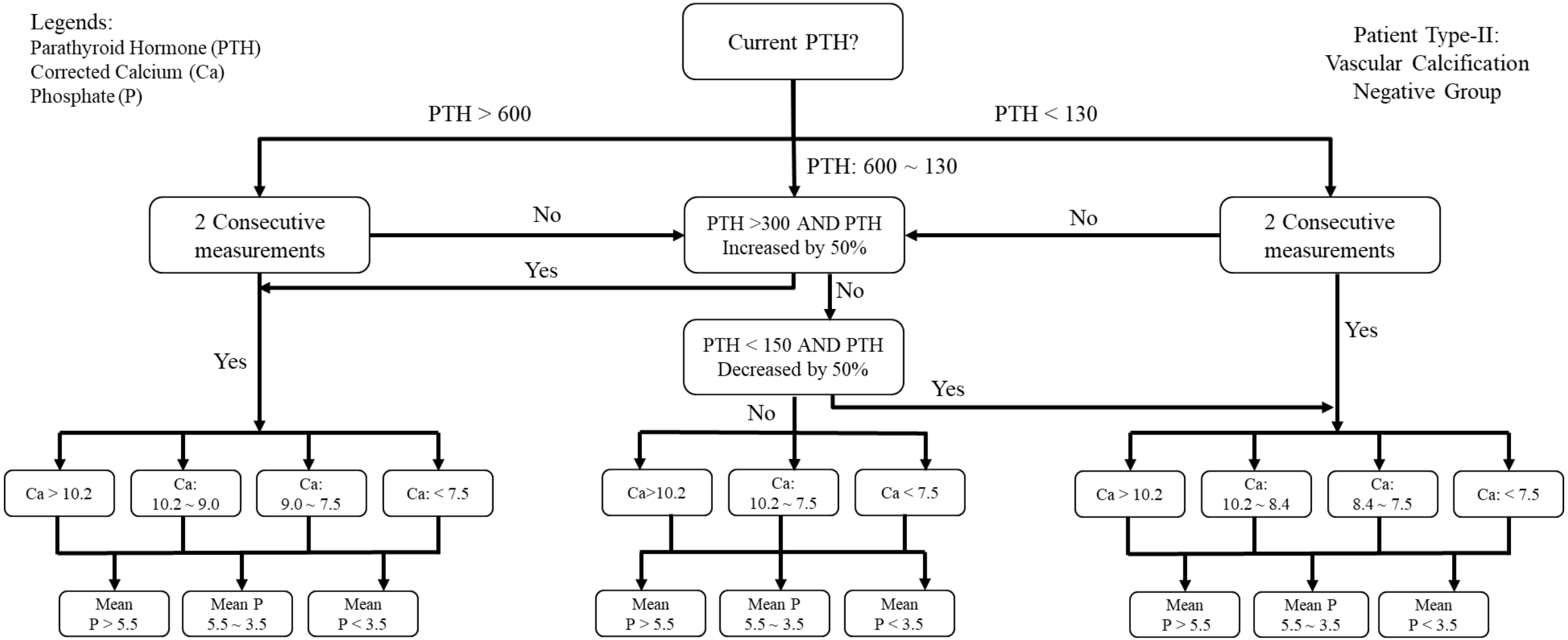
Case Study: CKD-MBD Treatment



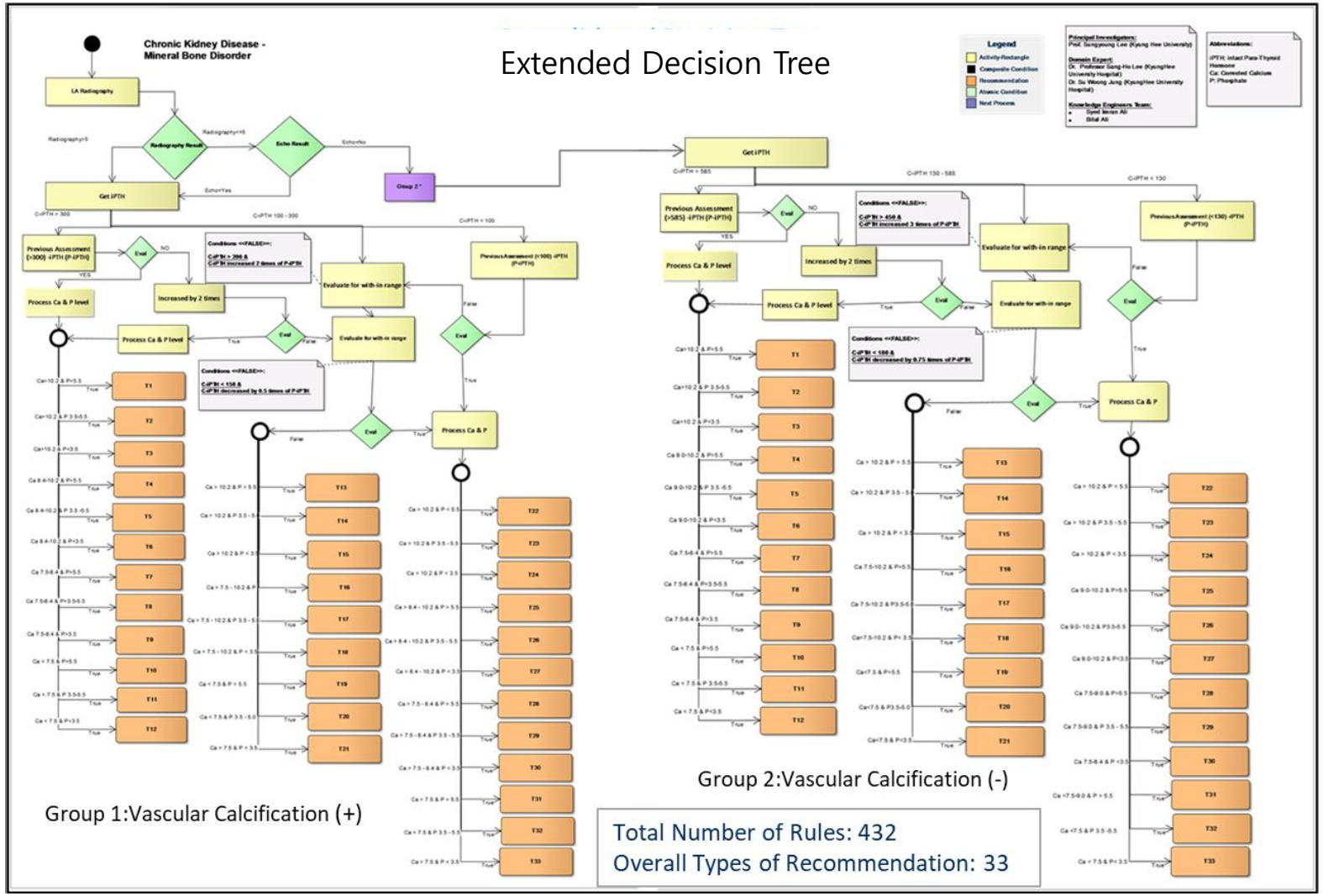
Expert Model (Type-I patients)

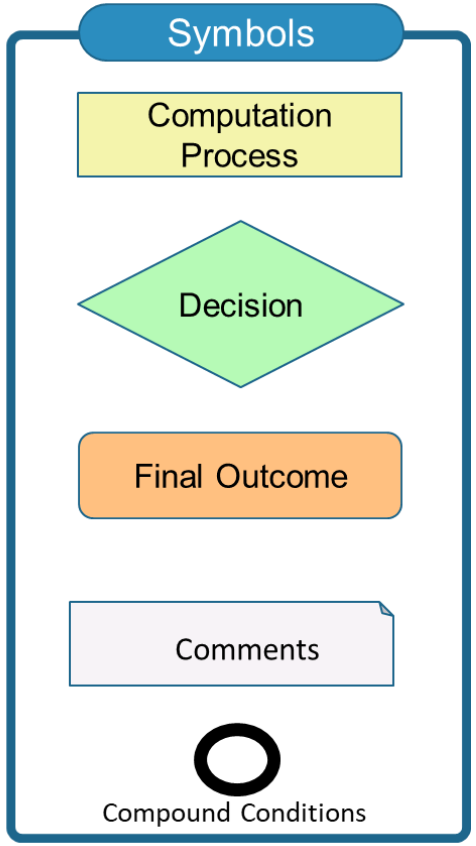


Expert Model (Type-II patients)



Extended Decision Tree based on Expert Model





Generic Recommendation Template

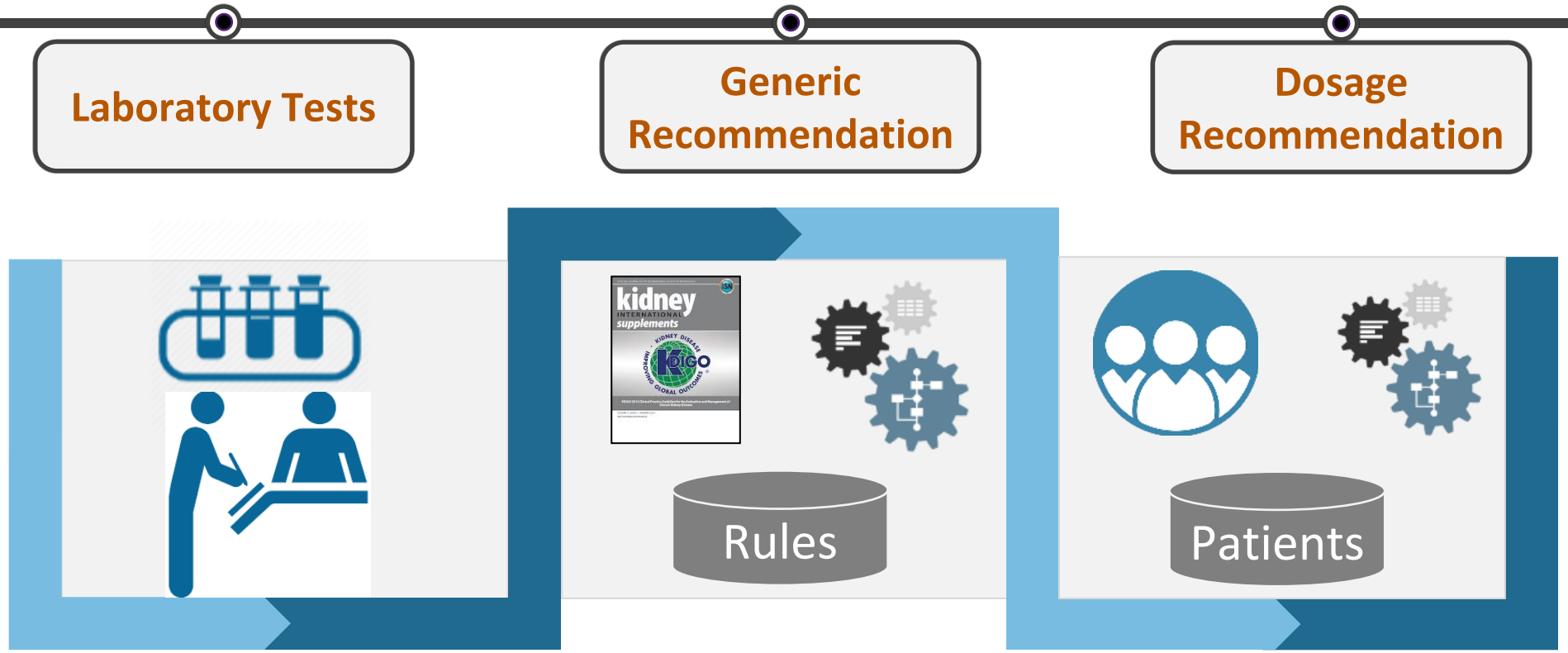
Recommendation Template

Recommendation Factors	Possible Treatment Options				
Calcimimetics	Start or Increase	As It Is	Stop or Decrease	Decrease or Stop	
Calcium-based Phosphate Binder	Start or Increase CPB	As It Is	Decrease CPB	Stop CPB	
Non-Calcium-based Phosphate Binder	Start or Increase NCPB	As It Is	Decrease NCPB	Stop NCPB	
Vitamin D receptor activators	Start or Increase	As It Is	Decrease	Stop	Consider Vitamin D Analogs
Calcitriol	Start or Increase	As It Is	Decrease	Stop	Consider Calcitroil
Dialysate Cal. Concentration	Increase by 0.25 mmol/L	Maintain the current dialysate concentration	decrease by 0.25 mmol/L		

Sample Recommendations

Recommendation Factors	Treatment 1 (T1)	Treatment 2 (T2)	...	Treatment 33 (T33)
Calcimimetics	Start or Increase	Start or Increase	...	Decrease of Stop
Calcium-based Phosphate Binder	Stop CPB	Stop CPB	...	Decrease or Stop CPB
Non-Calcium-based Phosphate Binder	Start or Increase NCPB	Maintain NCPB	...	Decrease or Stop NCPB
Vitamin D receptor activators	Stop vitamin D analogs	Stop vitamin D analogs	...	Decrease or Stop
Calcitriol	Stop Calcitriol	Stop Calcitriol	...	Start or Increase Calcitriol
Dialysate Cal. Concentration	Reduce by 0.25 mmol/L	Reduce by 0.25 mmol/L	...	Increase by 0.25 mmol/L

CKD-MBD Treatment Execution Process Flow



Step 1

Conduct **laboratory** tests for the kidney patient and acquire the results

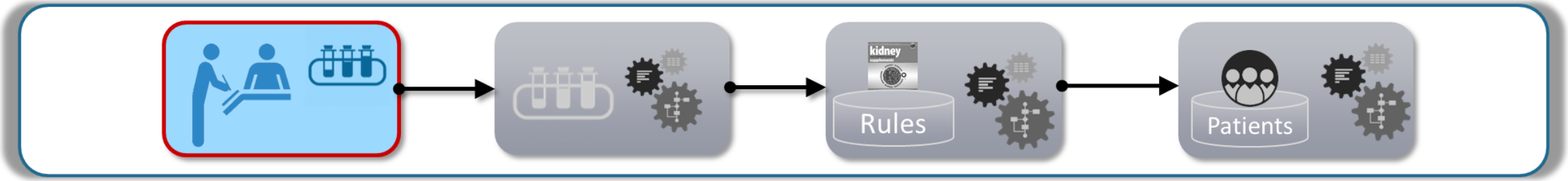
Step 2

Provide **general medication** intake recommendation based on guidelines

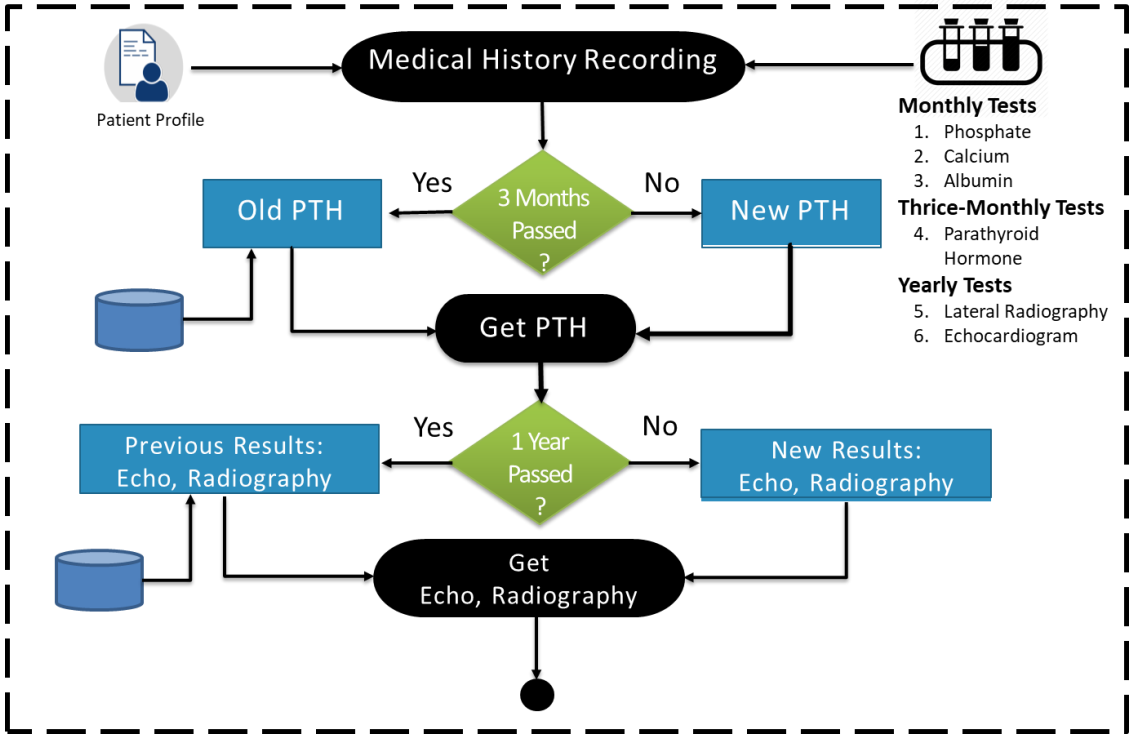
Step 3

Provide **medication dosage** recommendation based on similar reference patients

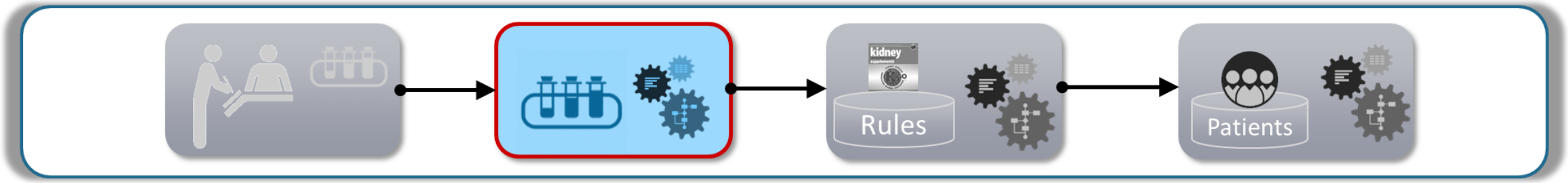
Step 1 : Laboratory Test Administration



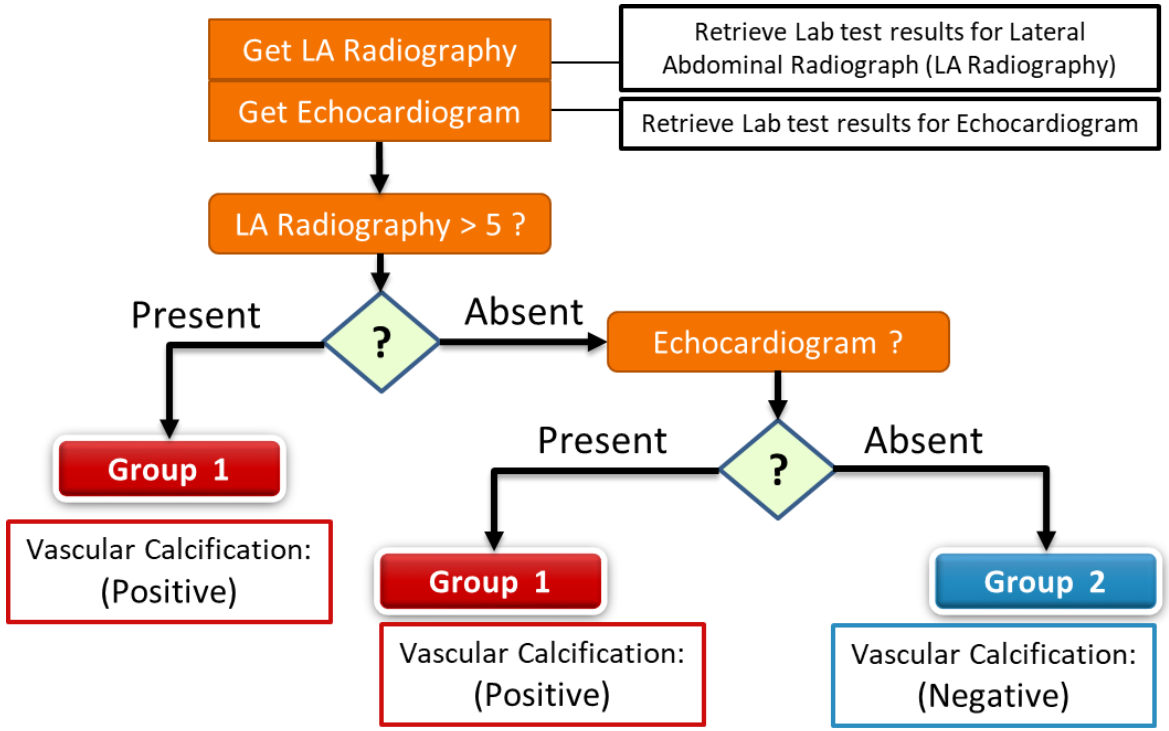
- Laboratory tests are performed at three different time scales
- Patient may visits every month for the checkup/ dialysis treatment
- PTH test is valid for three months
- Both lateral radiography and echocardiogram are performed on annual basis



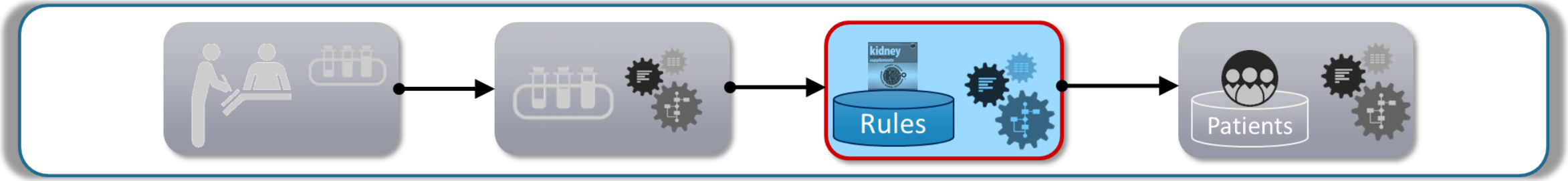
Step 2 : Patient Type Identification



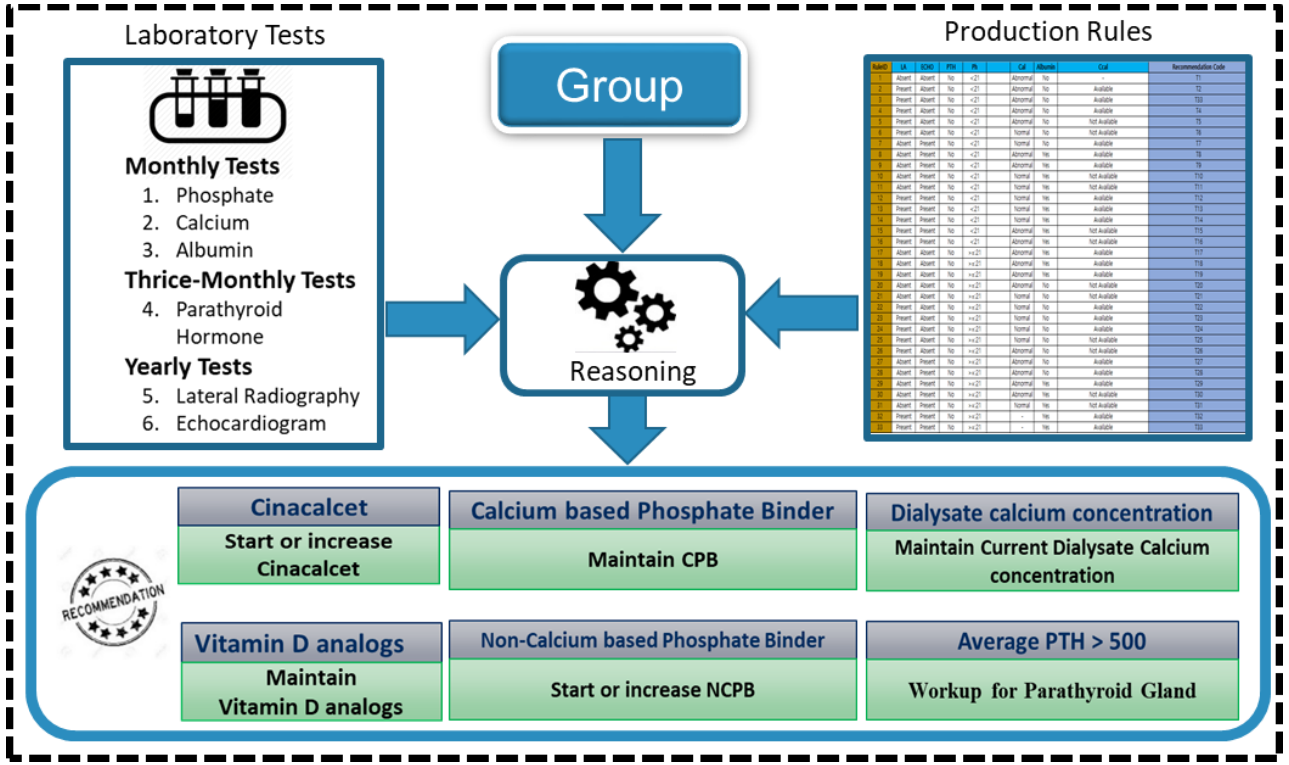
- Patients are divided into two groups
- Group 1 deals with those patients who are diagnosed positive for vascular calcification
- Group 2 deals with patients whose vascular calcification is negative
- Group identification is based on lateral radiography and echocardiogram tests



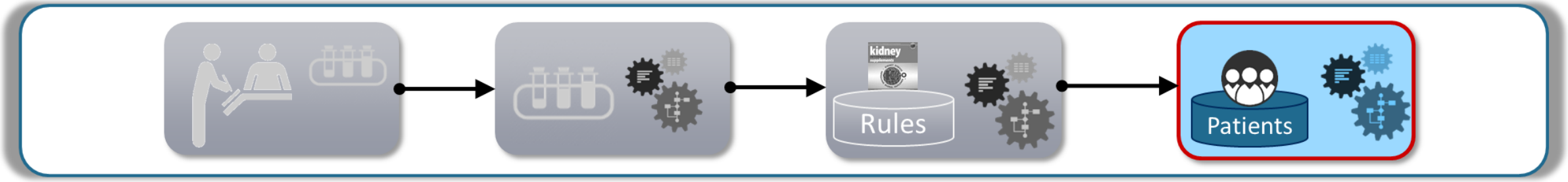
Step 2 : Generic Recommendation based on Guidelines

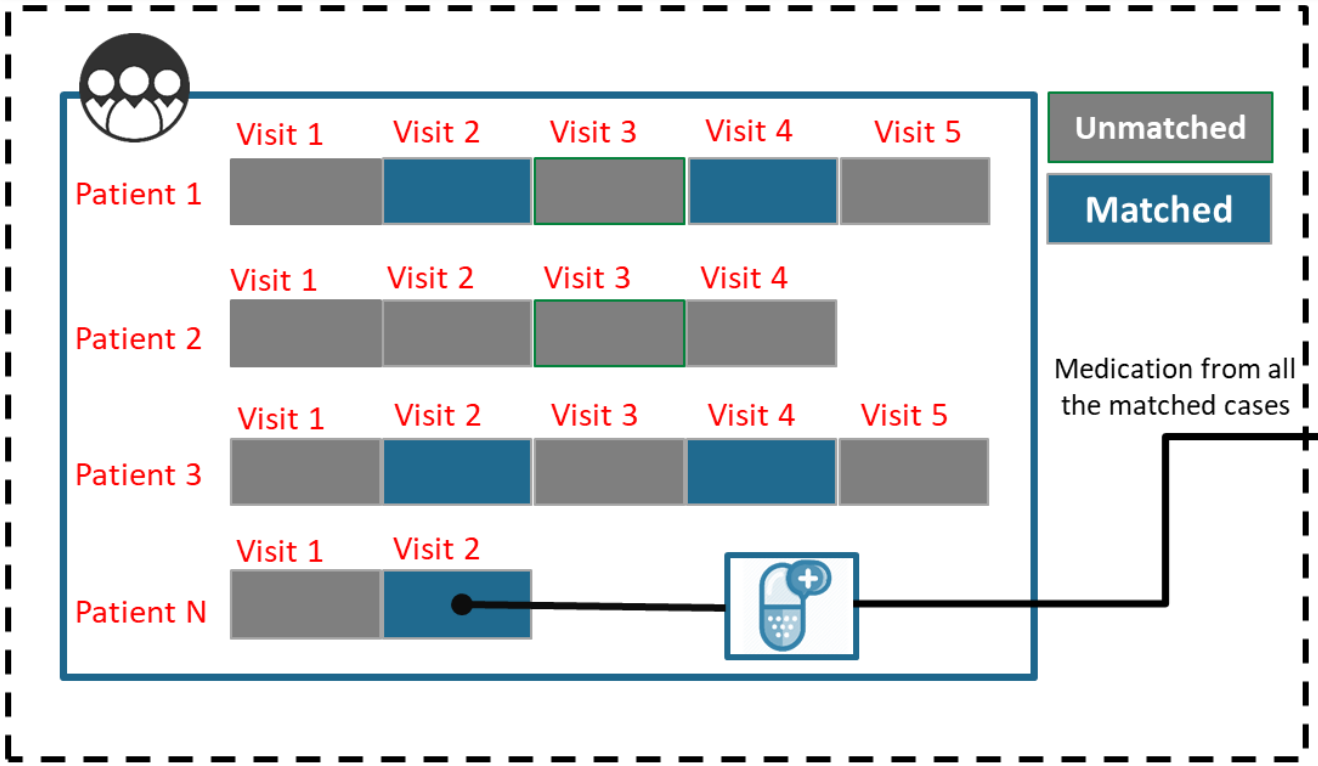


- Based on patient's group identification and lab. test results the reasoning process initiatives
- A general recommendation is generated based on stored rules which were acquired from knowledge engineering process
- Contents of this recommendation are: a recommendation code e.g. T1 and general guideline to manage medication



Step 3 : Dosage Recommendation based on Similar Patients



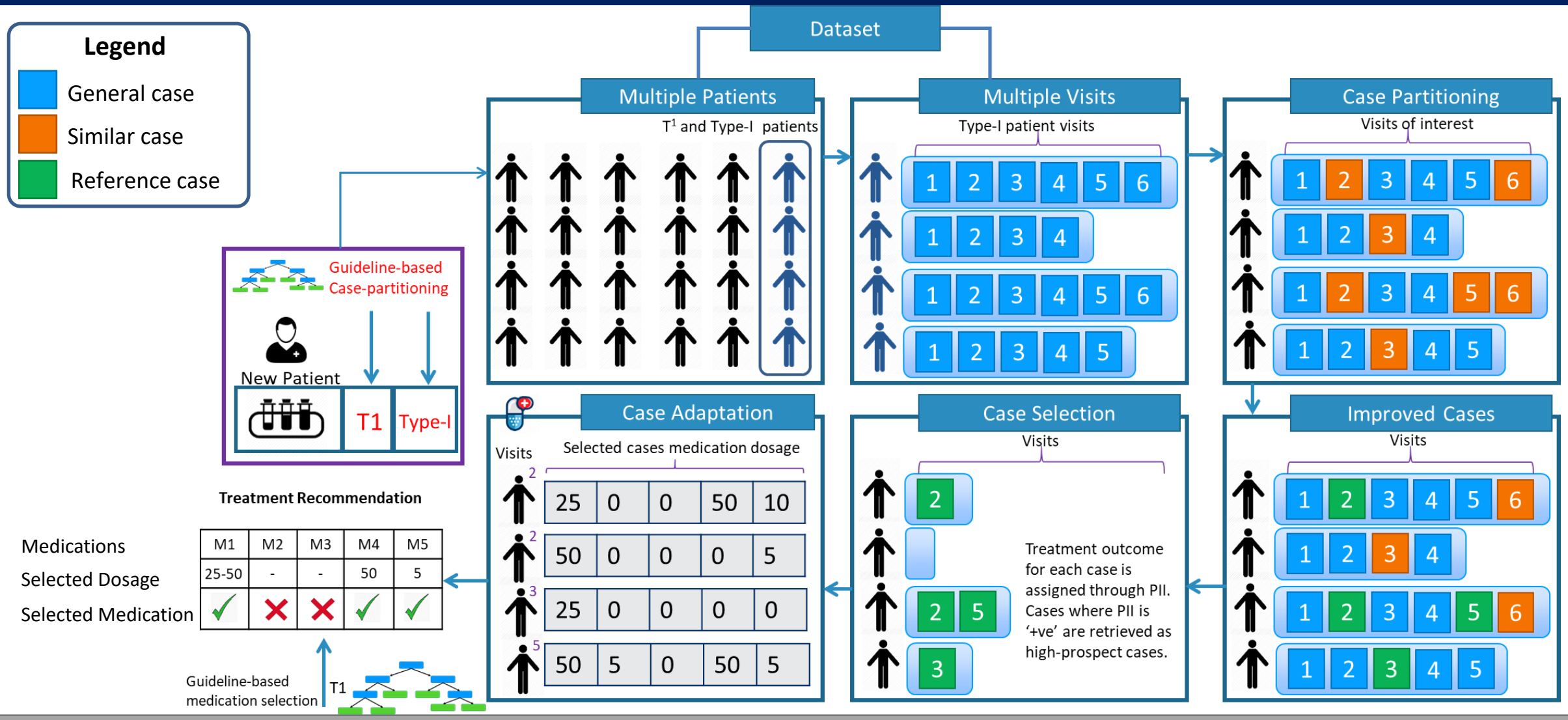


Dosage Recommendation based on Similar Patients

Medications of patients with similar visits

Visits							
1	25	0	0	50	10	…	40
1	50	0	0	10	5	…	0
3	25	5	5	0	0	…	30
3	50	5	0	50	0	…	10
N	50	0	0	40	0	…	50

End-to-end illustration of the Hybrid Case-based Reasoning



Experimentation

Experimental Setup

Dataset Description

Total Patients: 66	Test Cases: 250
Total Case-base: 850	Initial Case-base: 600
Patient Type-I: 374	Patient Type-I: 107
Patient Type-II: 476	Patient Type-II: 143

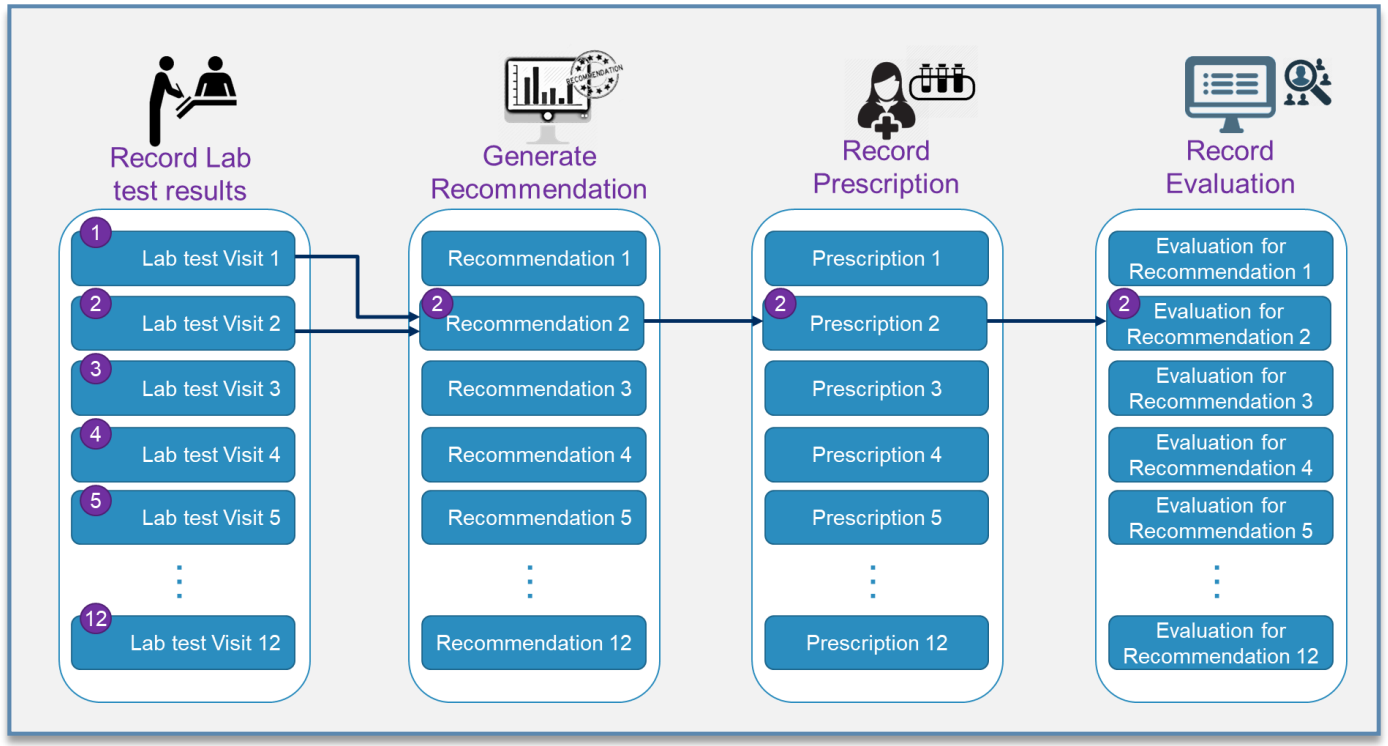
System-centric Experimentation (250 cases)

- Case insufficiency detection
- Compliance between expert model and clinical practice
- Concordance between dosage and clinical practice

User-centric Experimentation

- Find out usability experience of the CDSS through a pilot study
- Participants: 11 (clinicians)

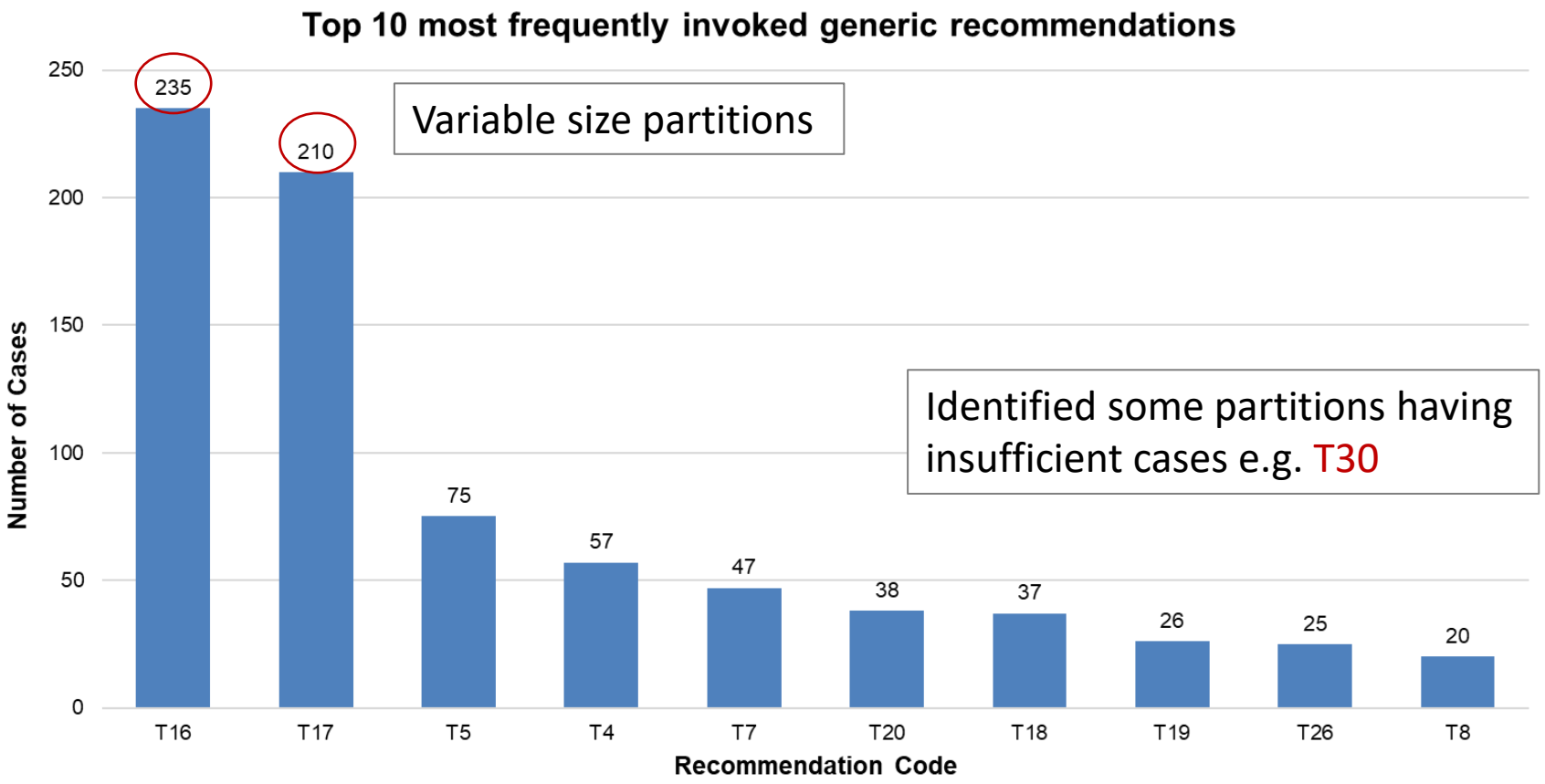
System and User-centric Experimentation



CKDMBD-CDSS Evaluation (System-centric)

Experiment objective:
To find out case partitions having insufficient cases at data acquisition stage

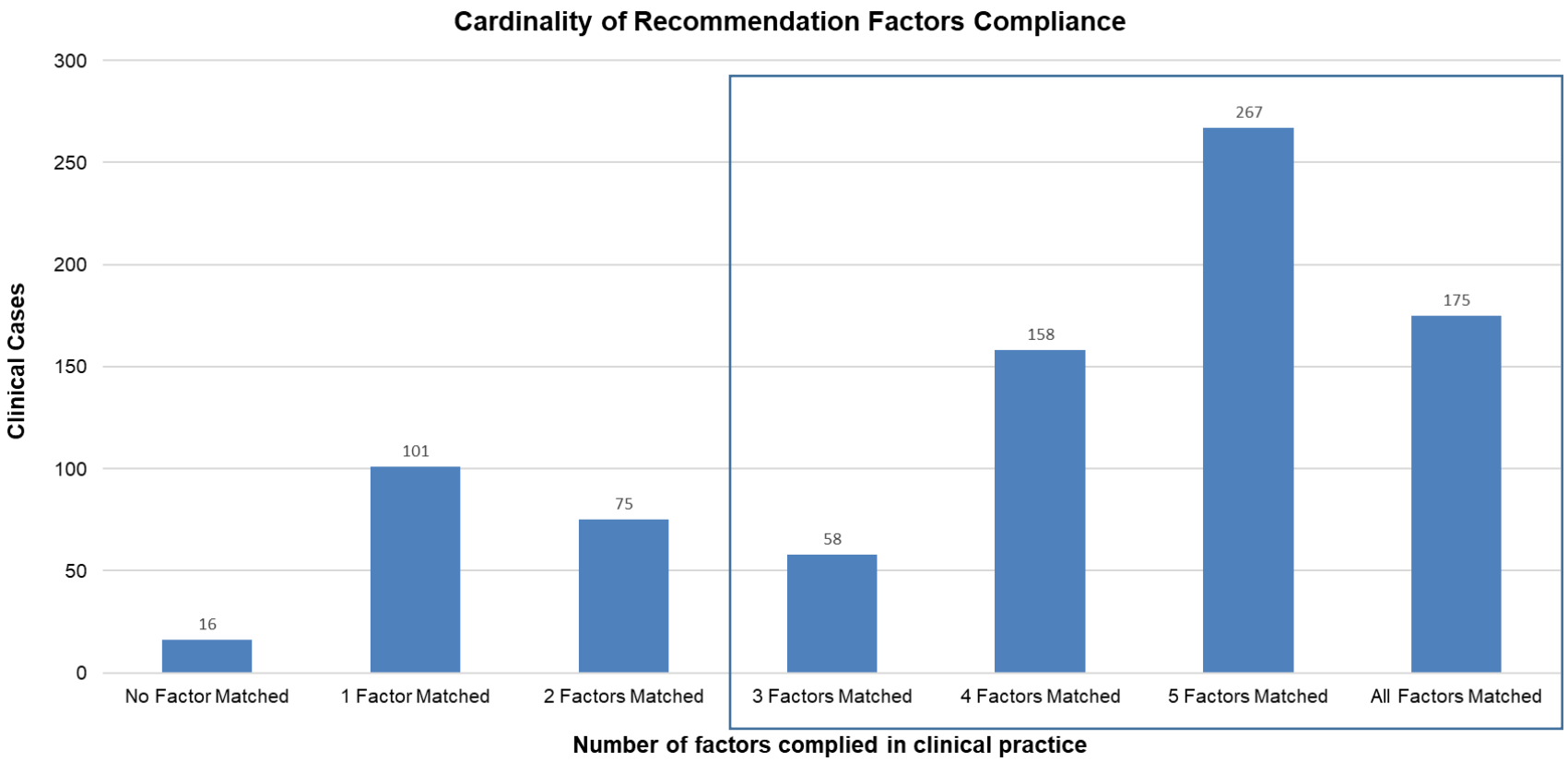
Findings:
1. Recommendations T^{16} and T^{17} mostly deal with maintaining the current medication prescription
2. Consistent with the clinical practice where abrupt changes in treatment are avoided



CKDMBD-CDSS Evaluation (System-centric)

Experiment objective:
To evaluate overall compliance between generic recommendation and routine clinical practice

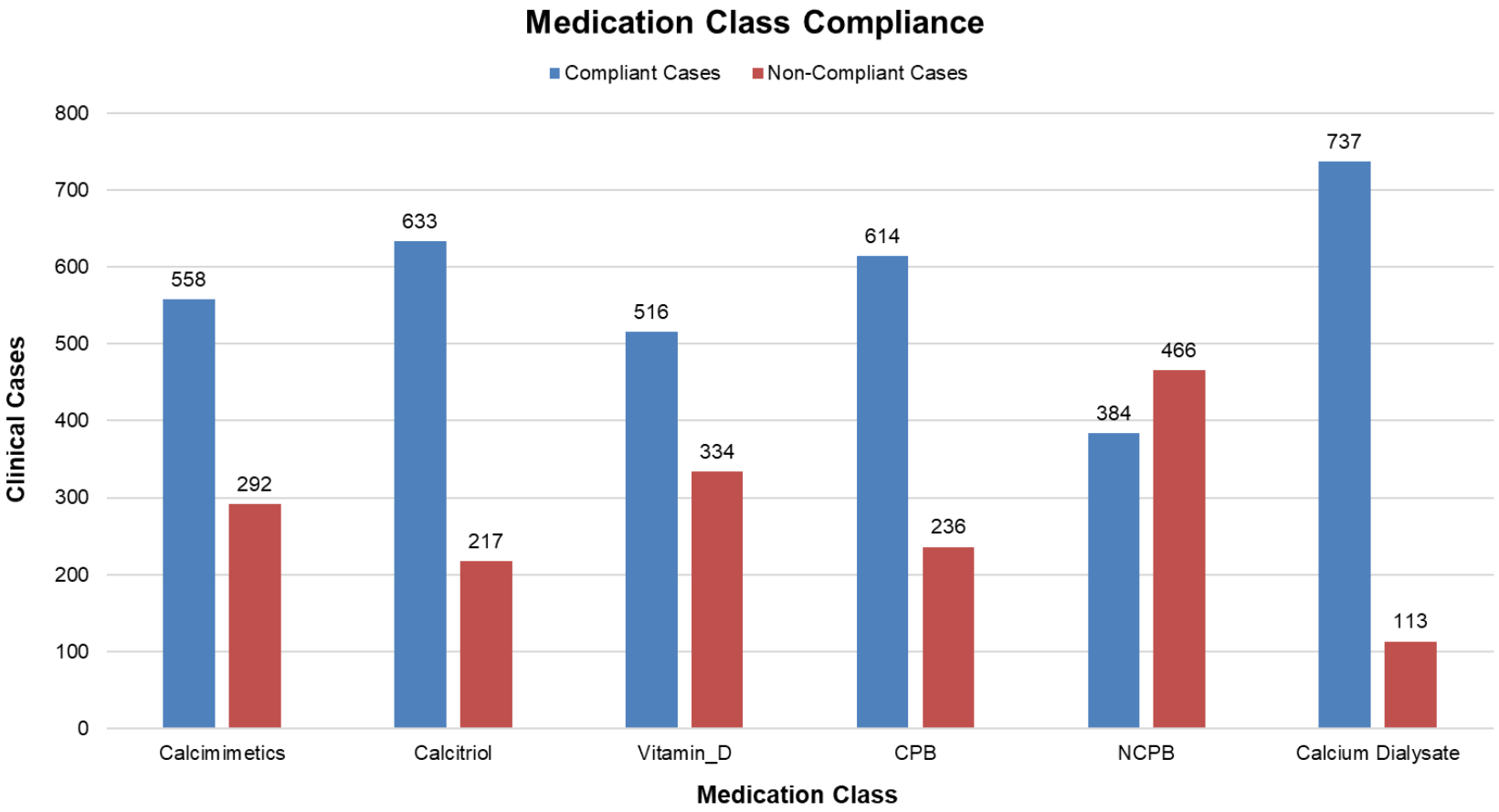
Findings:
1. In general most of the recommendations have high compliance with routine clinical practice
2. 77% compliance rate is recorded for recommendations factors matched 3 and above



CKDMBD-CDSS Evaluation (System-centric)

Experiment objective:
To evaluate breakdown of compliance rate of 6 medication classes

Findings:
1. In non-compliant cases '*dosage decrease*' slightly dominated i.e. the CDSS recommended to '*maintain*' while the physician decreased the dosage



CKDMBD-CDSS Evaluation (System-centric)

Confusion Matrix

Calcimimatics

Actual \ Predicted	Start/Increase	Maintain	Stop/Decrease
Start/Increase	167	132	17
Maintain	29	334	23
Stop/Decrease	19	72	57

Calcitriol

Actual \ Predicted	Start/Increase	Maintain	Stop/Decrease
Start/Increase	173	31	13
Maintain	18	448	11
Stop/Decrease	14	74	68

Vitamin D & Analogs

Actual \ Predicted	Start/Increase	Maintain	Stop/Decrease
Start/Increase	154	31	13
Maintain	18	448	11
Stop/Decrease	14	74	68

Calcium-based Phosphate Binders

Actual \ Predicted	Start/Increase	Maintain	Stop/Decrease
Start/Increase	140	66	8
Maintain	16	488	19
Stop/Decrease	3	41	69

Non-Calcium-based Phosphate Binders

Actual \ Predicted	Start/Increase	Maintain	Stop/Decrease
Start/Increase	71	101	19
Maintain	49	259	52
Stop/Decrease	9	187	103

Calcium Dialysate Concentration

Actual \ Predicted	Start/Increase	Maintain	Stop/Decrease
Start/Increase	45	7	0
Maintain	2	766	0
Stop/Decrease	0	8	22

CKDMBD-CDSS Evaluation (System-centric)

Experiment objective:
To evaluate concordance between dosage recommendation and routine clinical practice

Concordance Findings:

1. Cinacalcet = 85.71%
2. Calcitriol (po) = 81.81%
3. Calcitriol (iv) = 66.66%
4. Paricalcitrol (iv) = 82.24%
5. Calcium Carbonate = 76.47%
6. Calcium Acetate = 81.81%
7. Sevelamer = 76.12%
8. Lanthanum = 55%
9. Dialysate Cal. Concent. = 98.40%

Concordance evaluation for the medication dosage recommendation

Management Class	Total Cases	Present Cases	In-Range Cases	Out-of-Range Cases
† Cinacalcet	250	49	42	7
Calcitriol, po	250	11	9	2
Calcitriol, iv	250	15	10	5
Paricalcitol, iv	250	148	122	26
† Alfacalcidol	250	0	0	0
† Calcium Carbonate	250	34	26	8
† Calcium Acetate	250	11	9	2
† Sevelamer	250	155	118	37
† Lanthanum	250	20	11	9
Dialysate Calcium Concentration	250	250	246	4

† Cinacalcet, alfacalcidol, calcium carbonate, calcium acetate, sevelamer, and lanthanum are orally taken tablets.

Evaluation Metric:

$$Concordance = \frac{\sum_{i}^{j}(System \cap Physician)}{j}$$

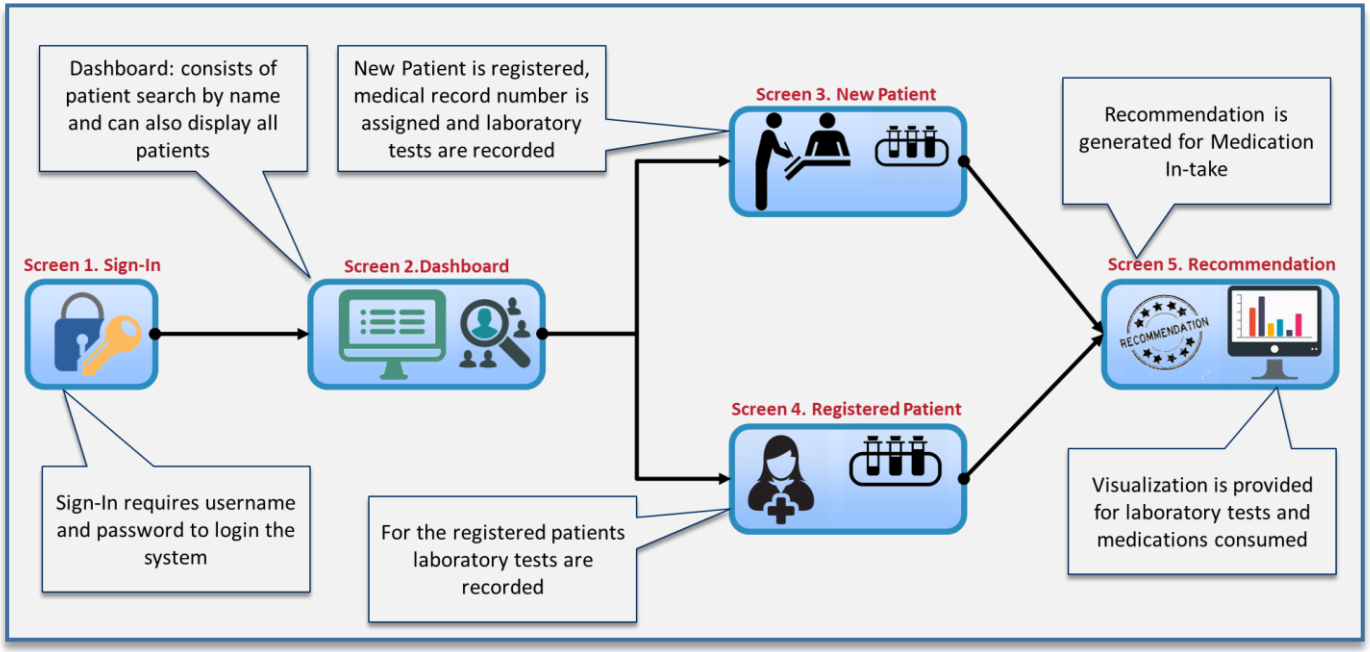
CKDMBD-CDSS Evaluation (User-centric)

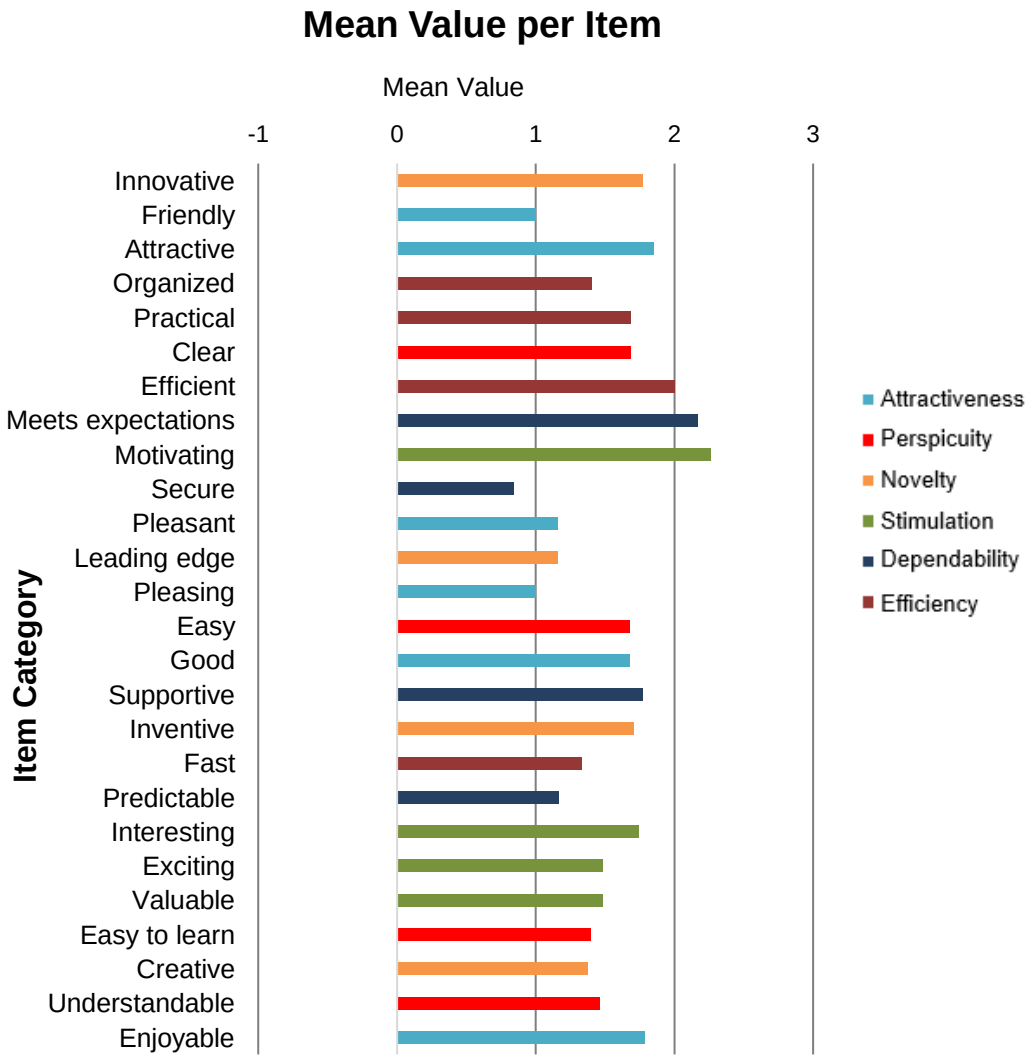
User Experience Evaluation

To evaluate user experience in executing various tasks related to CDSS e.g. recommendation generation, treatment insights, etc.

Findings

1. Received higher feedback score on **Stimulation**, **Dependability**, **Efficiency**
2. Moderately **innovative**
3. Room for improvement in **Attractiveness** and **Perspicuity**

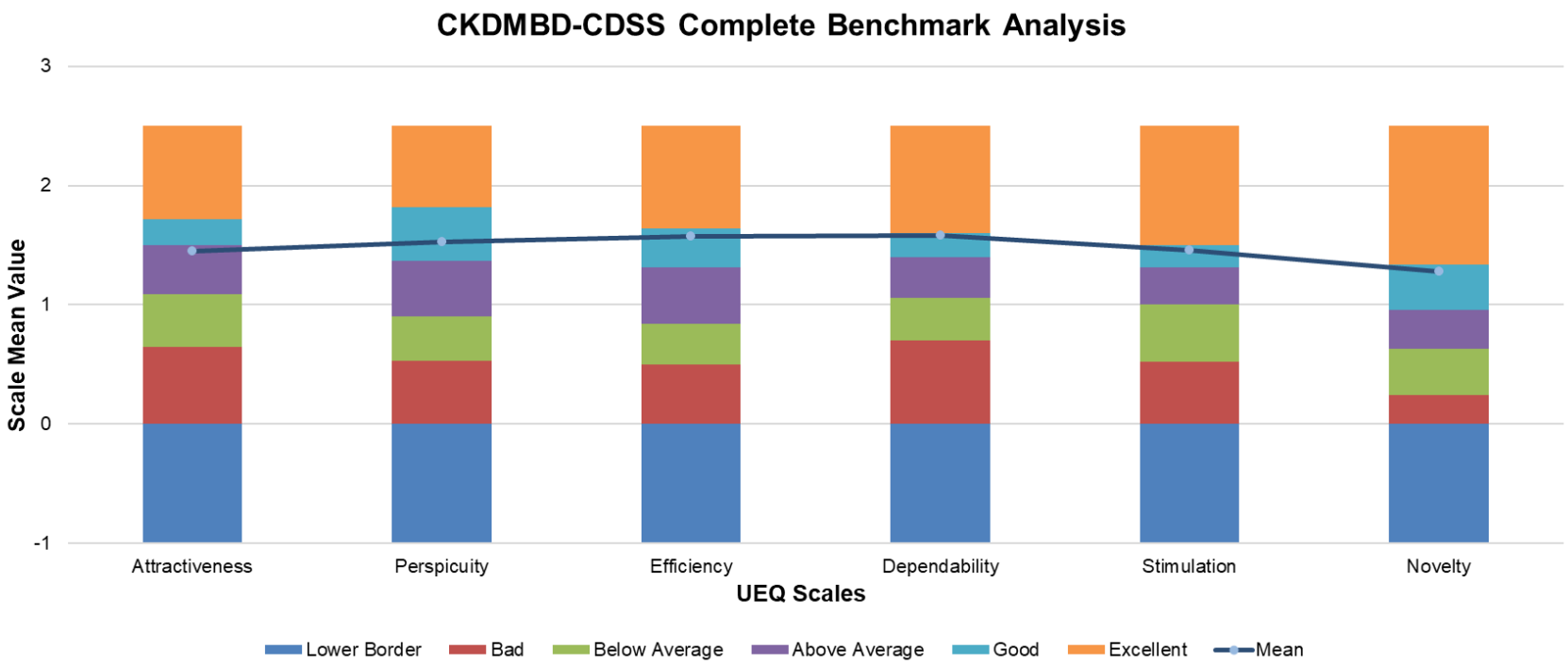




CKDMBD-CDSS Evaluation (User-centric)

Experiment objective:
User Experience of the CDSS with other services

Findings:
1. CDSS provides higher dependability due to transparency and incorporating domain knowledge
2. Shows general acceptance across participants



Conclusion

- Domain model based on clinical practice guidelines provide general framework to guide clinicians
- Lack of operational details can be complemented by clinicians' experience gained through trial and error
- Domain knowledge guided clinical case selection and adaptation provide clinician with insights into the complex recommendation generation process
- CKD-MBD CDSS based on proposed methodology demonstrated both high-level of conformance with clinicians' decision and usability of the system

Contributions:

- **Case insufficiency detection** through active case-base partitioning
- **Case selection** based on feedback information
- **Case adaptation** based on domain knowledge and selected cases

Publications

Published papers

- **SCIE Journals (11)**
  - First Author: 3 Published
  - Co-author: 8 Published
- **Local Journals (3)**
  - Co-Author: 3 Published
- **Conferences (10)**
  - First Author International: 6
  - Co-Author International: 1
  - Local Conferences: 3
- **Domestic Patents (2)**
  - Registered: 1
  - Applied: 1

Publication

Total Publications (26)

First Author Publications (10)

REFERENCES

[1] Souza-Pereira, L., Pombo, N., Ouhbi, S., Felizardo, V., & Garcia, N. (2020). Clinical decision support systems for chronic diseases: A systematic literature review. Computer Methods and Programs in Biomedicine, 195, 105565.

[2] Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ digital medicine, 3(1), 1-10.

[3] Laka, M., Milazzo, A., & Merlin, T. (2021). Factors That Impact the Adoption of Clinical Decision Support Systems (CDSS) for Antibiotic Management. International journal of environmental research and public health, 18(4), 1901.

[4] Choi, D. J., Park, J. J., Ali, T., & Lee, S. (2020). Artificial intelligence for the diagnosis of heart failure. NPJ digital medicine, 3(1), 1-6.

[5] Hussain, M., Afzal, M., Malik, K. M., Ali, T., Khan, W. A., Irfan, M., ... & Lee, S. (2020). Acquiring guideline-enabled data driven clinical knowledge model using formally verified refined knowledge acquisition method. Computer Methods and Programs in Biomedicine, 197, 105701.

[6] Ali, S. I., Jung, S. W., Bilal, H. S. M., Lee, S. H., Hussain, J., Afzal, M., ... & Lee, S. (2021). Clinical Decision Support System Based on Hybrid Knowledge Modeling: A Case Study of Chronic Kidney Disease-Mineral and Bone Disorder Treatment. International Journal of Environmental Research and Public Health, 19(1), 226.

[7] Ting, S. L., Kwok, S. K., Tsang, A. H., & Lee, W. B. (2011). A hybrid knowledge-based approach to supporting the medical prescription for general practitioners: Real case in a Hong Kong medical center. Knowledge-Based Systems, 24(3), 444-456.

[8] Niazkhani, Z., Fereidoni, M., Rashidi Khazaee, P., Shiva, A., Makhdoomi, K., Georgiou, A., & Pirnejad, H. (2020). Translation of evidence into kidney transplant clinical practice: managing drug-lab interactions by a context-aware clinical decision support system. BMC medical informatics and decision making, 20(1), 1-13.

[9] Demner-Fushman, D., Mork, J. G., Rogers, W. J., Shooshan, S. E., Rodriguez, L., & Aronson, A. R. (2018). Finding medication doses in the liteature. In AMIA Annual Symposium Proceedings (Vol. 2018, p. 368). American Medical Informatics Association.

[10] Russell, S., & Norvig, P. (2002). Artificial intelligence: a modern approach.

REFERENCES

[11] Alazzam, Malik Bader, et al. "Nursing care systematization with case-based reasoning and artificial intelligence." Journal of Healthcare Engineering 2022 (2022).

[12] Shemeikka, T., Bastholm-Rahmner, P., Elinder, C. G., Vég, A., Törnqvist, E., Cornelius, B., & Korkmaz, S. (2015). A health record integrated clinical decision support system to support prescriptions of pharmaceutical drugs in patients with reduced renal function: design, development and proof of concept. International Journal of Medical Informatics, 84(6), 387-395.

[13] Helldén, A., Al-Aieshy, F., Bastholm-Rahmner, P., Bergman, U., Gustafsson, L. L., Höök, H., ... & Odar-Cederlöf, I. (2015). Development of a computerised decisions support system for renal risk drugs targeting primary healthcare. BMJ open, 5(7), e006775.

[14] Awdishu, L., Coates, C. R., Lyddane, A., Tran, K., Daniels, C. E., Lee, J., & El-Kareh, R. (2016). The impact of real-time alerting on appropriate prescribing in kidney disease: a cluster randomized controlled trial. Journal of the American Medical Informatics Association, 23(3), 609-616.

[15] Pirnejad, H., Amiri, P., Niazkhani, Z., Shiva, A., Makhdoomi, K., Abkhiz, S., ... & Bal, R. (2019). Preventing potential drug-drug interactions through alerting decision support systems: a clinical context based methodology. International journal of medical informatics, 127, 18-26.

[16] Van den Branden, Martijn, et al. "Integrating case-based reasoning with an electronic patient record system." Artificial Intelligence in Medicine 51.2 (2011): 117-123.

[17] Teodorović, Dušan, Milica Šelmić, and Ljiljana Mijatović-Teodorović. "Combining case-based reasoning with Bee Colony Optimization for dose planning in well differentiated thyroid cancer treatment." Expert Systems with Applications 40.6 (2013): 2147-2155.

[18] El-Sappagh, Shaker, and Mohammed Mahfouz Elmogy. "Medical case based reasoning frameworks: Current developments and future directions." Virtual and Mobile Healthcare: Breakthroughs in Research and Practice (2020): 516-552.

[19] Bichindaritz, Isabelle, and Cindy Marling. "Case-based reasoning in the health sciences: Foundations and research directions." Computational Intelligence in Healthcare 4. Springer, Berlin, Heidelberg, 2010. 127-157.

[20] Khussainova, Gulmira, Sanja Petrovic, and Rupa Jagannathan. "Retrieval with clustering in a case-based reasoning system for radiotherapy treatment planning." Journal of Physics: Conference Series. Vol. 616. No. 1. IOP Publishing, 2015.