PRECISION DOSING ACROSS THE LIFESPAN:

Tailoring medication from youth to the elderly

Birgit Koch, PharmD PhD
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Hospital Pharmacist-Clinical Pharmacologist

Erasmus MC
University Medical Center Rotterdam

Disclosures

ZonMw GGG, Erasmus MC grants, Foundation de Merel, Foundation Coolsingel
Prinses Beatrix Foundation, Politie & Wetenschap, IMI grant


WHERE IS
ROTTERDAM?
NETHERLANDS
UK
Cambridge
Amsterdam
Rotterdam
AWAY TO THE CITY
London
GERMANY
Eindhoven
Cologne
Brussels
BELGIUM
FRANCE

Life in Erasmus MC

Pharmacy

Front Office

- *60 FTE*
- *At the wards*

Research &Teaching

- *30 FTE and partly in other institutions*
- *Teaching*
- *Residency*
- *Research*

Back Office

- *135 FTE*
- *Manufacturing, Logistics, Laboratory, Robots etc.*

Our patients

Louise*

* *Fictional name*

Nora*

* Fictional name

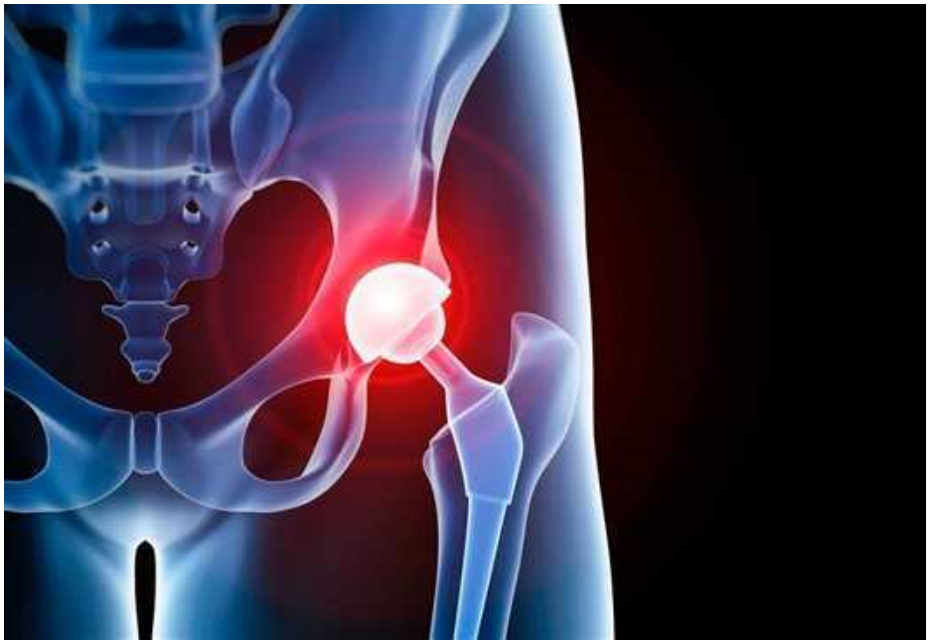
Bart*

* Fictional name

Robin*

* Fictional name

William*



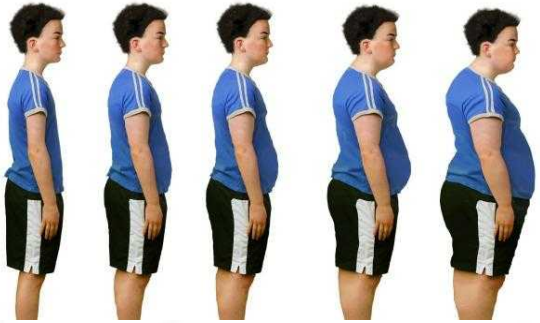
Erasmus MC

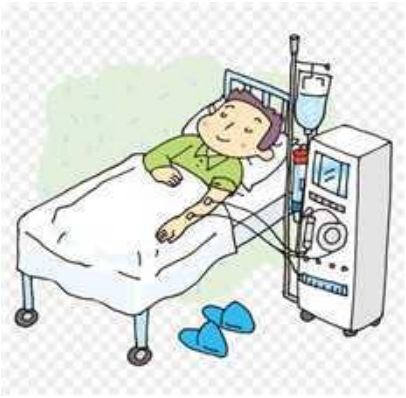
** Fictional name*

Ideal world of drug development

Erasmus MC

Our world





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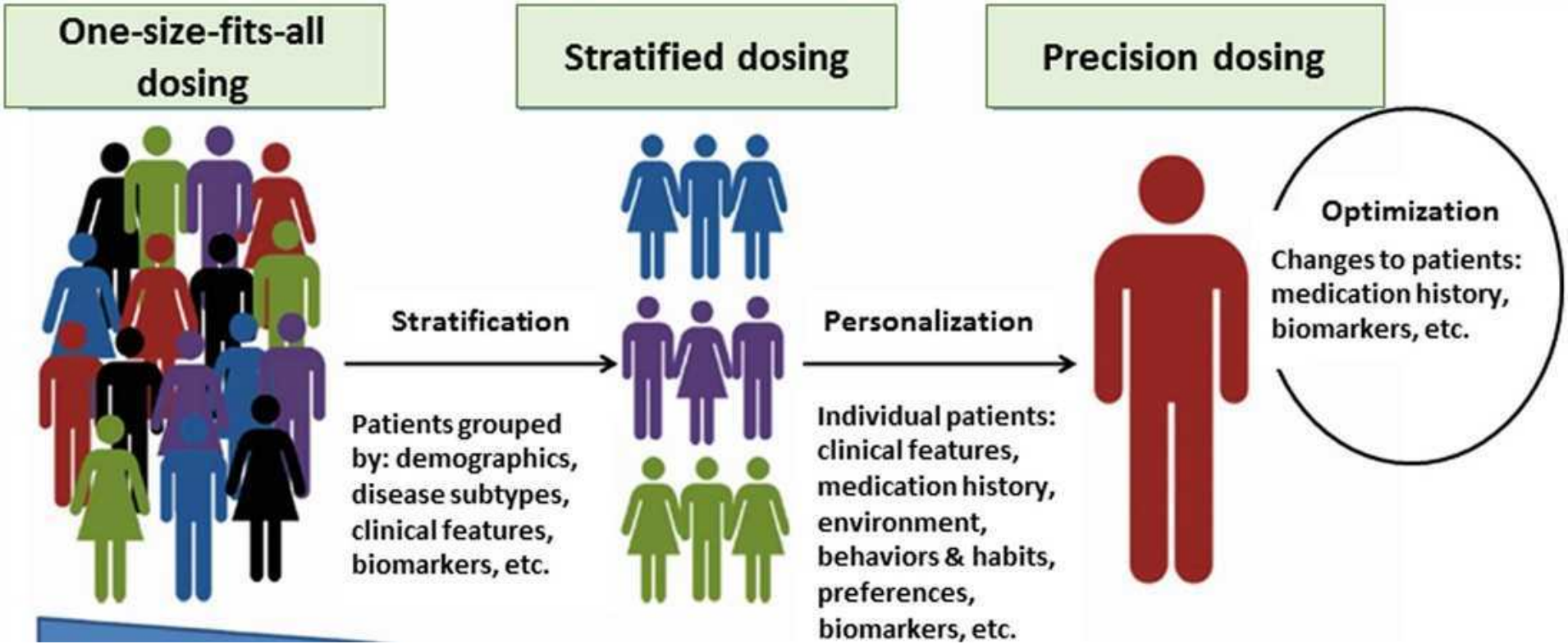
Why?

Roberts et al, CID 2014
Abdulla et al,
Critial Care 2020

De Lima Moreira et al,
TDM 2023

Vervalcke et al,
Clin PK 2023

Tang Girdwood
et al, Frontiers
in Pharmacology
2022


One-size-fits-all dosing
Stratified dosing
Precision dosing
Stratification
Patients grouped by: demographics, disease subtypes, clinical features, biomarkers, etc.
Personalization
Individual patients: clinical features, medication history, environment, behaviors & habits, preferences, biomarkers, etc.
Optimization
Changes to patients: medication history, biomarkers, etc.

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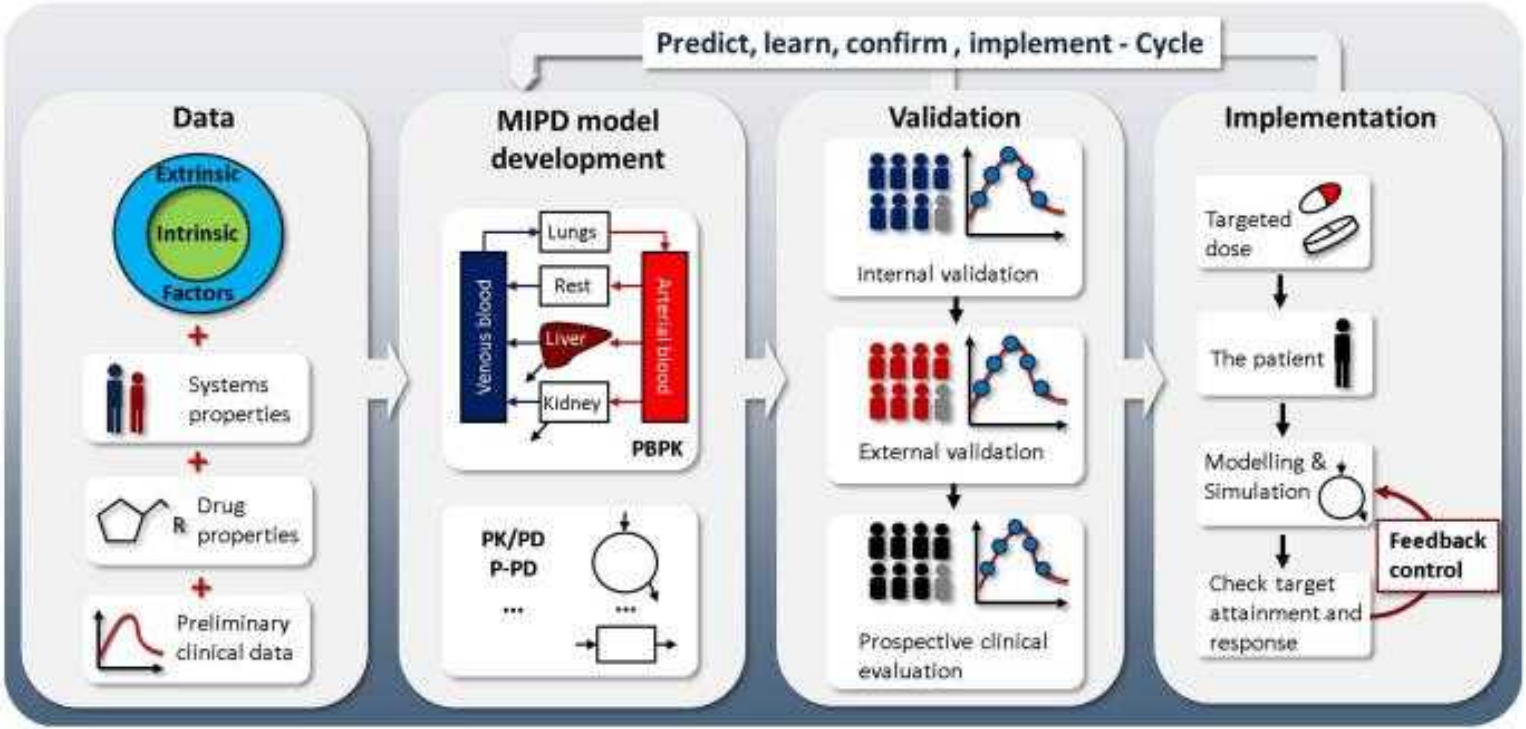
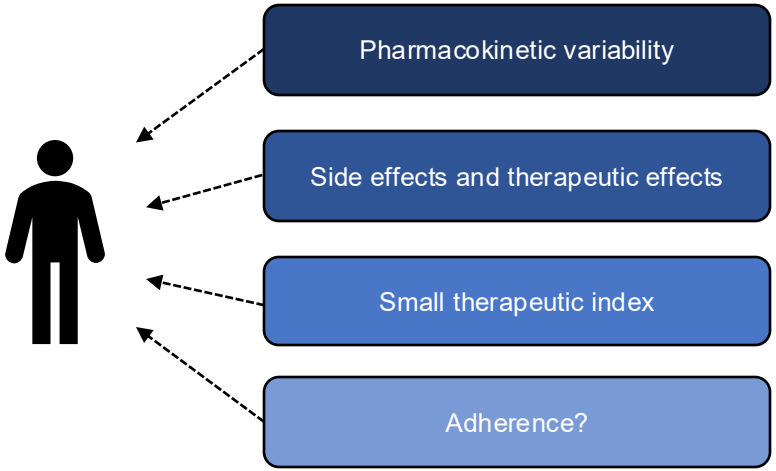
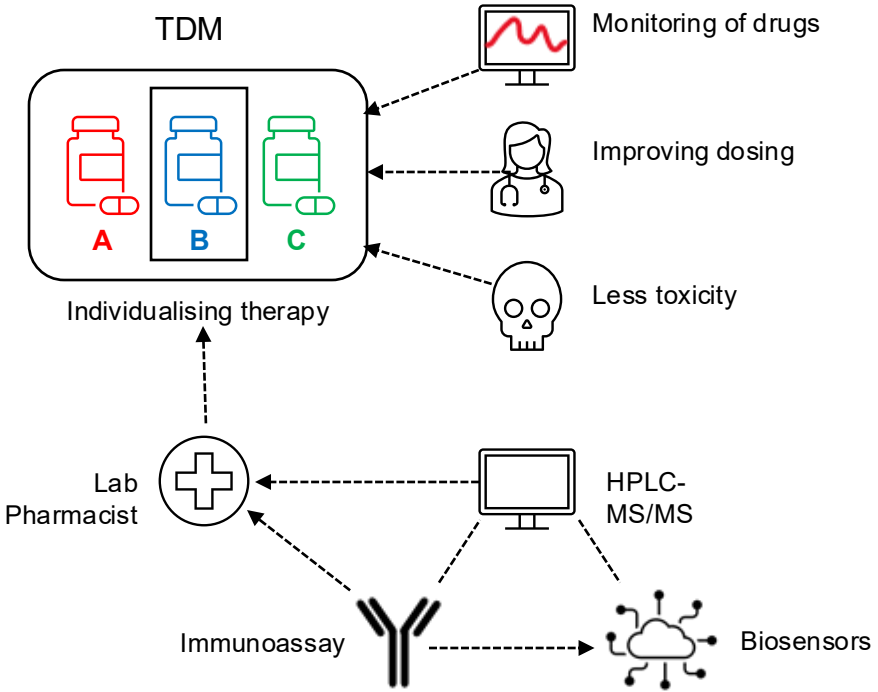
Model-informed Precison Dosing



Darwich et al, CPT 2017: 646-656

Therapeutic Drug Monitoring





During the lifespan

Pregnant Patients

Neonates (and antibiotics)

Children (and antipsychotics)

Intensive Care Patients

Older patients with PJI

Older patients with hypertension and (non)adherence -> polypharmacy

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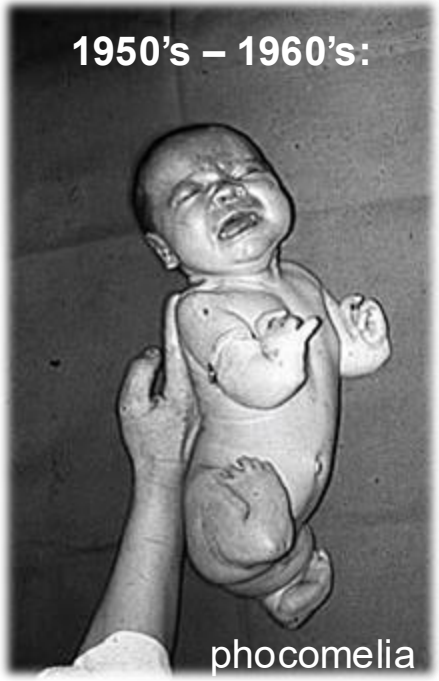
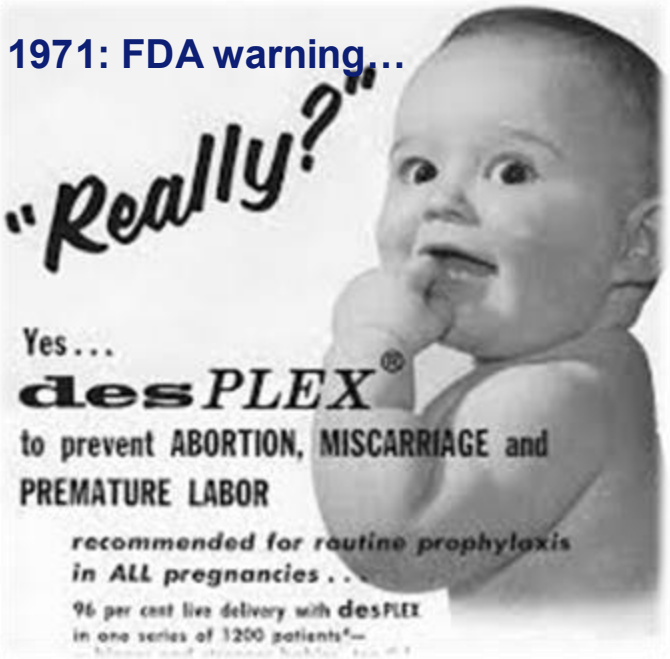
Louise*

* *Fictional name*

THALIDOMIDE CHANGED THE WORLD





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MATERNAL DRUG USE WITH EFFECT…

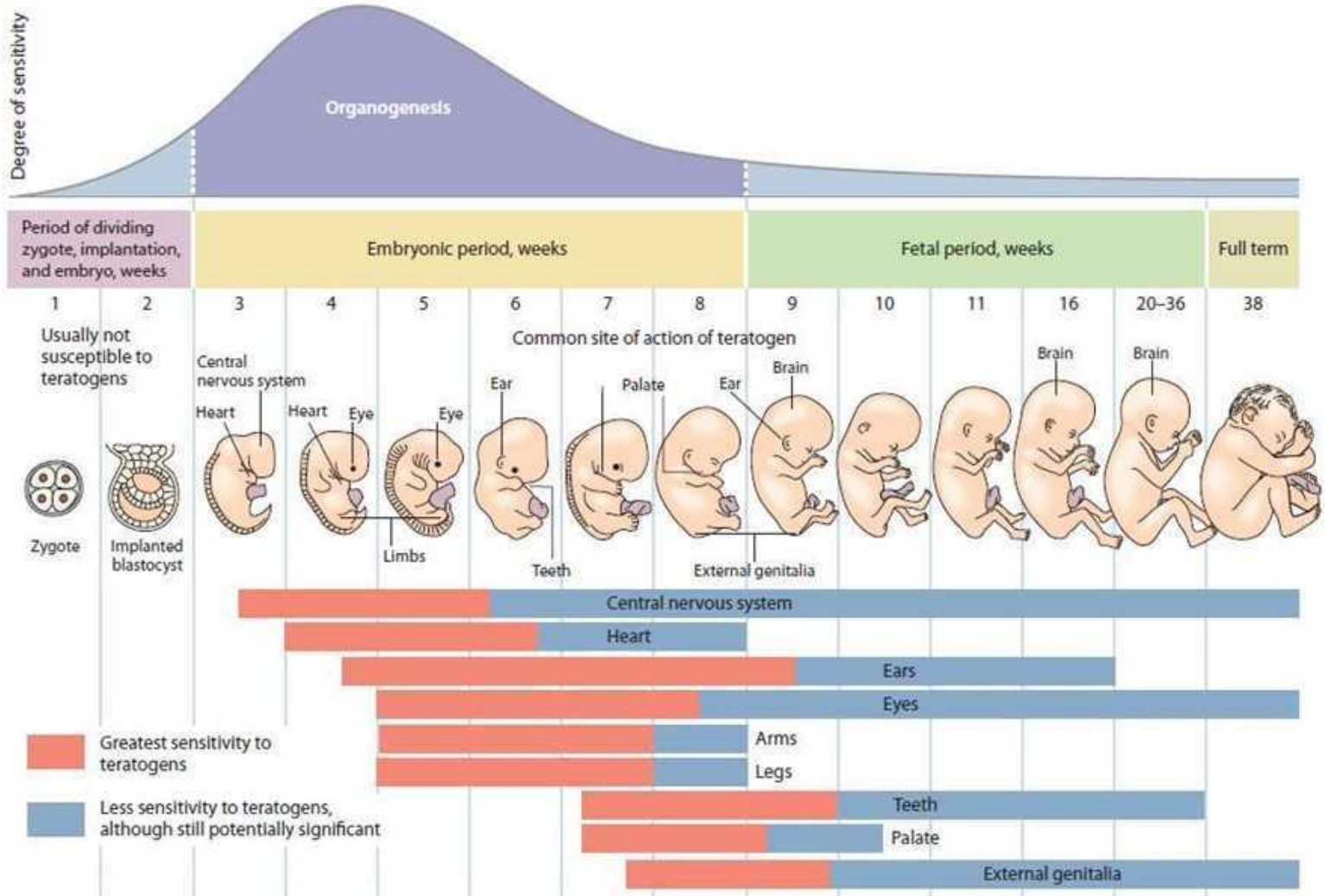
… intra-uterine

… on neonatal start

… on milk production

… on neonate via lactation

… benefits of lactation after intra-uterine exposure?


Degree of sensitivity
Organogenesis
Period of dividing zygote, implantation, and embryo, weeks
Embryonic period, weeks
Fetal period, weeks
Full term
1
2
3
4
5
6
7
8
9
10
11
16
20–36
38
Usually not susceptible to teratogens
Common site of action of teratogen
Central nervous system
Heart
Heart
Eye
Eye
Ear
Palate
Ear
Brain
Brain
Brain
Zygote
Implanted blastocyst
Limbs
Teeth
External genitalia
Central nervous system
Heart
Ears
Eyes
Arms
Legs
Teeth
Palate
External genitalia
Greatest sensitivity to teratogens
Less sensitivity to teratogens, although still potentially significant

MATERNAL DRUG USE WITH EFFECT...

... intra-uterine benefits

... on neonatal start

... on milk production

... on neonate via lactation

... benefits of lactation after intra-uterine exposure?

... intra-uterine benefits

ANTENATAL CORTICOSTEROIDS FOR FETAL LUNG MATURATION

	relative risk + 95 % CI
perinatal death	0.72, 0.58-0.89
neonatal death	0.69, 0.56-0.77
respiratory distress syndrome	0.59, 0.38-0.91
intraventricular haemorrhage	0.55, 0.40-0.76
necrotising enterocolitis	0.50, 0.32-0.78
mechanical ventilation needed	0.68, 0.56-0.84
systemic infections in early life	0.60, 0.41-0.88
hemodynamics, circulatory stability	any inotropics 67 to 47 %
	inotropic score

Roberts et al. Cochrane 2017; Moise et al. Pediatrics 1995

HARM ANTENATAL CORTICOSTEROIDS?

Research

JAMA | Original Investigation

Associations Between Maternal Antenatal Corticosteroid Treatment and Mental and Behavioral Disorders in Children

Katri Räikkönen, PhD; Mika Gissler, DrPhil; Eero Kajantie, MD, DMSc

Conclusion:

exposure to maternal antenatal corticosteroid treatment was significantly associated with **mental and behavioral disorders in children**

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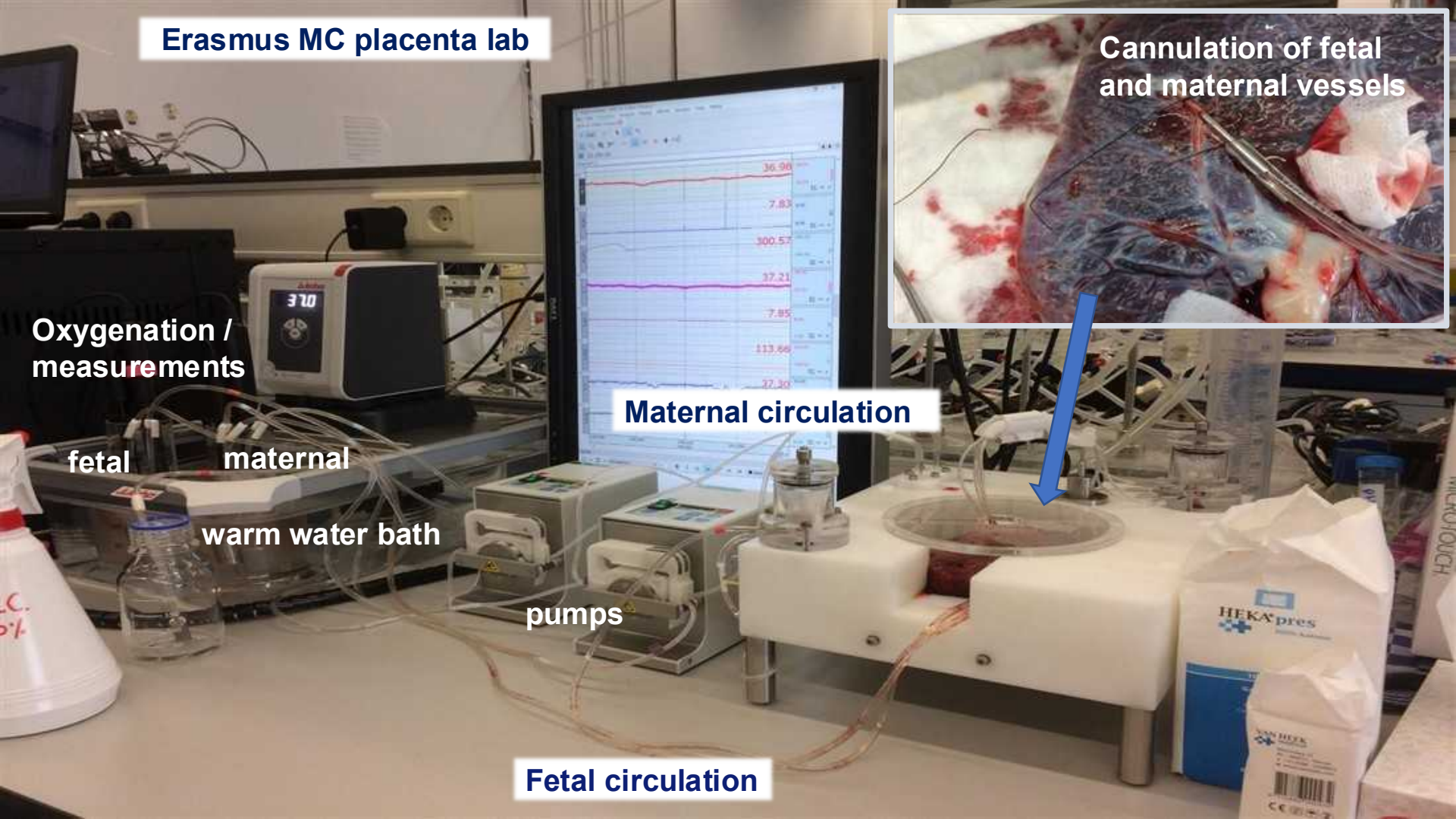
Raikkonen et al, JAMA 2020

Dosing of Corticosteroids

All patients receive the same dose, but do not have the same effect

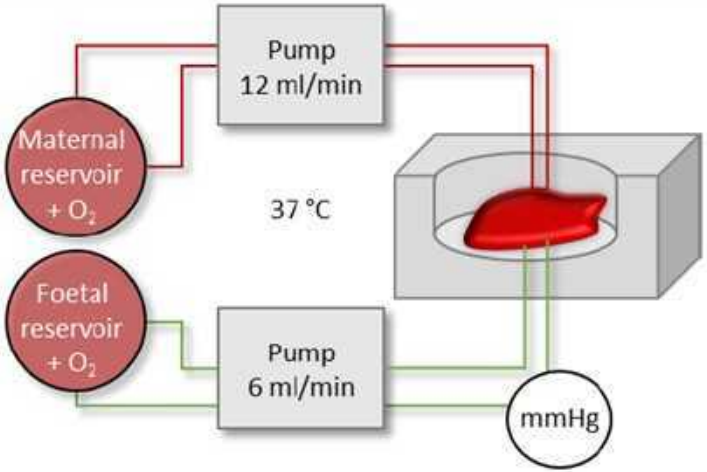
Influence of inflammation

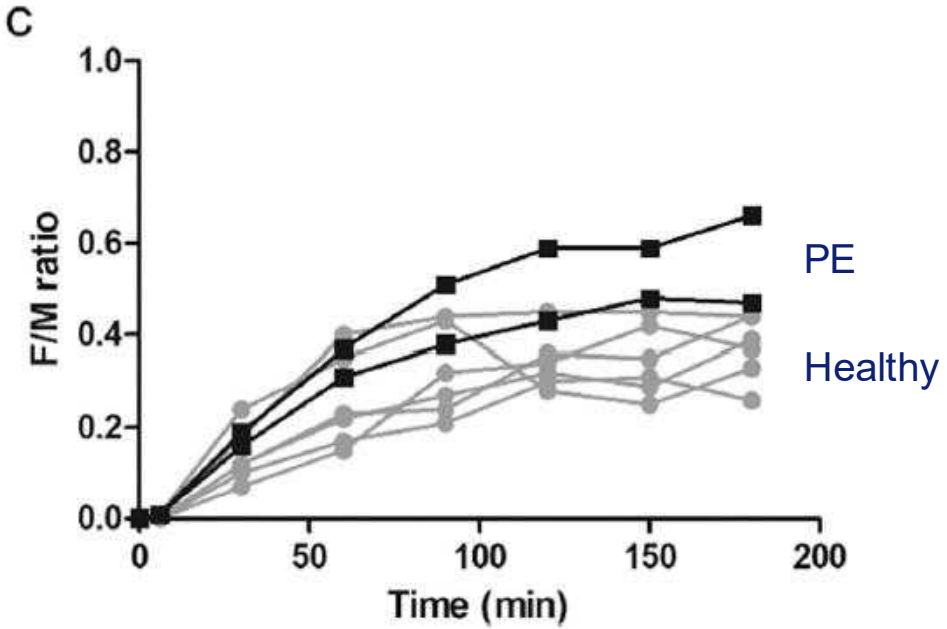
Pre-eclampsia


Erasmus MC placenta lab
Cannulation of fetal and maternal vessels
Oxygenation / measurements
Maternal circulation
fetal
maternal
warm water bath
pumps
Fetal circulation

... intra-uterine harm?

SILDENAFIL FOR PREECLAMPSIA





Hitzerd et al EBioMed 2019

… intra-uterine harm?

MATERNAL TACROLIMUS USE

In vivo placenta passage and tissue concentrations

Patient	Maternal C_{trough} level before delivery (ng/mL)	Placental tissue concentration (ng/g) as mean ± SEM	Venous umbilical cord blood concentration (ng/mL)
#1	4.2	55 ± 3	–
#2	7.6	68 ± 19	–
#3	3.9	82 ± 6	–
#4	6.6	75 ± 2	–
#5	2.9	62 ± 2	6.2
#6	4.0	82 ± 1	4.8

Ex vivo placenta perfusion experiments

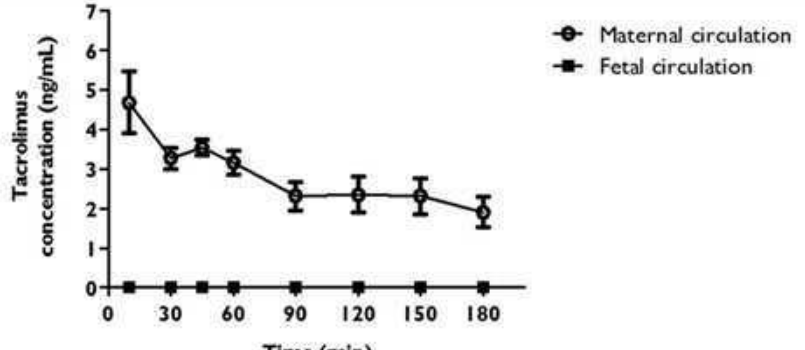
Tissue concentration

Perfusion	Maternal perfusate concentration at $t = 180$ min (ng/mL)	Placental tissue concentration (ng/g) as mean ± SEM	Placental tissue-to-maternal perfusate concentration ratio
#1	1.8	54 ± 8	31
#2	2.1	138 ± 85	65
#3	2.8	287 ± 103	102
#4	0.9	236 ± 76	253
Mean	1.9	179	113
SEM	0.4	52	49

Freriksen et al Eur J Pharm Sci 2018

Ex vivo placenta perfusion experiments

Placenta transfer



MATERNAL DRUG USE WITH EFFECT…

… intra-uterine

… on neonate

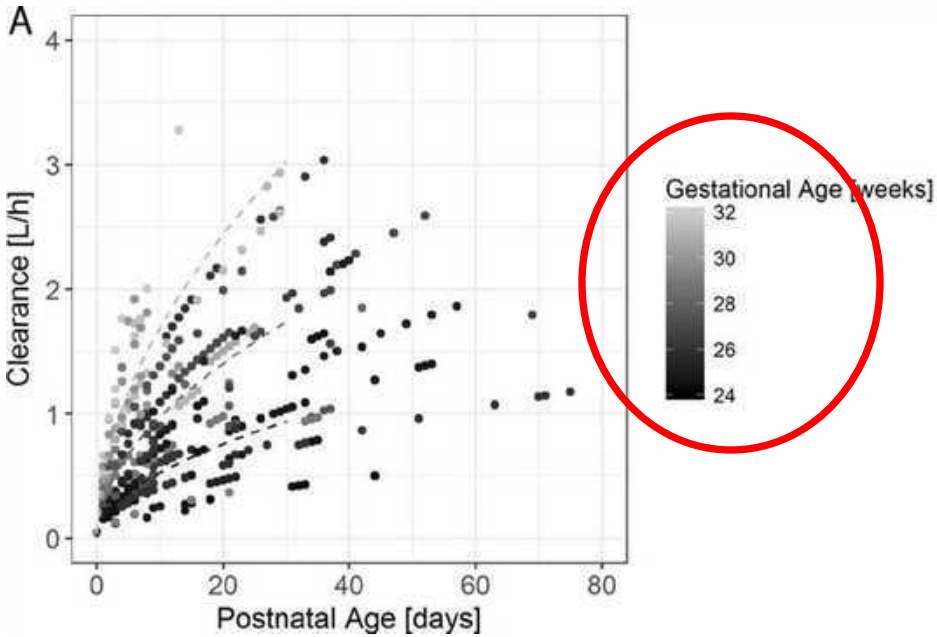
… on milk production

… on neonate via lactation

… benefits of lactation after intra-uterine exposure

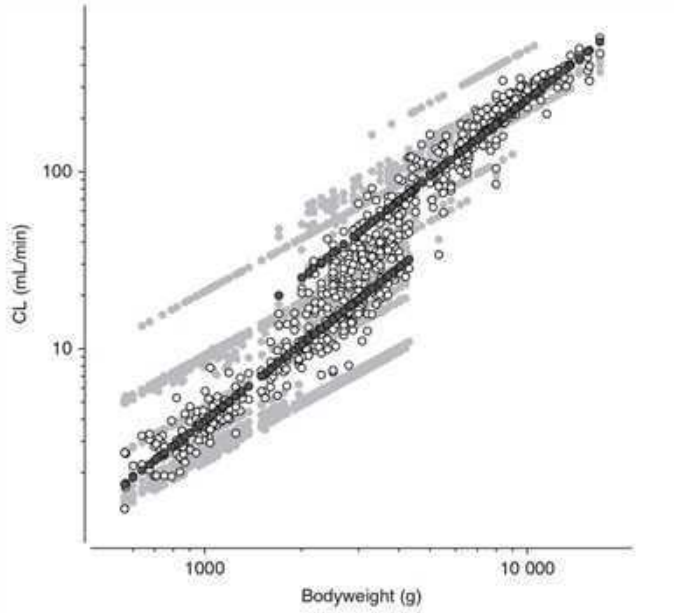
IT'S UP TO THE NEONATE...

Fentanyl



Swantje Völler et al. Arch Dis Child Fetal Neonatal Ed, 2019

Morphine



Elke Krekels et al. Clin PK, 2011

MATERNAL DRUG USE WITH EFFECT…

… intra-uterine

… on neonatal start

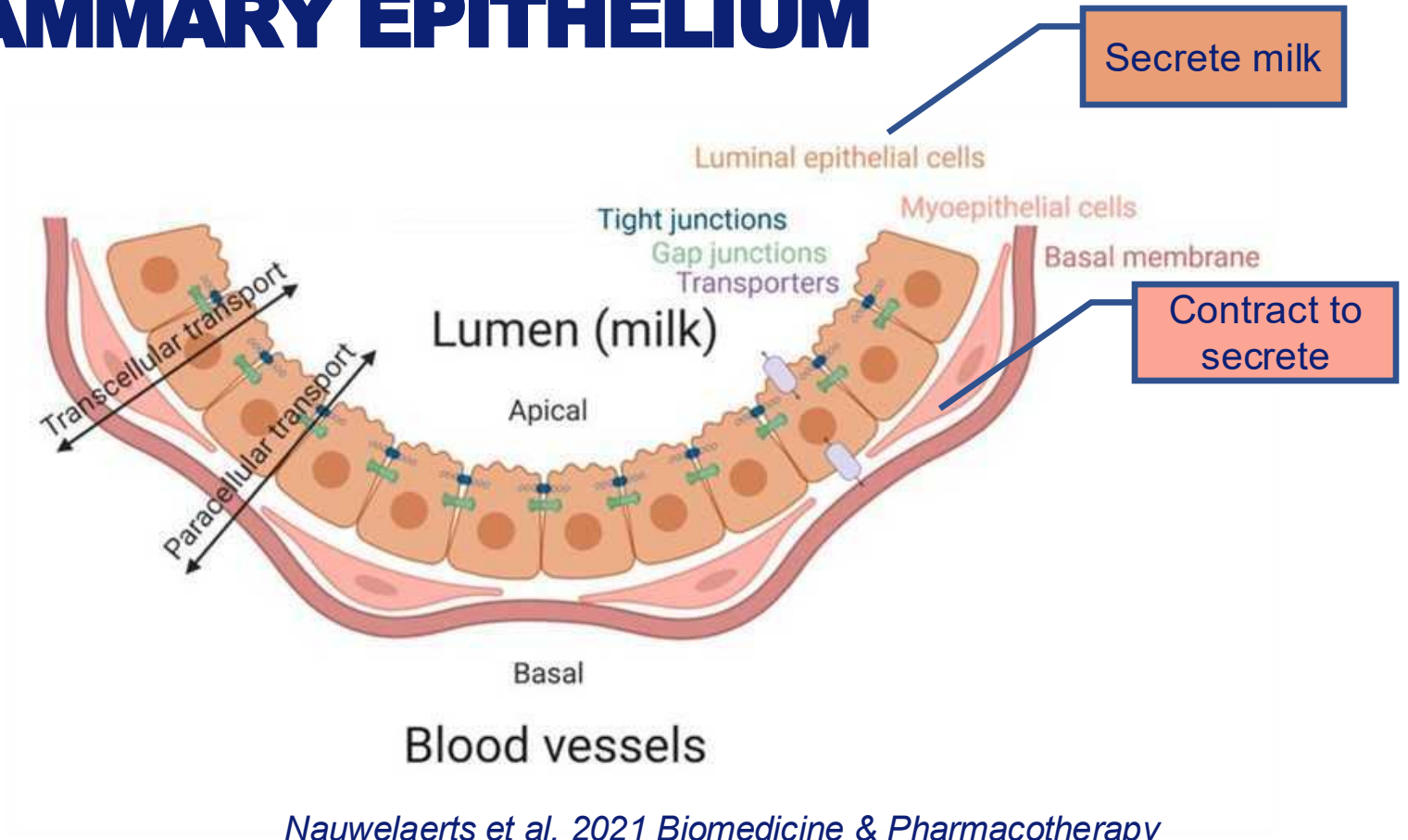
… on milk production

… on neonate via lactation

… benefits of lactation after intra-uterine exposure

… on neonate via lactation

MAMMARY EPITHELIUM



Nauwelaerts et al. 2021 Biomedicine & Pharmacotherapy

... on neonate via lactation

DRUG FACTORS IN FAVOR OF PASSAGE TO BREASTMILK

Lipid solubile (high logP value)

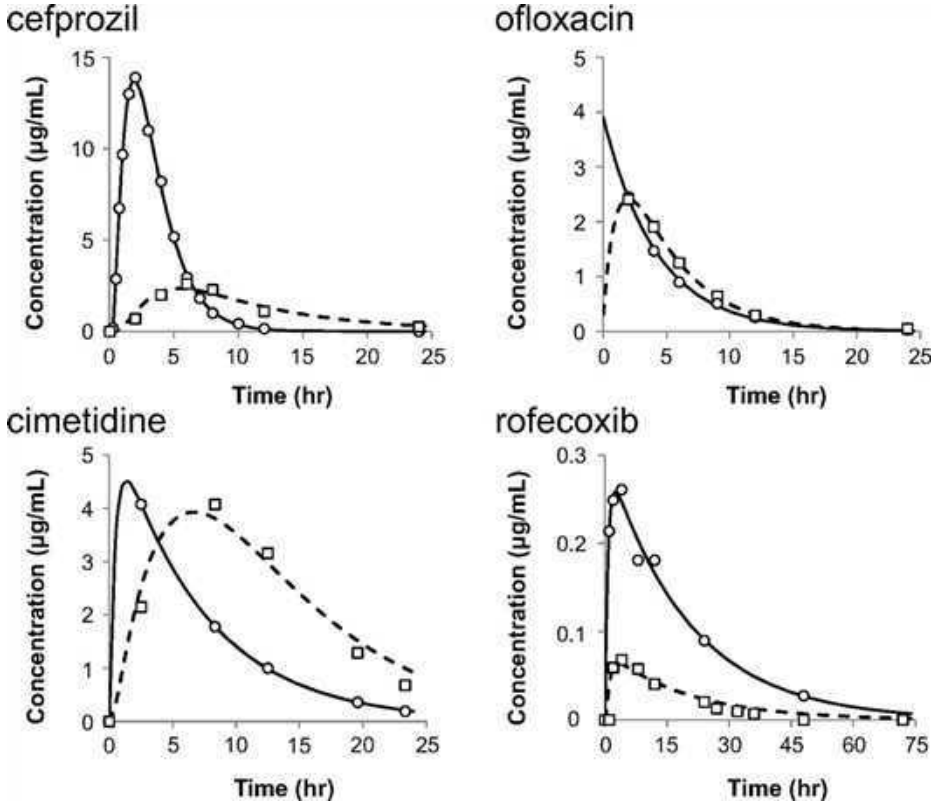
Low molecular weight

Not ionized (pKa value dependent)

Unbound to plasma protein

Long maternal elimination half life

CONCENTRATION PROFILES IN PLASMA AND MILK



IMPACT ON NEONATE: EXPOSURE CALCULATION

Milk to plasma ratio $(\mathrm{M{:}\,P}) = \dfrac{(\mathrm{AU})\mathrm{C}_{\mathrm{milk}}}{(\mathrm{AU})\mathrm{C}_{\mathrm{plasma}}}$

Absolute Infant Dose $(\mathrm{AID}) = \mathrm{C}_{\mathrm{milk}} \cdot \mathrm{V}_{\mathrm{milk}}$

Relative Infant Dose $(\mathrm{RID}) = \dfrac{\text{Dosage infant } (\mathrm{AID})_{\text{in ug/kg/day}}}{\text{Dosage mother}_{\text{in ug/kg/day}}}$

MATERNAL DRUG USE WITH EFFECT…

… intra-uterine

… on neonatal start

… on milk production

… on neonate via lactation

… benefits of lactation after intra-uterine exposure

MATERNAL ANTI-EPILEPTIC DRUG USE

At six years, **children of mothers on AEDs had a higher (11.5% instead of 4.8%) risk of impaired fine motor skills** compared with controls and a lower and dose dependent IQ (from −6 to −9 IQ point) following fetal valproate exposure when compared to other AEDs.

Subsequent breastfeeding in infants of women using AEDs **was associated with improved neurodevelopment outcome** compared with those with either no breastfeeding or breastfeeding for less than six months.

Overall, the adjusted **IQ was higher by 4 points for children who were breastfed** compared to those who were not. The difference in IQ was most pronounced in the valproate group (+12, range, 1–24 IQ).

Also beneficial for other drugs? Reduce abstinence symptoms

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Meador et al, JAMA Pediatr 2014

Nora*

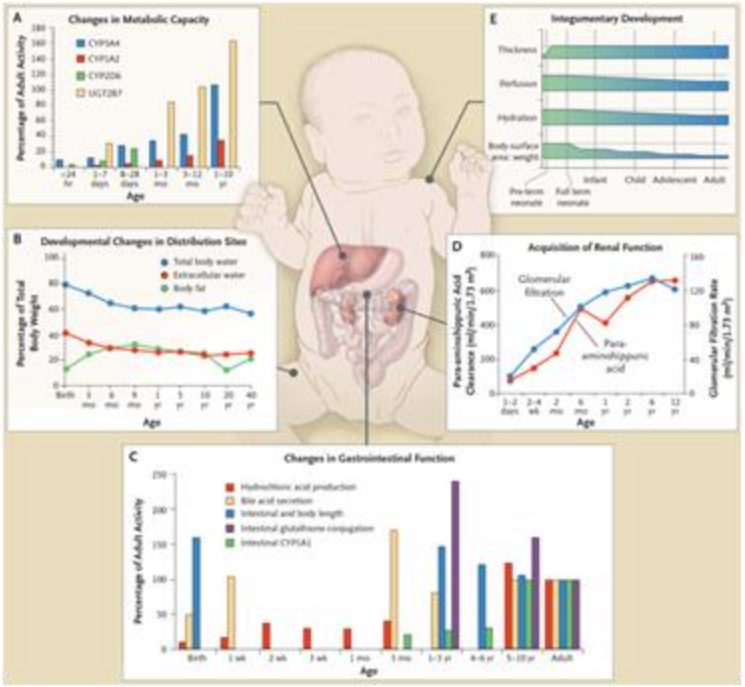
* Fictional name

Maturational covariates

rapid enzyme maturation

body composition

unpredictable absorption



kidney function

large between subject variability - receptor expression & sensitivity - validity of effect parameters

Kearns et al. NEJM 2003

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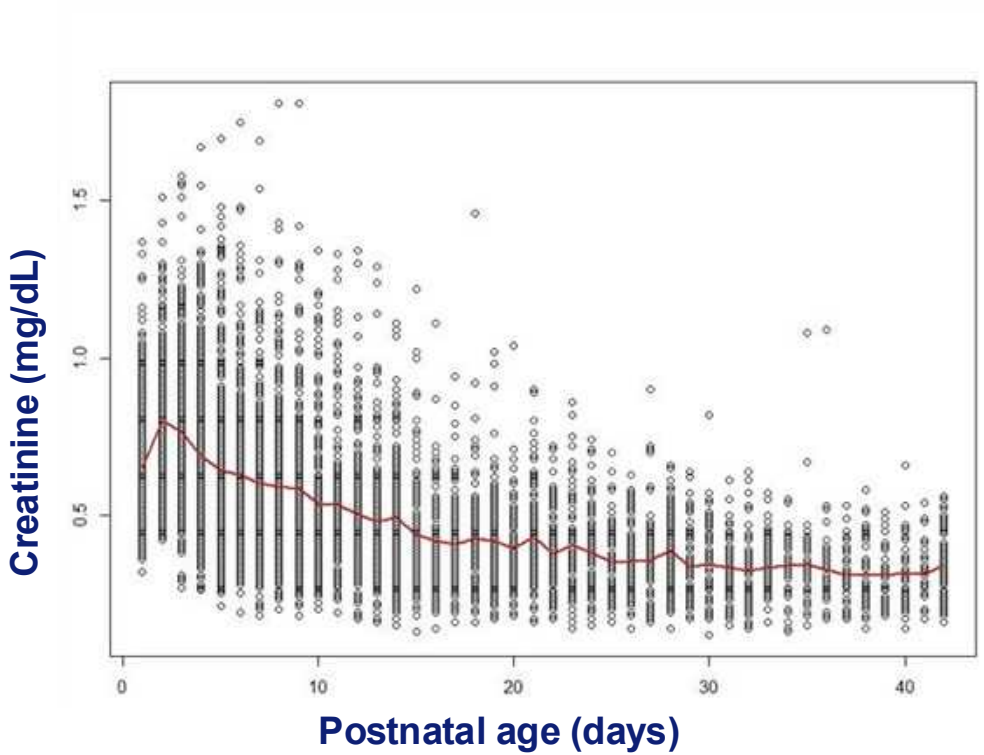
No adequate reflection of kidney function



Allegaert et al, Frontiers Pediatr 2020

Suggestions for individualized medicine in neonatology

Renal injury in neonates: use of "omics" for developing precision medicine in neonatology

Mandar S. Joshi[1], Kelsey A. Montgomery[1], Peter J. Giannone[1], John A. Bauer[1] and Mina H. Hanna[1]

Ped Research 2017

Individualized Hemodynamic Management in Newborns

*Willem P. de Boode**

Frontiers in Pediatrics October 2020 | Volume 8 |

Precision Medicine in Neonates: Future Perspectives for the Lung

Wes Onland[1], Jeroen Hutten[1], Martijn Miedema[1], Lieuwe D. Bos[2], Paul Brinkman[2], Anke H. Maitland-van der Zee[2] and Anton H. van Kaam[1]*

Frontiers in Pediatrics October 2020 | Volume 8 | Article 586061

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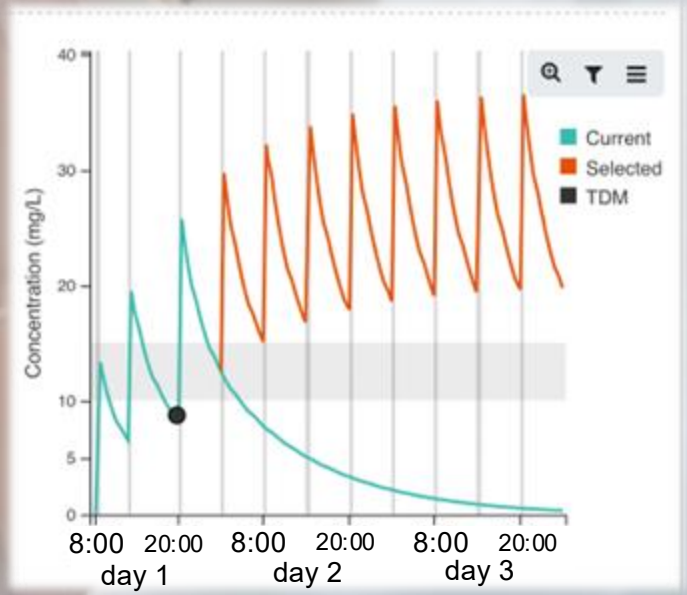
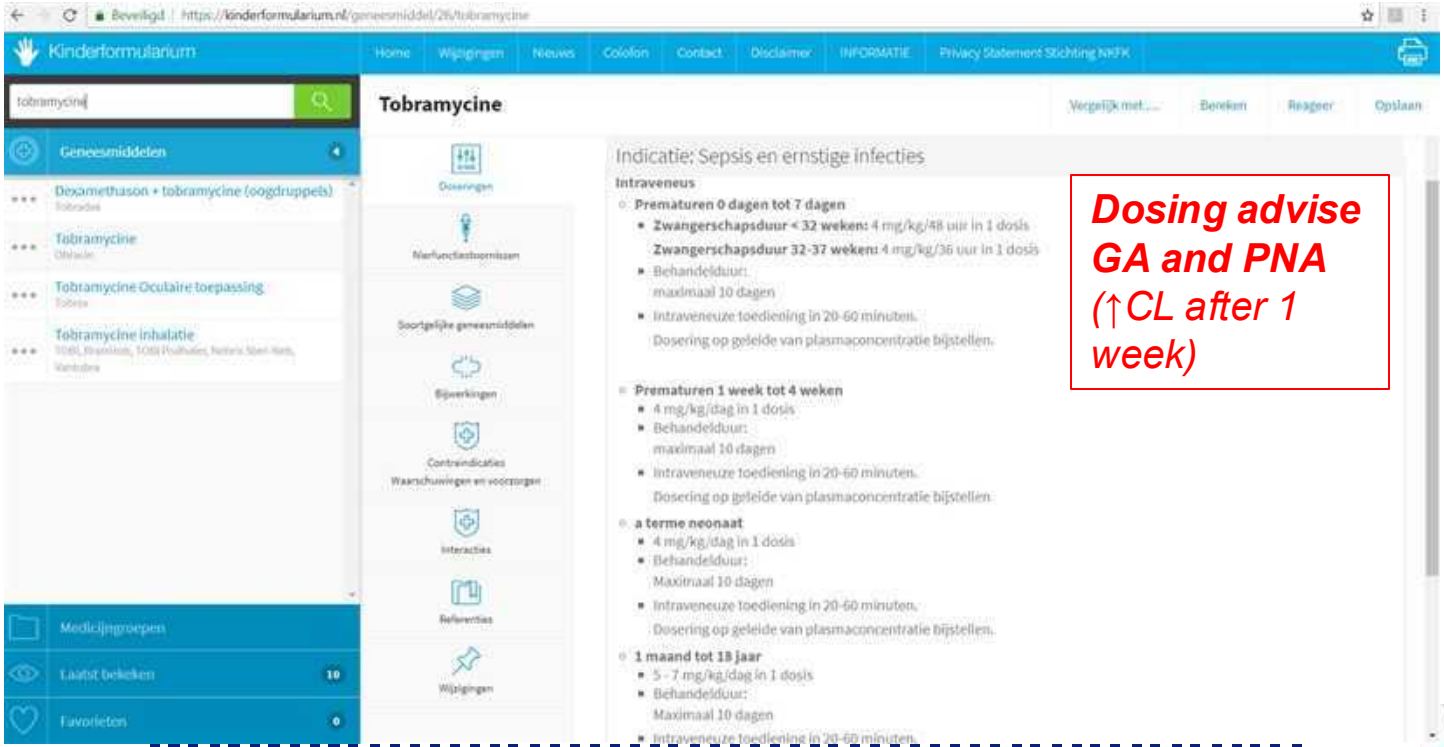
Translation to practice

- Label the appropiate PK models per patient and drug
- Use MIPD before start of antibiotocs
- Early sample collection
- Multidisciplinairy approach



Dutch pediatric formulary



Dosing advise GA and PNA (↑CL after 1 week)

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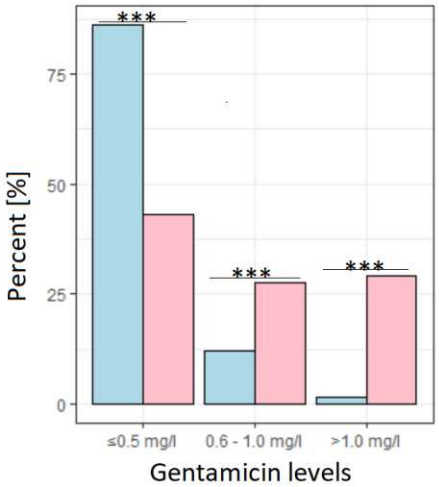
MIPD of aminoglycosides in children

Results: Target attainment (≤0.5 mg/L) evaluation



New dosing regimen
Previous dosing regimen

4. 5 mg/kg PNA, BW Intervals (24h-72h)

5 mg/kg/48h or 4 mg/kg/24h PNA

86% of trough concentrations were in the target range (≤0.5 mg/L)

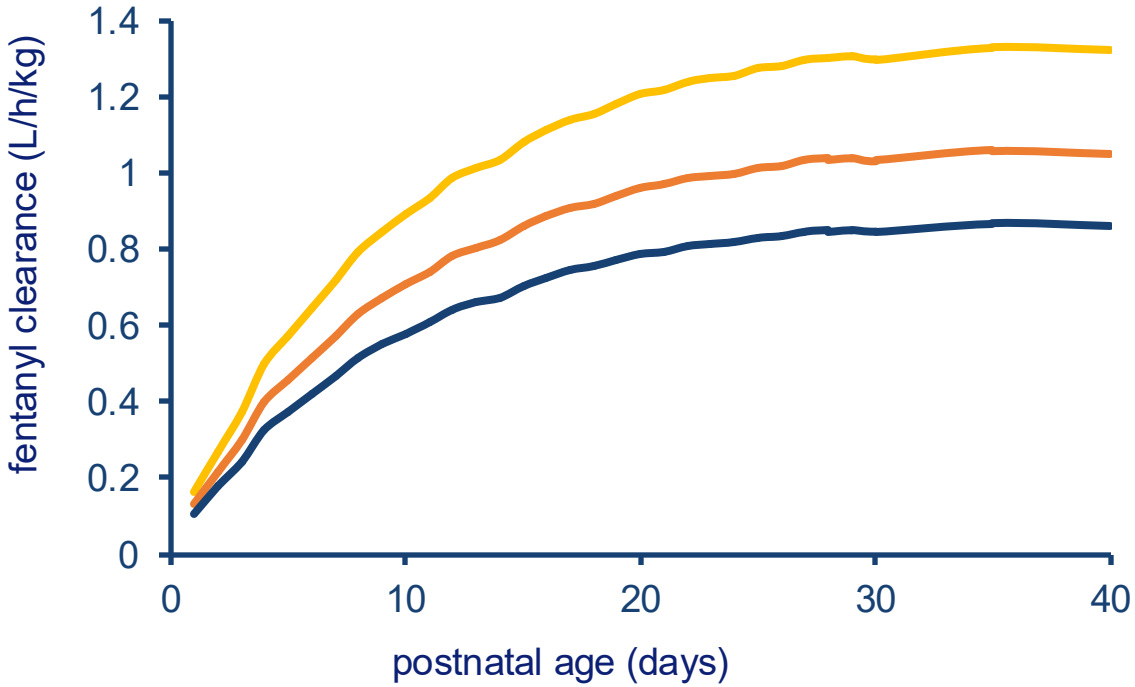
The dosing interval should be increased by 12 h if ibuprofen is coadministered for closure of a persistent ductus arteriosus.

J Antimicrob Chemother 2015; 70: 2074–2077

Pain

Erasmus MC Sophia

Pain – pharmacokinetics maturation of fentanyl clearance



Gestational age

31 weeks

28 weeks

25 weeks

Voller, Flint et al. Arch Dis Child Fetal, 2019

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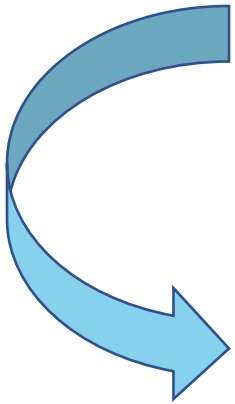
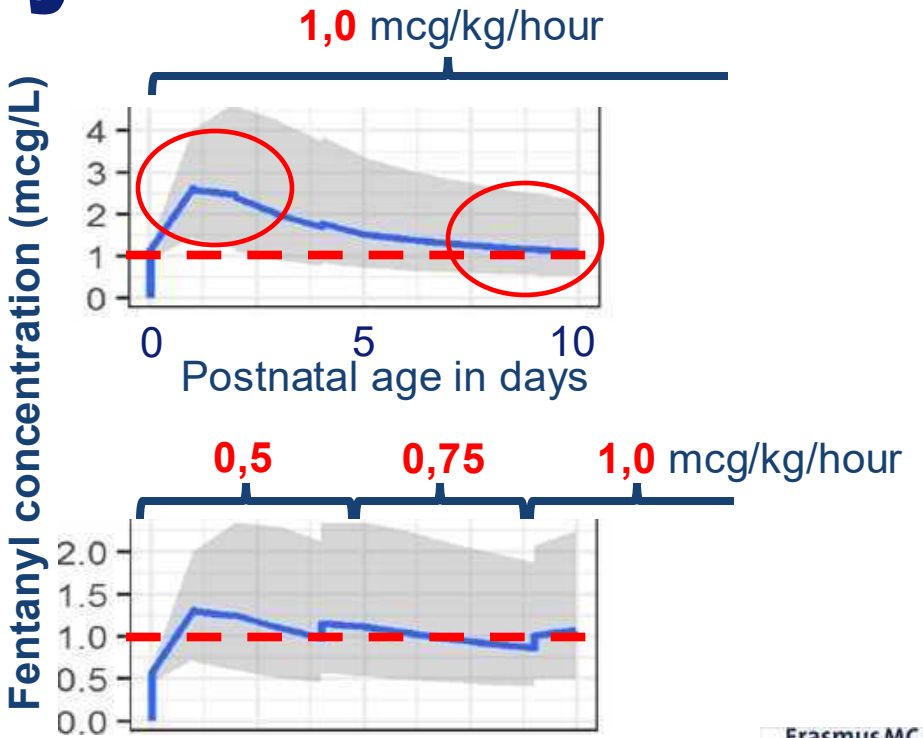
Pain – pharmacokinetics continuous fentanyl infusion

Grey area reflects **LARGE** between-subject variability of clearance (4-fold!)

50% dose at PNA ≤5 days
75% dose at PNA 6-9 days
100% at PNA ≥ 10 days





Voller, Flint et al. Arch Dis Child Fetal, 2019

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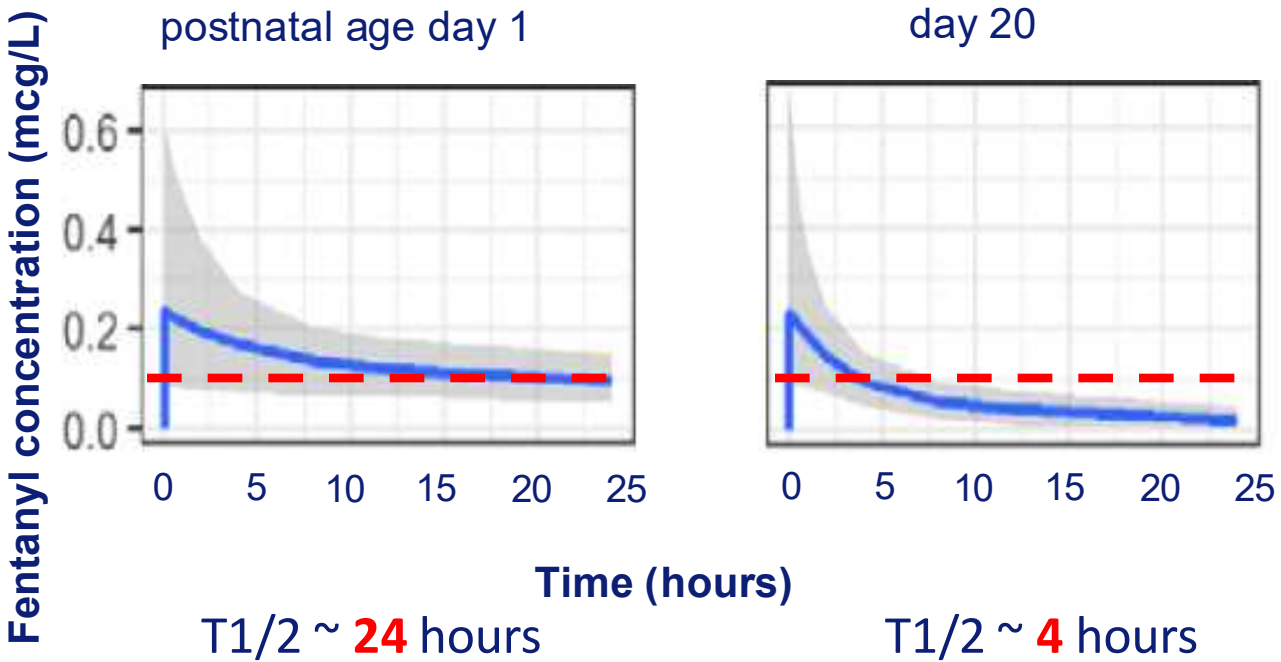
Pain – pharmacokinetics bolus dose fentanyl 2 mcg/kg

Grey area reflects **LARGE** between-patient variability of clearance (4-fold!)



T1/2 ~ **24** hours

T1/2 ~ **4** hours

Voller, Flint et al. Arch Dis Child Fetal, 2019

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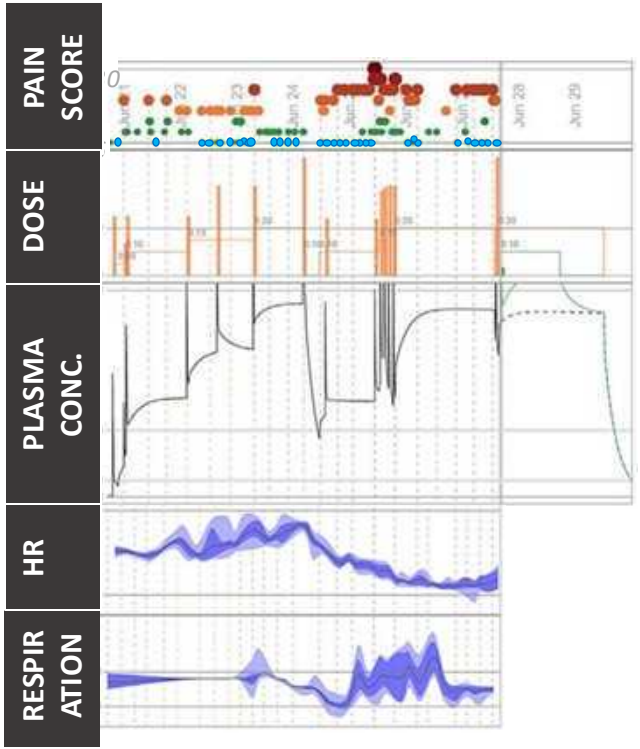
One bodyweight-based dose does NOT fit all

Implemented morphine individualization



Effectiveness

Dosages

Achieved exposure

Predicted exposure

(Side-) effects

SUGGESTED OPTIMIZATION:

Co-medication

Genomics

Algorhitm-alerts for:

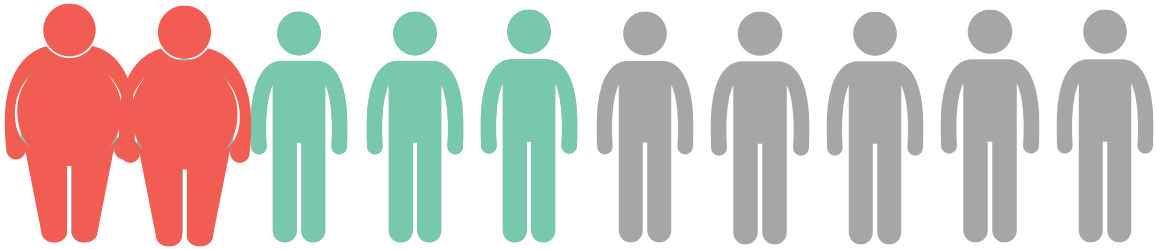
- **(Side-)effect data collection**
- **Dose-adjustments**
- **Register evaluation**
- **Organ function**

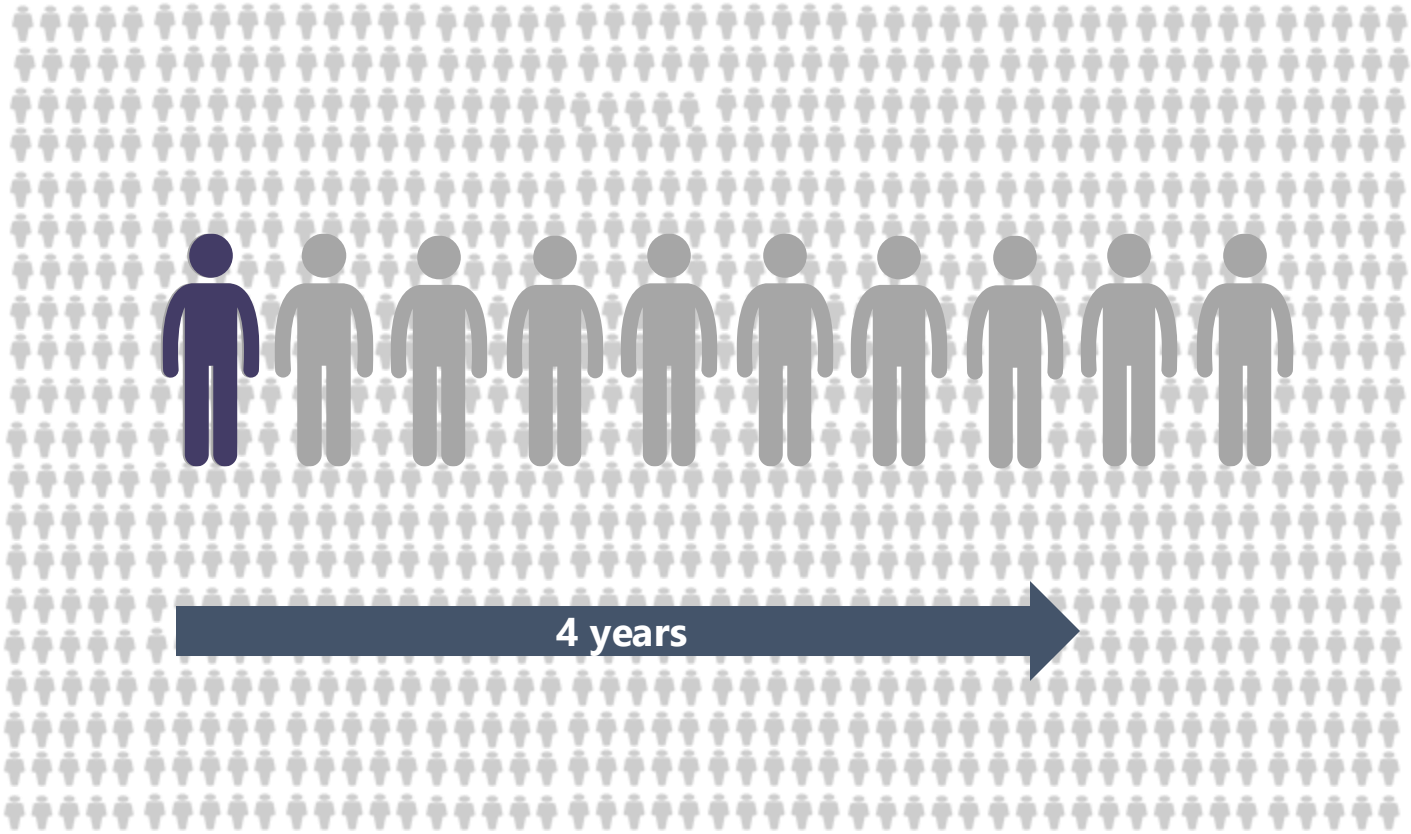
Vinks et al. 2020 CPT

Erasmus MC

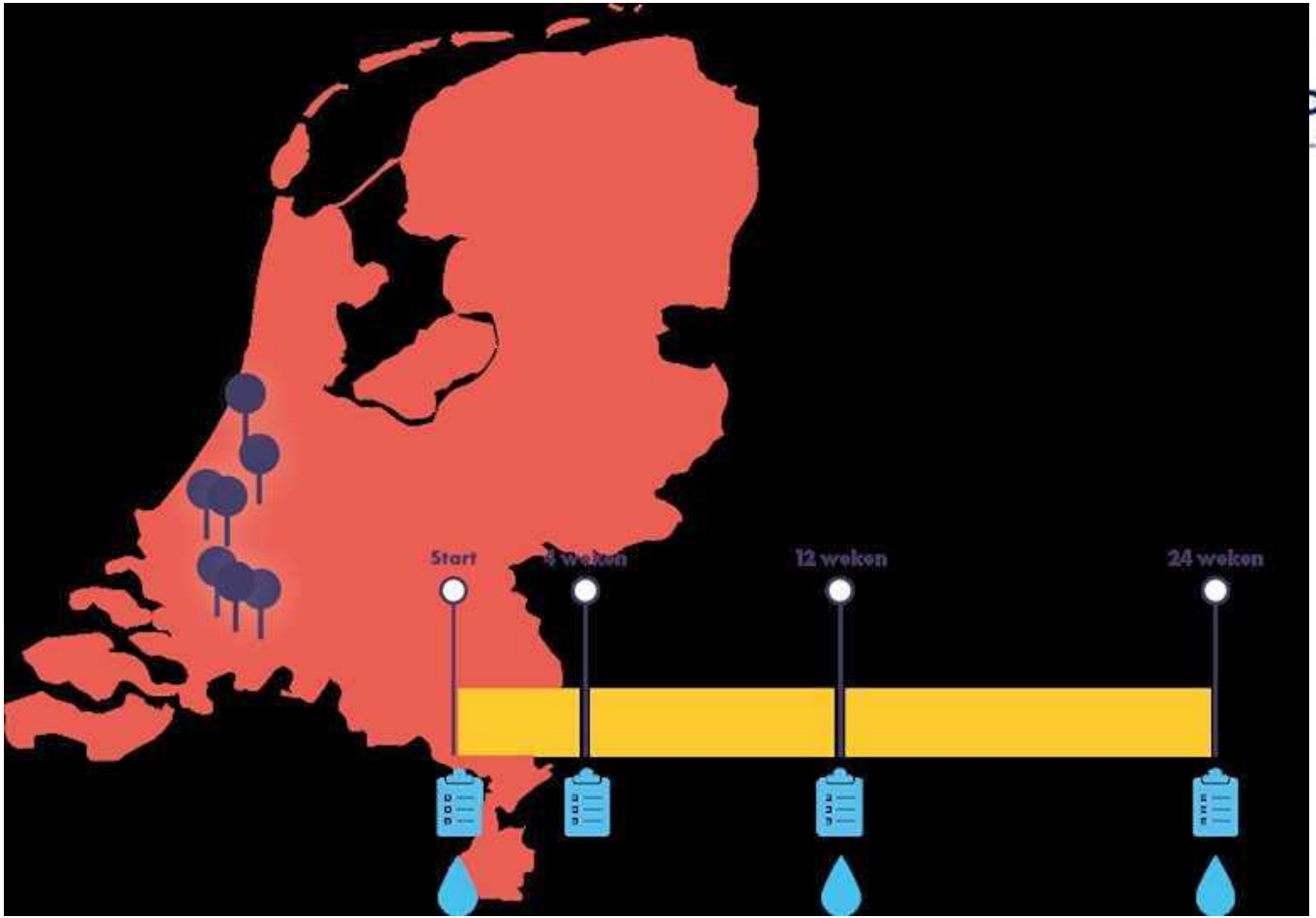
Bart*

* Fictional name





Antipsychotics in Dutch Youth: Prevalence, Dosages, and Duration of Use from 2005 to 2015.
Kloosterboer SM, el al. J Child Adolesc Psychopharmacol. 2018 Apr;28(3):173-179


Start
12 weken
24 weken

Feasibility of Dried Blood Spots in Children with Behavioral Problems.
Kloosterboer SM, et al.Ther Drug Monit. 2020; 42(4):648-651.

Measures

DBS/Venapunction: 2 x 2 moments (Risperidon/Aripiprazol en Pipamperon)

Efficacy:

- Questionnaires (CBCL, ABC and CGI)

Side effects

- Questionnaires (AIMS)
- Lab values
- Weight

Pharmacogenetics

Medication adherence (MARS and MEMS)

Assessing methods of measuring medication adherence in chronically ill children-a narrative review. Al-Hassany L, et al. Patient Prefer Adherence. 2019 Jul 22;13:1175-1189

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Analysis

LC-MS/MS

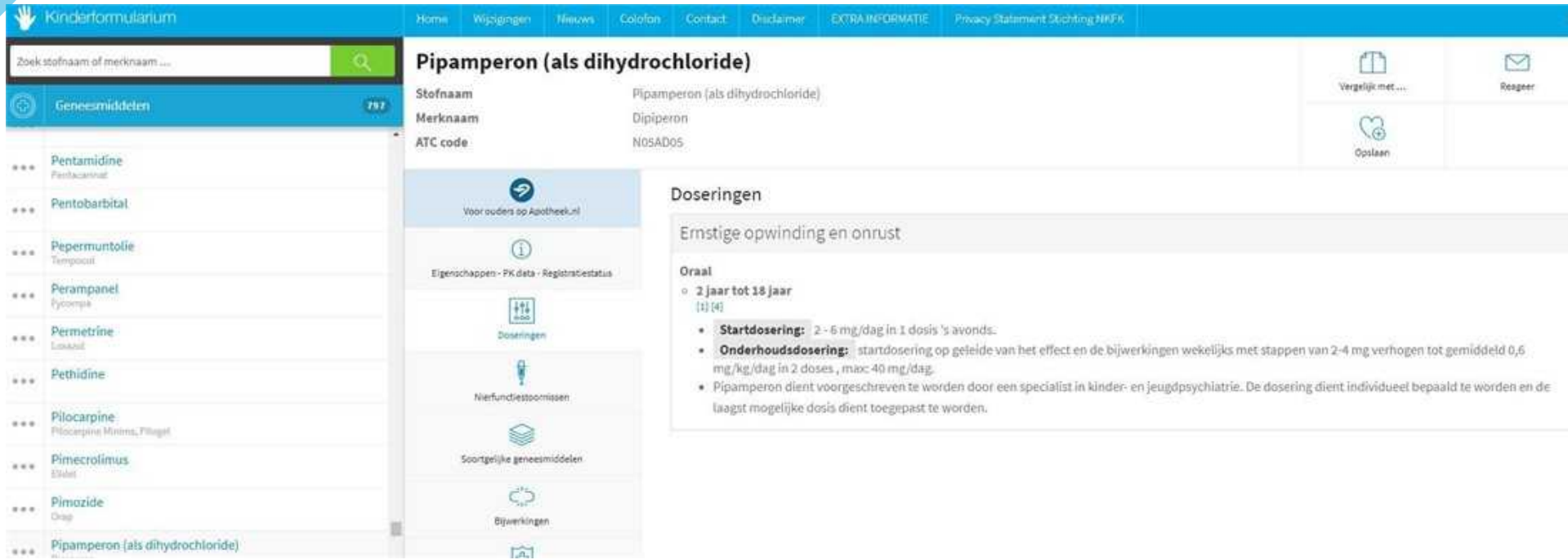
PK modeling via NONMEM

PD relate to PK via mixed modeling

Dried Blood Spot Analysis for Therapeutic Drug Monitoring of Antipsychotics: Drawbacks of Its Clinical Application. Kloosterboer SM, et al. Ther Drug Monit. 2018 Jun;40(3):344-350

Dried Blood Spots Combined With Ultra-High-Performance Liquid Chromatography-Mass Spectrometry for the Quantification of the Antipsychotics Risperidone, Aripiprazole, Pipamperone, and Their Major Metabolites. Tron C, et al. Ther Drug Monit. 2017 Aug;39(4):429-440

Erasmus MC



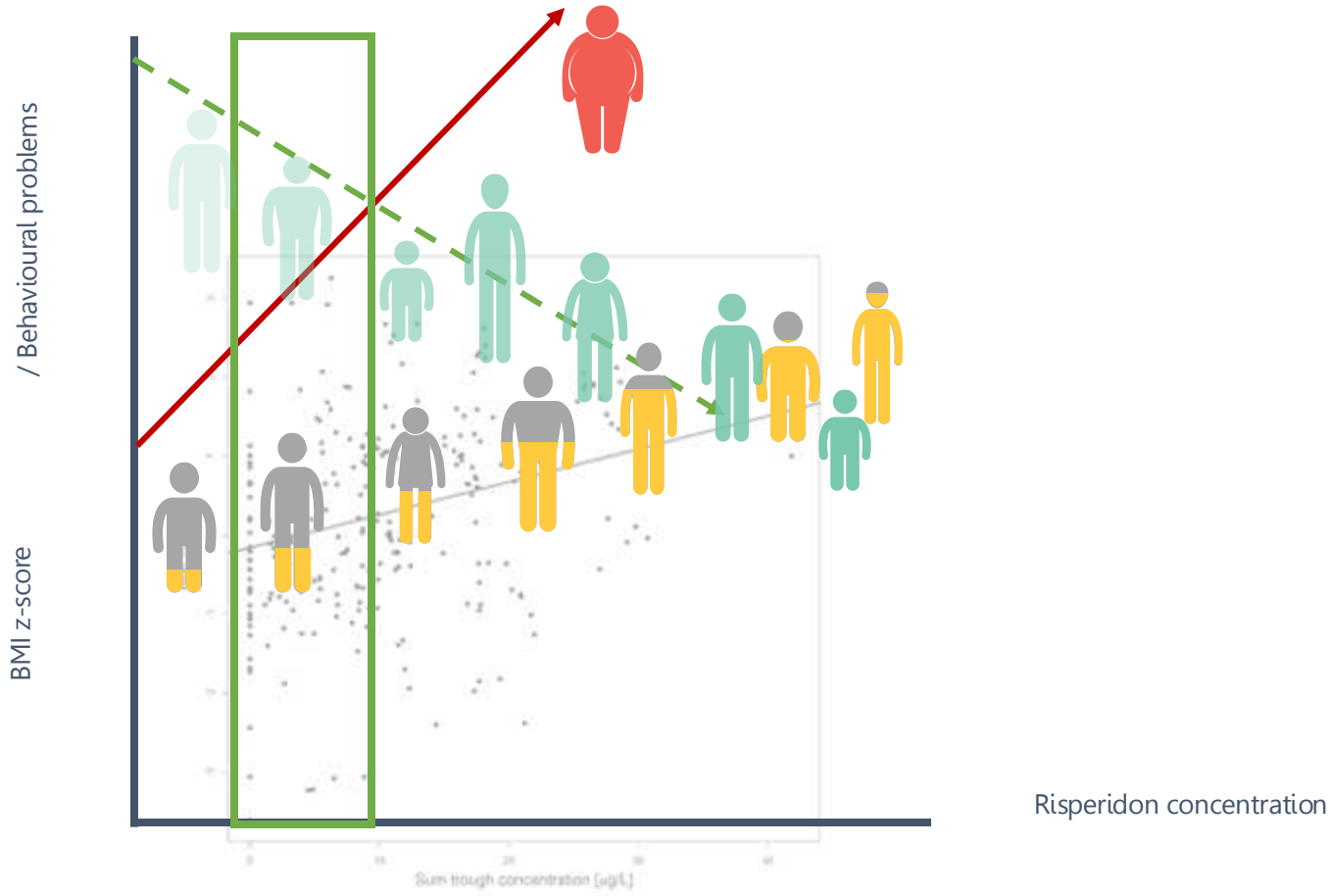
Pipamperone Population Pharmacokinetics Related to Effectiveness and Side Effects in Children and Adolescents. Kloosterboer SM, et al. Clin Pharmacokinet. 2020 Nov;59(11):1393-1405

Erasmus MC

PK analysis

Risperidone

Aripiprazole



Risperidone plasma concentrations are associated with side effects and effectiveness in children and adolescents with autism spectrum disorder. Kloosterboer SM, et al.Br J Clin Pharmacol. 2021 Mar;87(3):1069-1081

Follow-up research

SPACE 2 STAR

- TDM versus standaard dosing of risperidon
- ZonMW/Erasmus MC grant
- Multi-center International

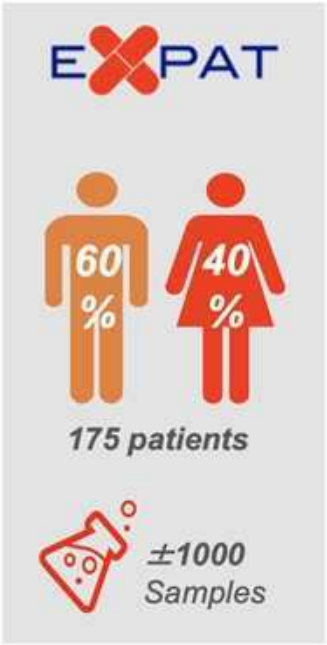
TORPEDO

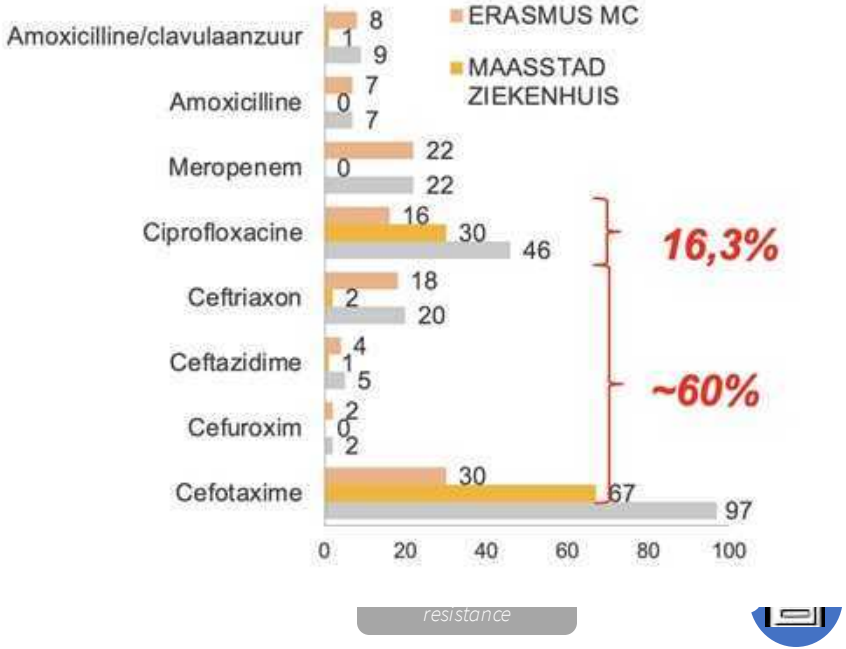
- Precision dosing of olanzapine in AN patients

Erasmus MC

Robin*

Patients on the ICU





Hyperdynamic status
Increased cardiac output/Clearance

Changing Fluid balance
Differemces in Vd

Renal/hepatic failure

RRT/ECMO

ECMO: extracorporeal membrane oxygenation. RRT: renal replacement therapy. Abdulla et al, Crit Care 2020

Dose individualization of antibiotics in ICU patients: to TDM or not to TDM and the effects on outcome

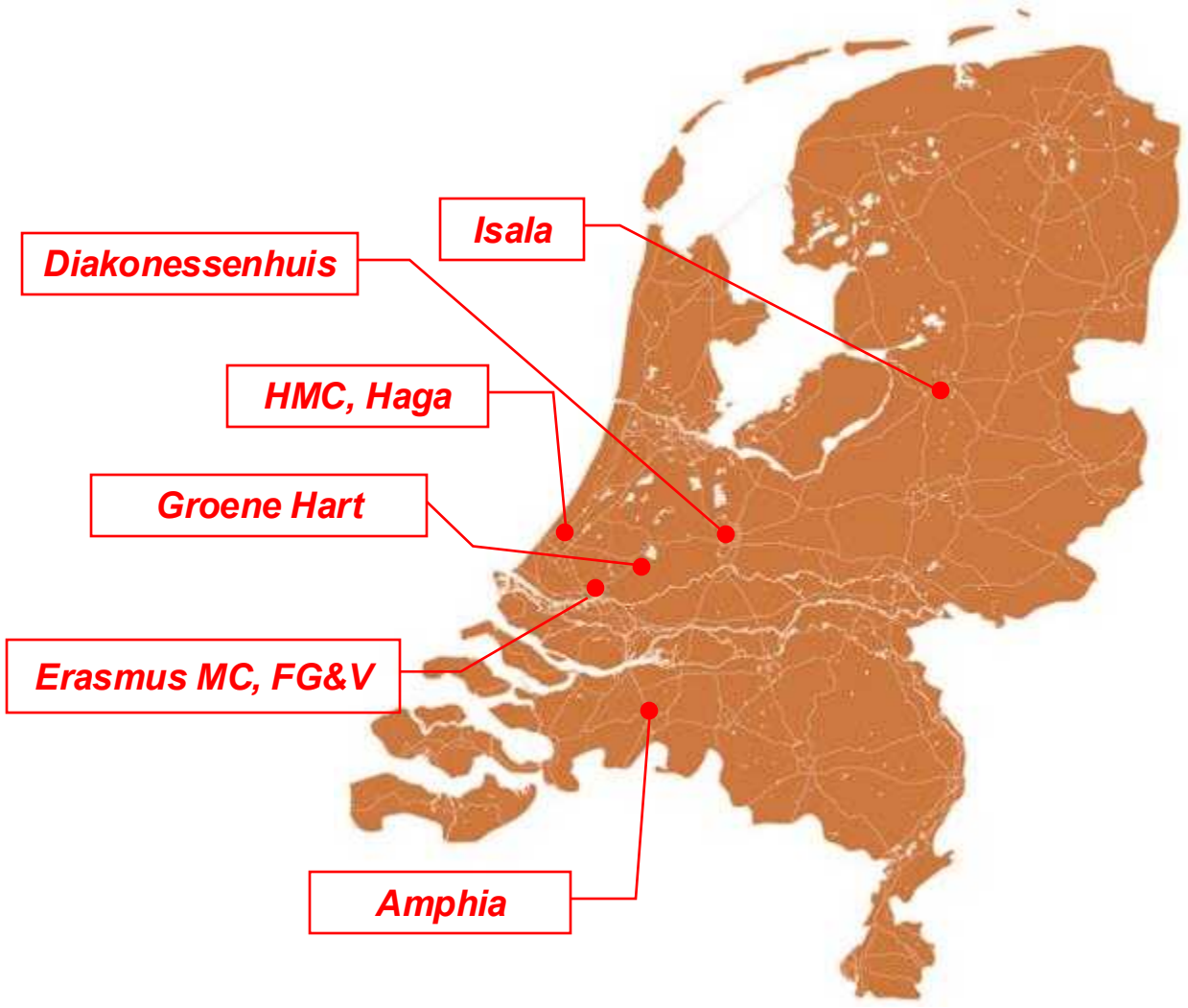
Study design
Multicenter, prospective randomized study active TDM vs no-TDM

Study population
Adult ICU patients, started with antibiotics (beta-lactams or ciprofloxacin

Aim
Fast adaptation of dosing ->TDM -> shorter ICU admittance

Abdulla et al, BMC Infec Dis. 2020: 20(1): 57

N = 450 (450)



De Merel, ZonMw, Erasmus grant

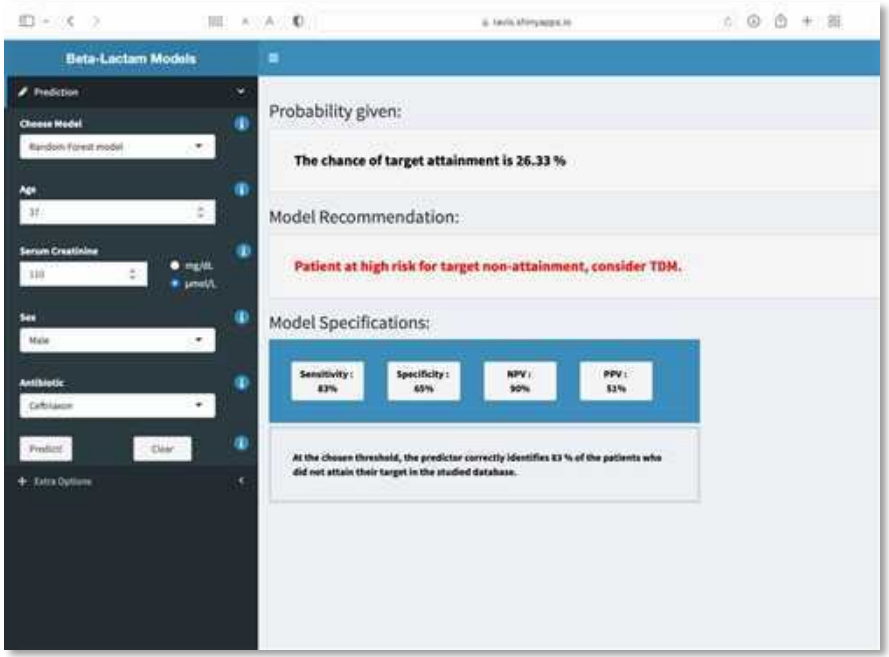
Post-hoc analysis

- SOFA < 8 (Mortality)
- Intervention within 24 hours (ICU LOS)
- Neurotrauma

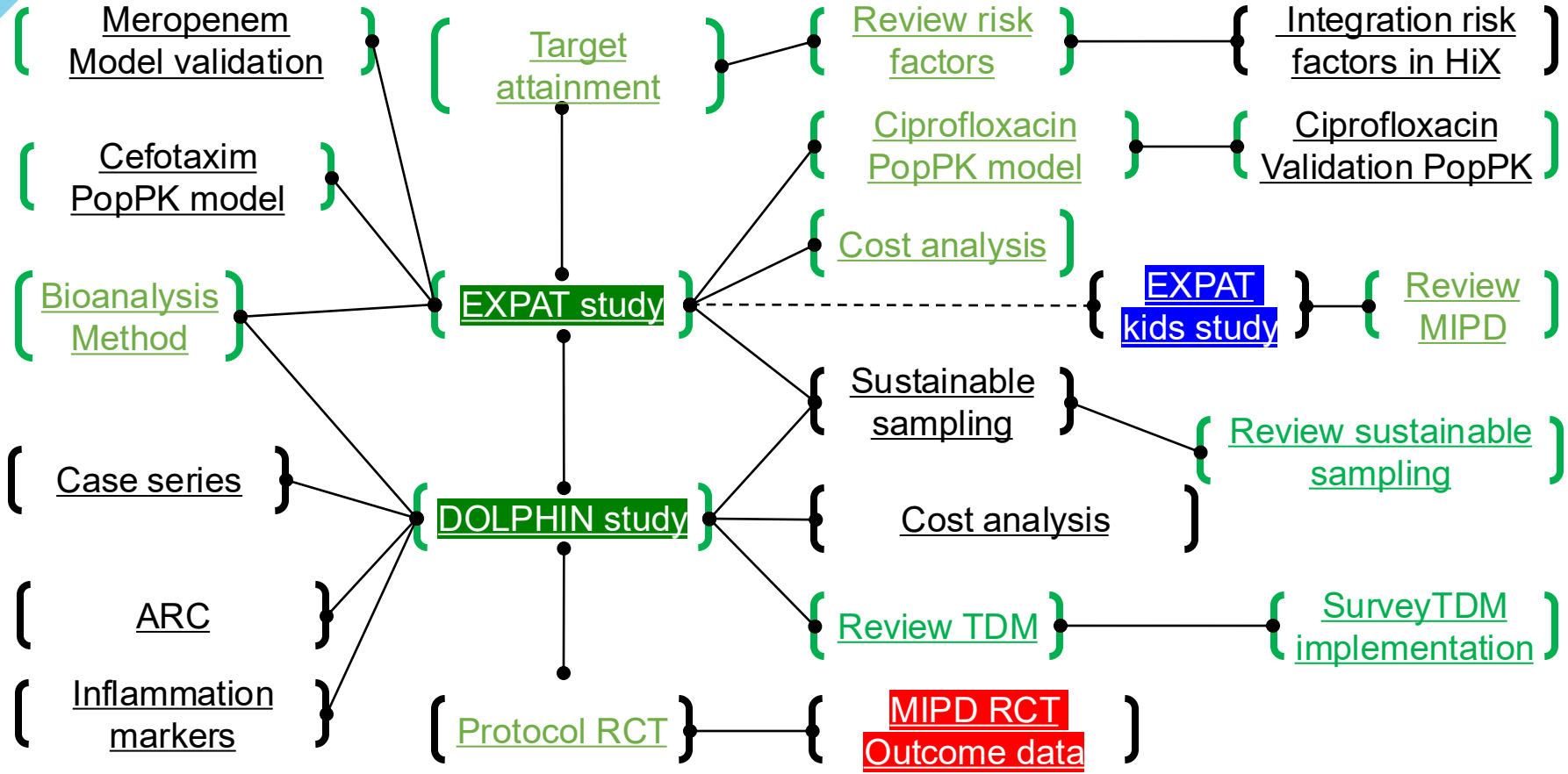
Ewoldt et al, IJAA 2023

Wieringa, Antibiotics 2023

Ergezen, ECICM 2023

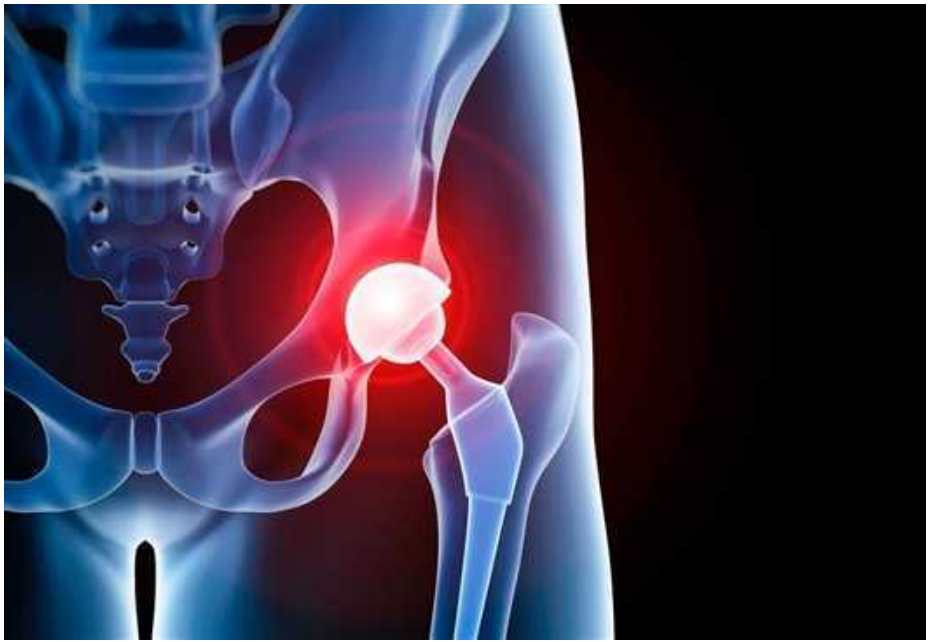


Erasmus MC



Abdulla et al, 31952493, 32933574, 32307575 33463382, 33708753, 34657093, 28618388
Ewoldt et al, 33770020

William*



Erasmus MC

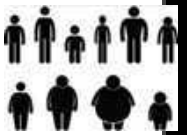
** Fictional name*

Changes in PK and PD

PK

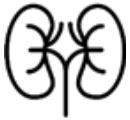
Absorption

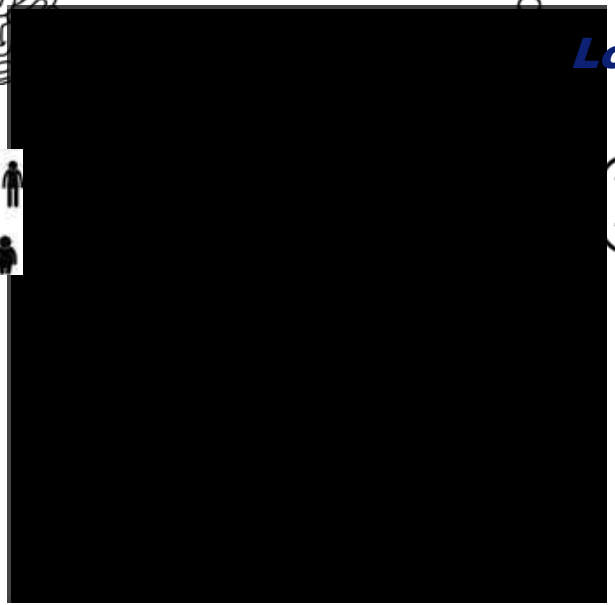
Distribution



Metabolism

Excretion





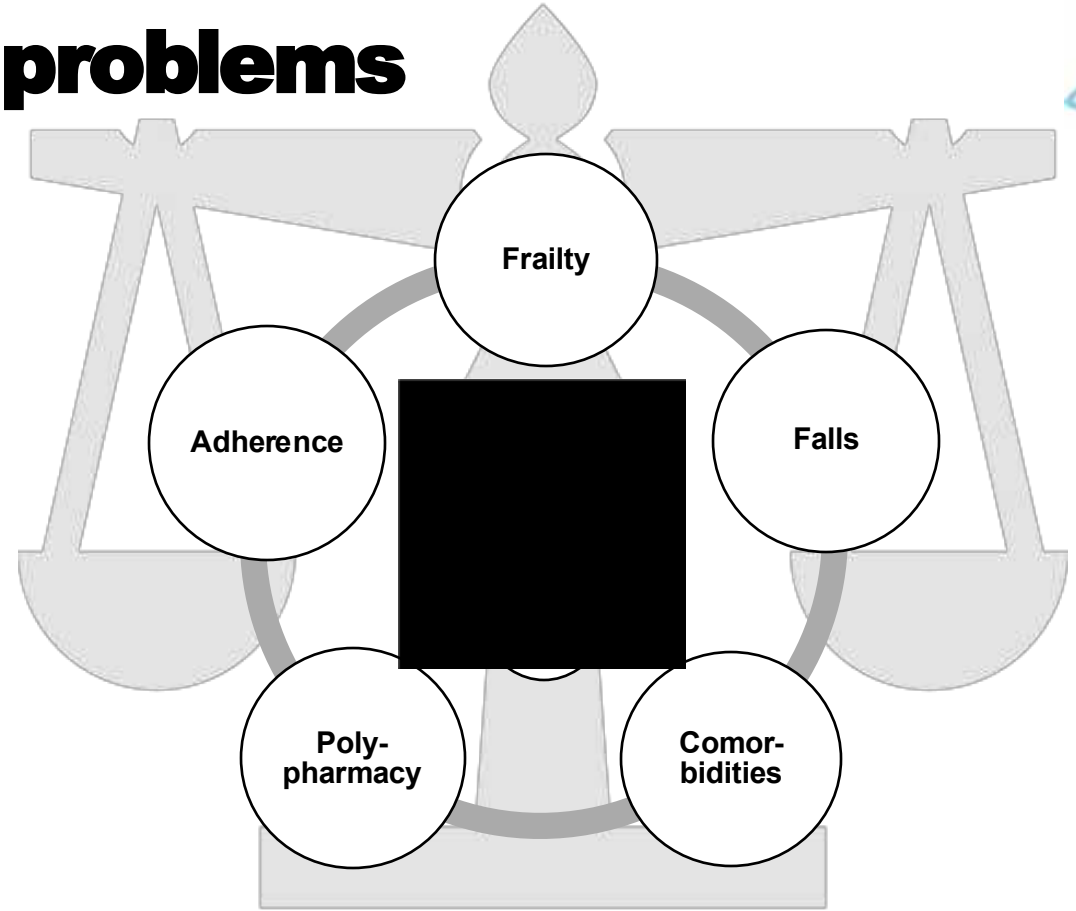
PD

Loss of arterial elasticity

Kidney function ↓

RAAS-system ↓

Other problems



Starting dose recommendation elderly

- *In general: elderly patients have higher plasma concentrations when taking the seem amount of drug as younger patients*

Table 2. Overview of recommendations for starting dose to treat elderly patients with hypertension based on published data.

Drug category	Author	Year	Age of patients	Drug	Starting dose advise for elderly patients (≥ 65 years)
Calcium channel blockers	Mion et al. [104]	2004	66.3 ± 5.3 years	Amlodipine	2.5 mg daily
	van Ree et al. [105]	1996	50–80 years	Felodipine	2.5 mg ER daily
Angiotensin-converting-enzyme inhibitor	Lees et al. [119]	1988	71 ± 3 years	Perindopril (tert-butylamine)	2 mg daily
	Thomson et al. [117]	1989	>65 years	Lisinopril	2.5 mg daily
	Kaiser et al. [116]	1990	65–85 years	Benazepril HCl	5 mg daily (dependent on kidney function)
Angiotensin receptor blocker	Sioufi et al. [135]	1998	65–89 years	Valsartan	40 mg daily
	De Rosa et al. [132]	2002	> 65 years	Irbesartan	75 mg daily (dependent on kidney function)
	Pareek et al. [106]	2008	51.88 ± 9.96 years	Losartan	25 mg daily
Diuretics (thiazides)	Pareek et al. [106]	2008	51.88 ± 9.96 years	Chlortalidone	6.25 mg daily
	Duprez et al. [107]	2011	>70 years	Hydrochlorothiazide	12.5 mg daily
	Shiga et al. [152]	2011	68 ± 10 years	Hydrochlorothiazide	6.25 mg daily
Beta blockers	Eugene et al. [108]	2016	61–88 years	Metoprolol	25 mg daily (possibly lower in geriatric females)
	Baxter et al. [109]	2002	70–89 years	Bisoprolol	1.25 mg daily

ER = Extended release

Plasma concentration and age

Table 3. Average Difference in Plasma Concentrations in Relation to Sex, Time After Intake, Dosage, Body Weight, and Age

Drug [Metabolite], µg/L	Female, %	Male vs Female	Time, h	Dose, mg	Weight, kg	Age, y
Amlodipine, µg/L	30.5	−4.8	−0.21*	1.5†	−0.16	0.12
[Enalaprilate], µg/L	39.4	−12	−3.1‡	−1.9	−0.93	−0.03
Hydrochlorothiazide, µg/L	43.5	−31	−3.0	0.74	−0.75	1.1
[Losartan-ca], µg/L	47.6	17	−9.4†	5.8‡	−6.28‡	12
Nifedipine, µg/L	51.4	−4.5	−1.0	0.12	0.20	0.73
[Perindoprilate], µg/L	27.5	1.9	−0.50†	0.55	−0.03	0.26*
[Canrenone], µg/L	42.3	30*	−2.1†	0.17*	−0.32	−3.33‡
Valsartan, µg/L	48.8	408	−109†	8.3‡	24	12

Results are based on multivariable linear regression, including the listed covariates.
*P=0.01–0.05
†P<0.001
‡P=0.001–0.01.

P = 0.05

Erasmus MC

1 question remains..

Do elevated plasma concentrations antihypertensive drugs in elderly lead to lower blood pressure values and more adverse events?

And is it necessary to lower the starting dose?

DECISION

Differences in antihypertensive drug levels in patients with hypertension: old vs young

What is old and what is young?

- Biological age vs Chronological age
- Definition of what age is old is unclear
  Elderly are often defined as > 65 years or >70 years
- Definition of ‘younger’ patients even more unclear
  <65 years?
  <60 years?
  Previous study of amlodipine: 28-45 years
  → We choose < 50 years

Objective

Primary objective:
Is a difference in the AUC of losartan and perindopril when comparing elderly (>70 years) with younger patients (<50 years)?

Secundary objective:
Is there a difference in the drop of blood pressure in response to losartan or perindopril between older (>70 years) and younger (<50 years) patients; and if so, can this difference be explained by a difference in the plasma concentration of the drug?

Measurements

- 24 hour ABPM → most reliable method to determine blood pressure
  - Before and after the use of antihypertensive drugs
- Dried Blood Spot
  - 5 measurements
  - Easy to use
  - Good instruction is crucial for correct sampling
- Restmaterial → RAAS-activity

Erasmus MC

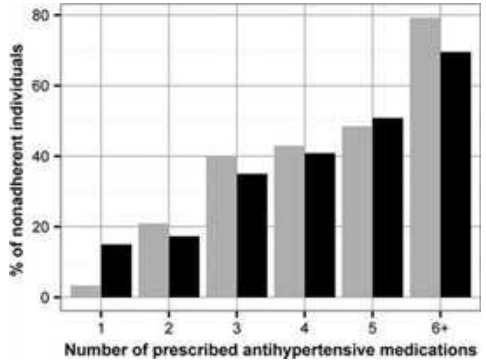
Non-adherence

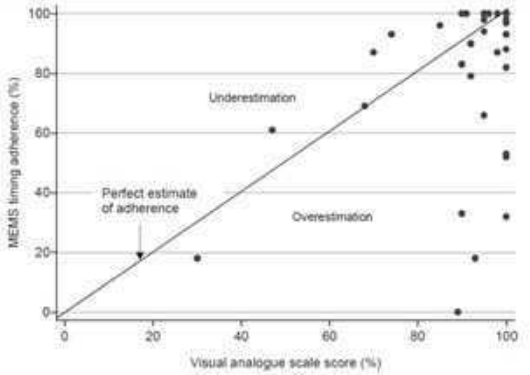
10-50%

cause resistant hypertension

More non-adherence with increased number of prescribed antihypertensives

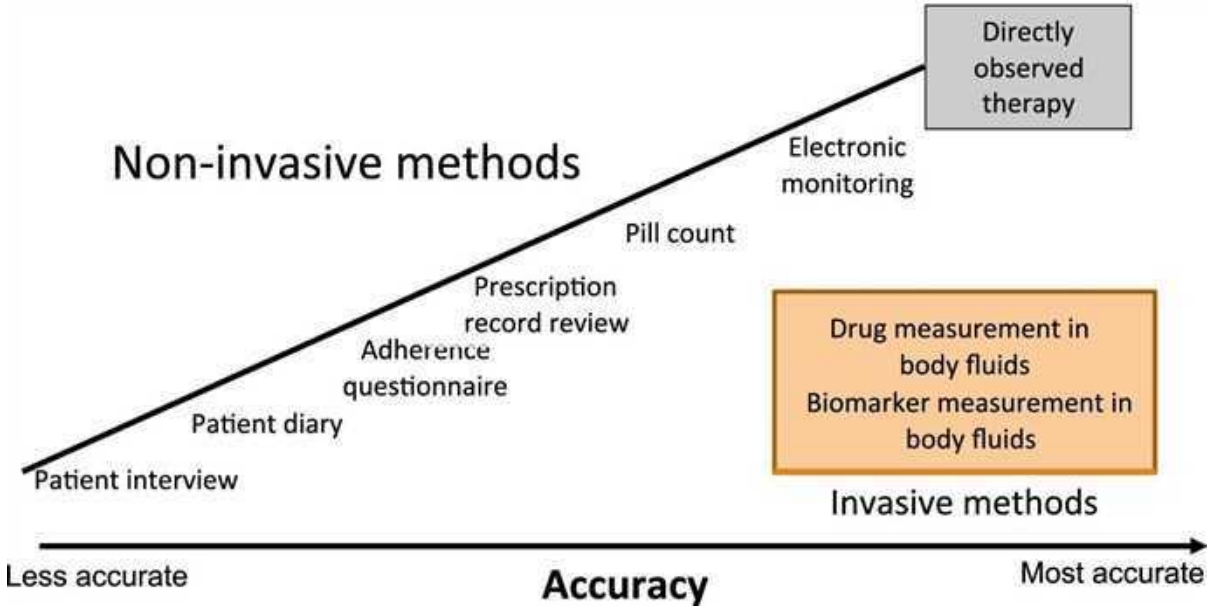
Overestmination by health care providers





Gupta et al. 2017; Zeller et al. 2008

Identification of non-adherence



Burnier M. Drug adherence in hypertension. Pharmacological Research 2017;125.

To measure is to know...

RHYME-AHD: Measuring Hypertension & Measurement of Hypertensive drugs

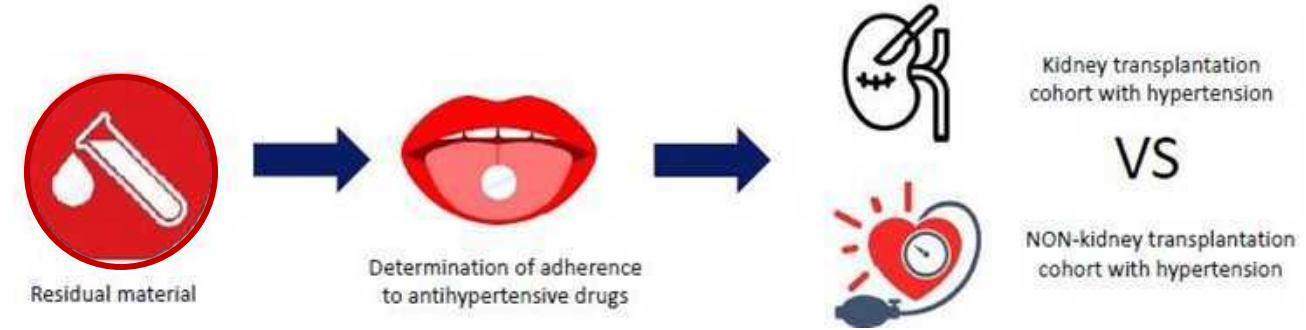
Prospective observational study

Inclusion of patients at vascular and nephrology outpatient clinics

Inclusion criteria:

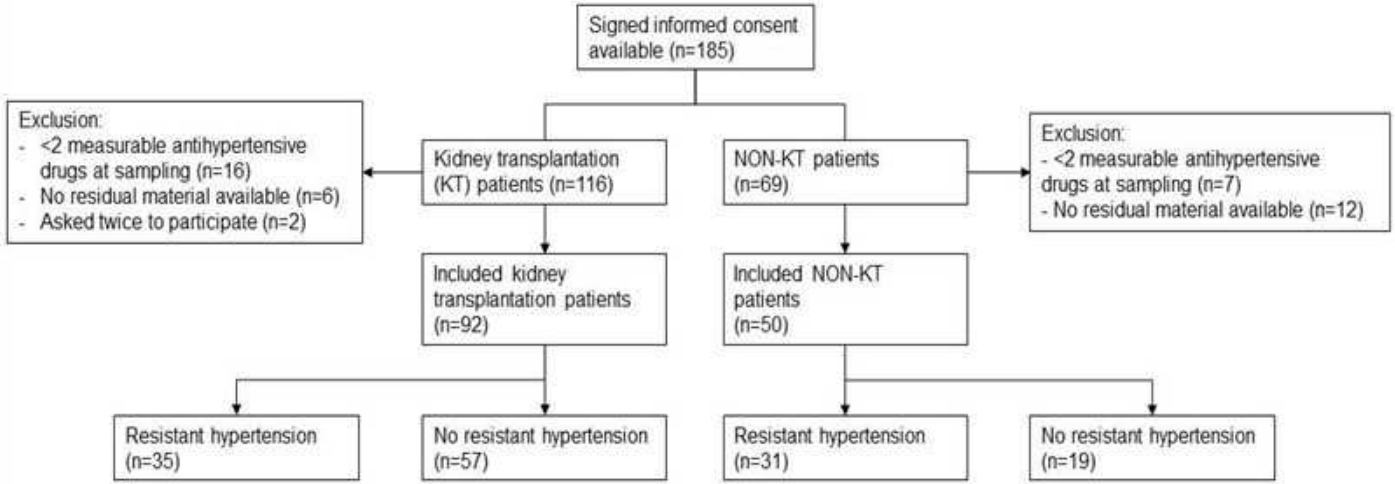
- *Use of ≥ 2 AHDs that could be measured with a validated UHPLC-MS/MS method*

  enalapril [enalaprilate], perindopril [perindoprilate], irbesartan, valsartan, losartan [losartan-carboxylic acid], bumetanide, spironolactone [canrenone], amlodipine, barnidipine, nifedipine, metoprolol and doxazosin



Results RHYME-aD

Inclusion flowchart



Peeters et al, J Hypertens 2023.

Results RHYME-AD

Adherence

78.2 %

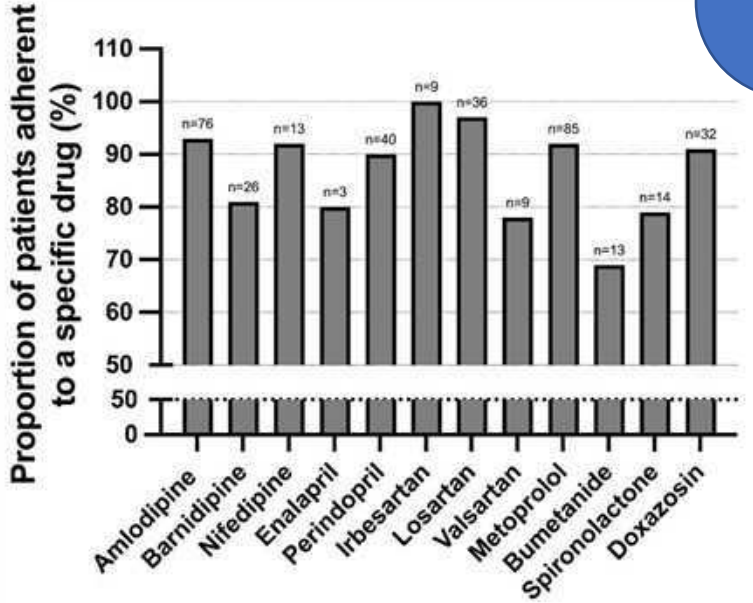
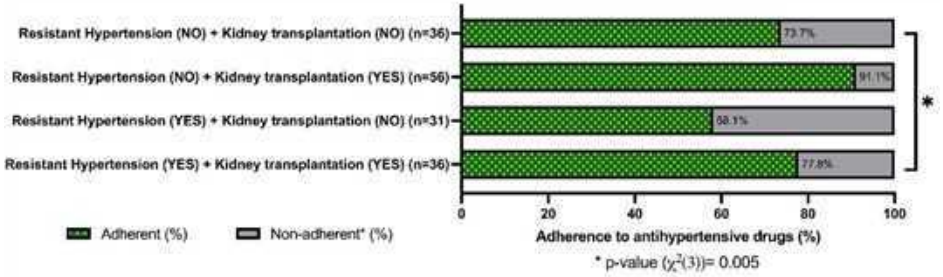


Figure 1 *Adherence to antihypertensive drugs in hypertensive patients visiting the outpatient clinic assessed by means of drug concentrations in blood*

Less non-adherence after kidney transplantation, more non-adherence after fullfilling the criteria of resistant hypertension



*combination of partial and total non-adherence to antihypertensive drugs

Figure 2 *Prevalence of adherence to antihypertensive drugs measured by drug concentrations in blood in patients with and without resistant hypertension (YES/NO) and/or with and without kidney transplantation (YES/NO)*

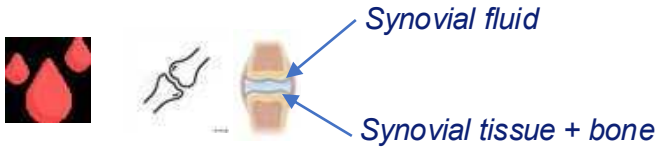
Peeters et al, J Hypertens 2023.

Erasmus MC

ASTERICS study

Sampling:

1. Surgery hip/knee prosthesis extraction
   - 15-30 minutes after start AB
   - 90-120 minutes after start AB



2. 2 weeks after first surgery:

3. a. OK prosthesis herimplantation: see 1
   b. Antibiotics free interval: see 2

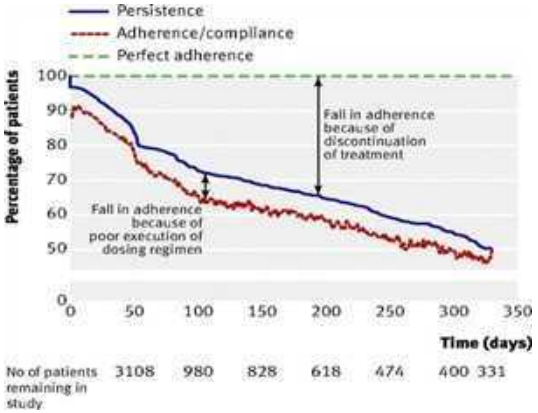
PopPK model (now n = 70)

Demir et al, J Chrom B 2021 /Ringeling et al, Bahmany et al.

Erasmus MC

A randomized controlled trial: improving non-adherence = improving blood pressure

- ***Selection of patients***
  - *Resistant hypertension*
  - *Phase of medication use*
- ***Blood pressure measurement***
  - *24-h ABPM*
- ***Adherence measurement***
  - *Drug concentrations in blood*
- ***Intervention***
  - *A solution for as many patients as possible*

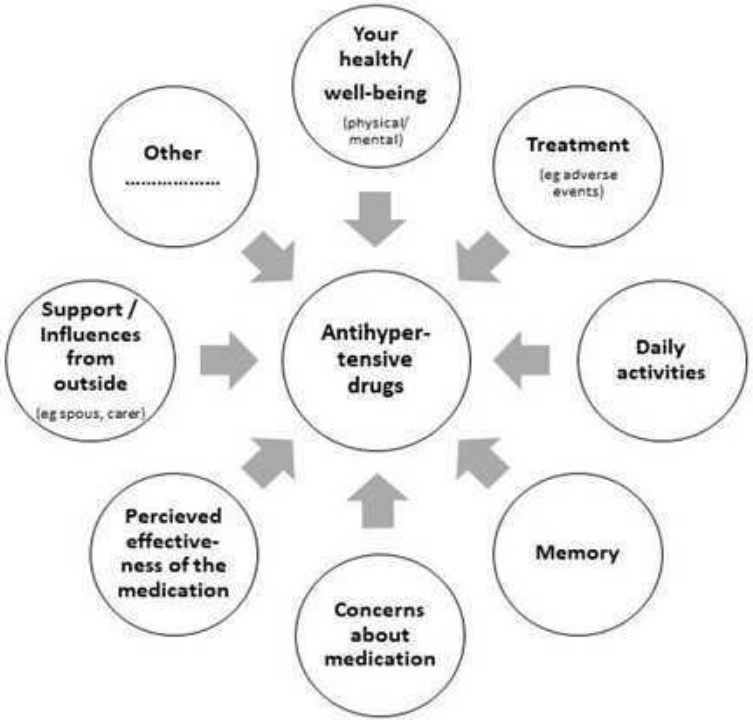


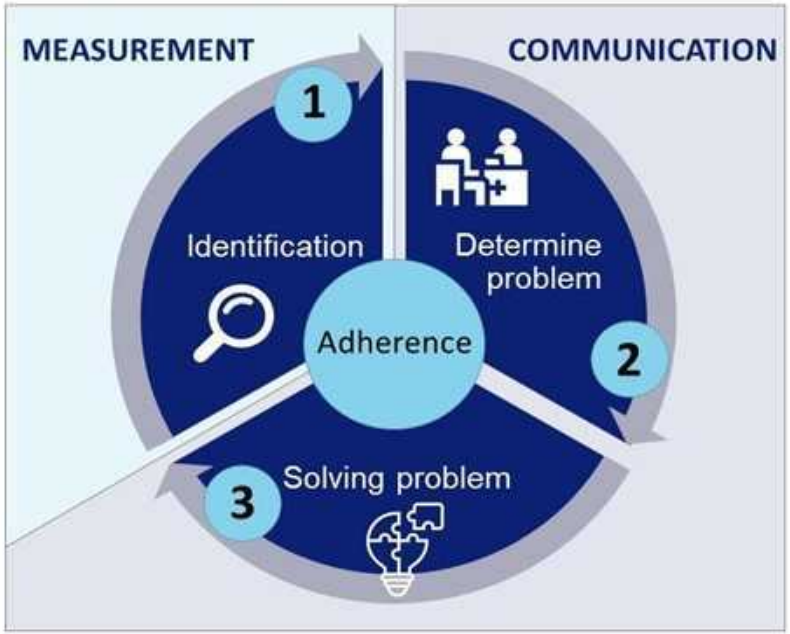
Vrijens et al. BMJ 2008;336:1114-1117

Erasmus MC

Adherence intervention

Communication tool





Under pressure: improving adherence and optimizing antihypertensive drug therapy

Peeters et al, J Hypertens 2022.

Erasmus MC

RHYME-RCT

Resistant hypertension: Measure to reach targets

Does the prevalence of RH decrease after 12 months due to an increase in adherence by the use of measuring drug concentrations with a DBS sampling method combined with

Primary objective

RHYME-RCT
Resistant HYpertension: MEasure to ReaCh Targets

Methods

RHYME-RCT

Multicenter, single-blinded randomized, controlled trial *(RHYME-RCT, ICTRP NTR6914)*

Patients selection

- office blood pressure >140/90mmHg
- use of 3 antihypertensive drugs including a diuretic or ≥antihypertensive drugs
- 2 antihypertensive drugs that could be measured with UPLC-MS/MS

Randomization

- Standard of care (SoC) OR Intervention

SoC *= BP measurement and DBS sampling at baseline, 3 months (t3), 6 months (t6), and 12 months (t12), but results on antihypertensive drug concentrations were not reported in this arm.*
- Researcher and analysist unblinded

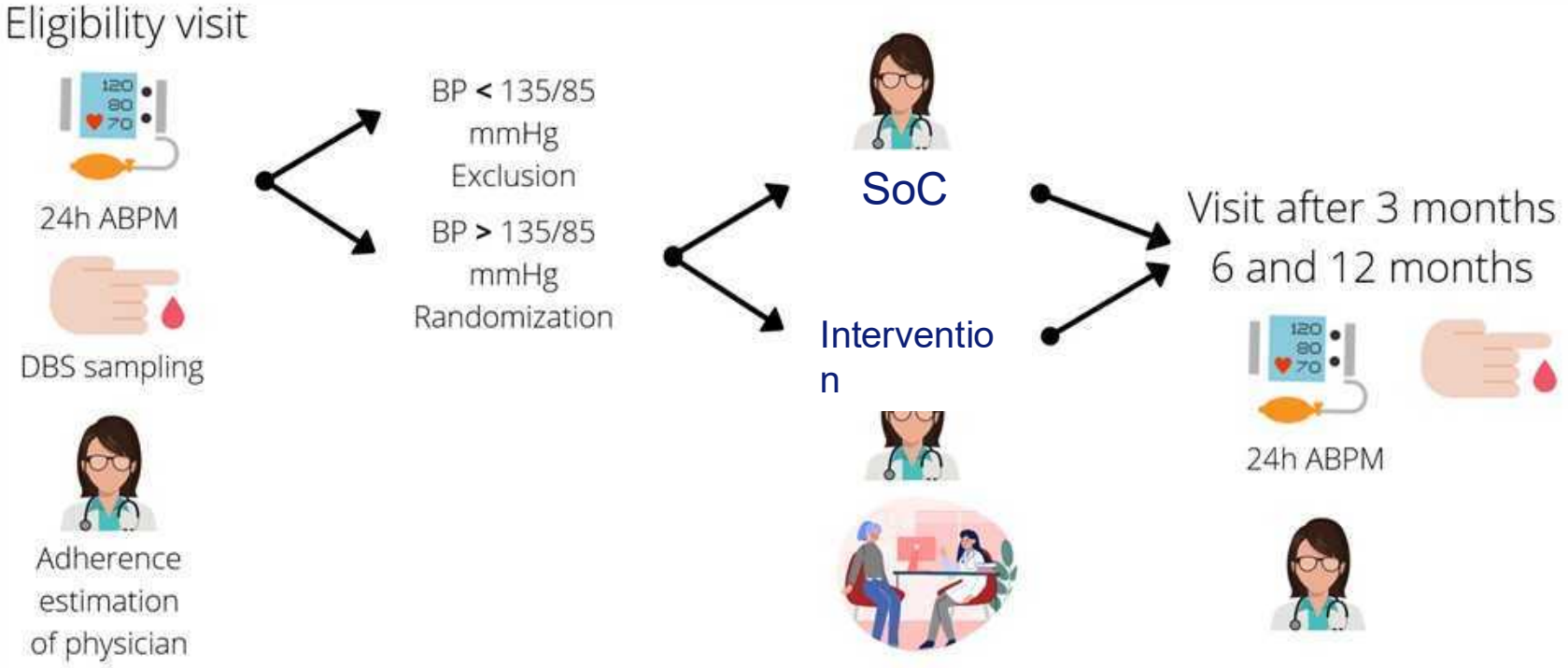
Intervention *= results on antihypertensive drug concentrations were discussed during a personalized feedback conversation at baseline and t3.*

Adherence *= all drugs detected in blood*

Peeters et al. BMC Cardiovasc Disord. 2023

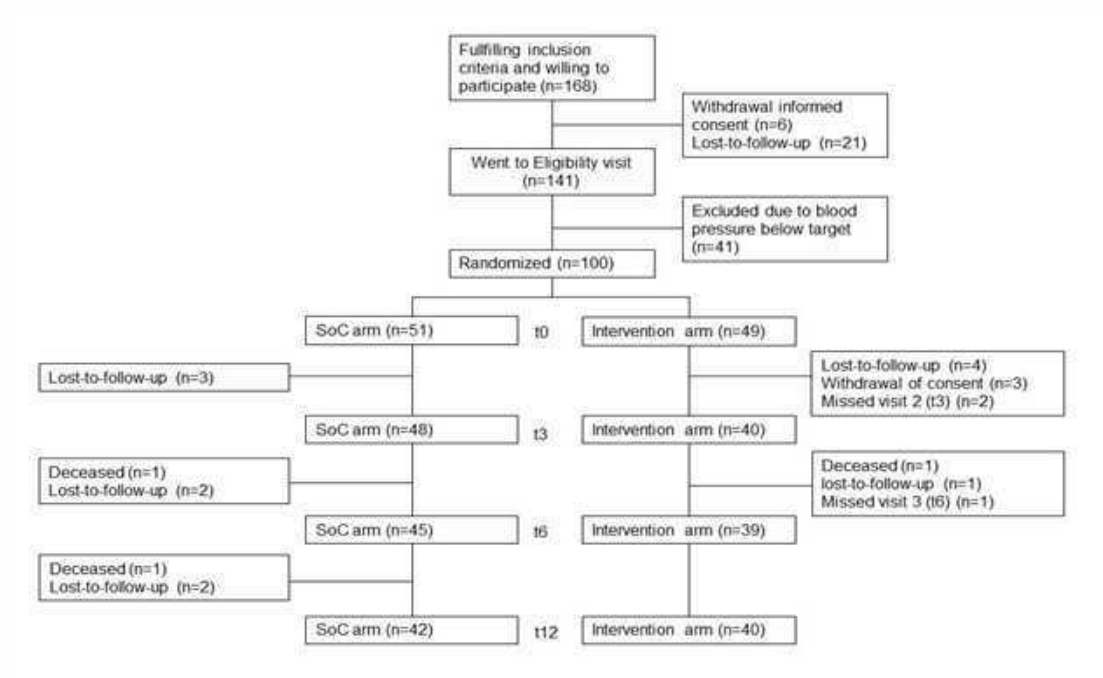
Erasmus MC

Methods (2)


Eligibility visit
24h ABPM
DBS sampling
Adherence estimation of physician
BP < 135/85 mmHg Exclusion
BP > 135/85 mmHg Randomization
SoC
Interventio n
Visit after 3 months 6 and 12 months
24h ABPM

Results

Inclusion flowchart



Results

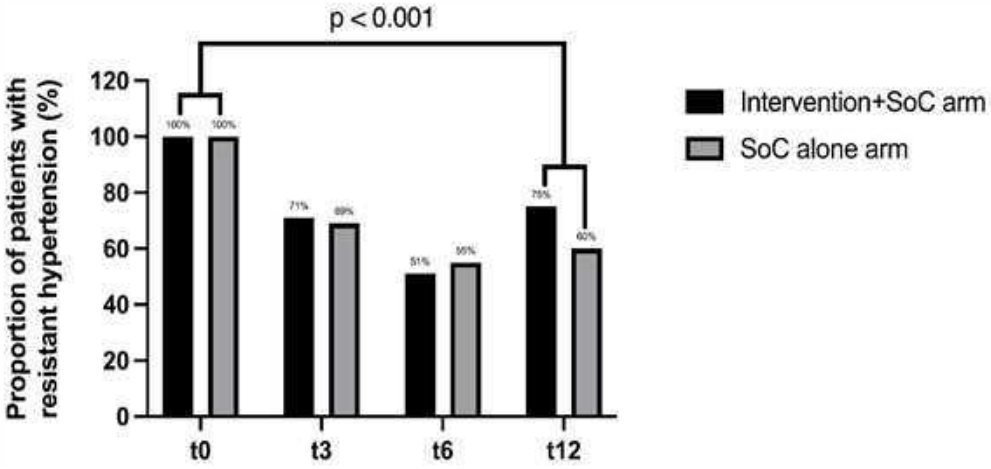
Patient characteristics

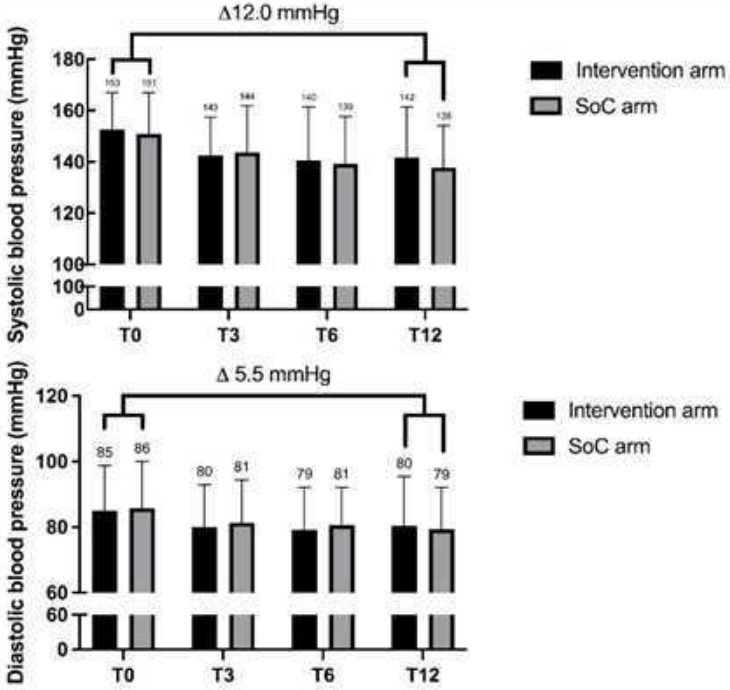
		Excluded patients (n=41)	Randomized patients (n=100)		
			Total	SoC alone arm (n=51)	Intervention+SoC arm (n=49)
Male, n (%)		27 (65.9)	70 (70.0)	35 (68.6)	35 (71.4)
Age, year		59.6 ± 12.3	59.4 ± 11.1	58.1 ± 12.0	60.7 ± 10.0
BMI, kg/m²		31.5 ± 5.3	30.3 ± 5.2	30.4 ± 5.6	30.2 ± 4.8
CKD-EPI eGFR, mL/min/1.73m²		69.0 (45.5 – 82.0)	75.0 (48.0 - 90.0)	80.0 (52.0 - 90.0)	70.0 (46.0 - 89.0)
Creatinine, µMol/L		116.5 ± 55.3	109.4 ± 57.5	108.9± 66.6	109.9 ± 46.9
Mean SBP, mmHg		125.3 ± 10.0	151.8 ± 15.3	150.7 ± 15.4	152.9 ± 15.2
Mean DBP, mmHg		75.0 ± 9.5	85.9 ± 13.7	85.9 ± 14.2	85.9 ± 13.3
Adherence rate at baseline (t=0) (%)		78.0	68.0	69.0	67.0
Diabetes mellitus, n (%)		19 (46.3)	37 (37.0)	20 (39.2)	17 (34.7)
Myocardial infarction, n (%)		10 (24.4)	21 (21.0)	7 (13.7)	14 (28.6)
Stroke, n (%)		5 (12.2)	11 (11.0)	5 (9.8)	6 (12.2)
Atrial Fibrillation, n (%)		5 (12.2)	9 (9.0)	3 (5.9)	6 (12.2)
Heart Failure, n (%)		1 (2.4)	4 (4.0)	4 (7.8)	0
Hypercholesterolemia, n (%)		11 (26.8)	38 (38.0)	20 (39.2)	18 (36.7)
Asthma/COPD, n (%)		4 (9.8)	13 (13.0)	6 (11.8)	7 (14.3)
Mean number of used drugs, n		9.7 ± 4.0	10.2 ± 4.7	9.5 ± 4.0	10.9 ± 5.4
Mean number of used AHDs, n		4.0 ± 0.9	4.28 ± 1.0	4.4 ± 0.8	4.2 ± 1.1
Number of patients with number of measured AHDs, n	≤2	17	41	18	23
	3+4	23	54	30	24
	≥5	1	5	3	2
Mean DDD of used AHDs		5.4 ± 0.9	6.4 ± 2.1	6.6 ± 1.9	6.2 ± 2.2
Average measured AHDs of total used AHDs (%)		71.2	68.2	69.5	66.8
Groups used AHDs , n (%)					
ACEi		15 (36.6)	45 (45.0)	26 (51.0)	19 (38.8)
ARBs		22 (53.7)	54 (54.0)	26 (51.0)	28 (57.1)
Beta blockers		30 (73.2)	61 (61.0)	28 (54.9)	33 (67.3)
Calcium antagonists		37 (90.2)	89 (89.0)	47 (92.2)	42 (85.7)
Diuretics		41 (100.0)	90 (90.0)	48 (94.1)	42 (85.7)
Other incl. doxazosin		11 (26.8)	45 (45.0)	22 (43.1)	23 (46.9)

Erasmus MC

Results

Resistant hypertension and blood pressure

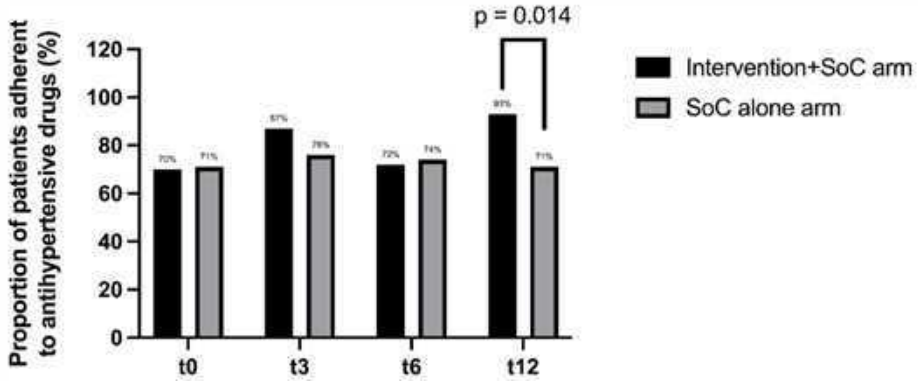




Erasmus MC

Results

Adherence



	Adherent (t0) – Adherent (t12)	Adherent (t0) – Non-adherent* (t12)	Non-adherent (t0) – Adherent (t12)	Non-adherent (t0) – Non-adherent (t12)	p-value ($\chi^2(3)$)
SoC arm (n=42) n (%)	23 (54.8)	7 (16.7)	7 (16.7)	5 (11.9)	0.086
Intervention+SoC arm (n=40) n (%)	27 (67.5)	1 (2.5)	10 (25.0)	2 (5.0)	

SoC = standard of care, t0 = baseline, t12 = 12 months follow-up, n = number of patient

** non-adherence is defined as the absence of one or more measured antihypertensive drug concentrations in blood used by the patient*

Erasmus MC

Conclusion

After 12 months of follow-up we found:

- **Adherence rate** in the intervention arm ↑
- **Resistant hypertension** in both arms ↓
- **Blood pressure** in both arms ↓

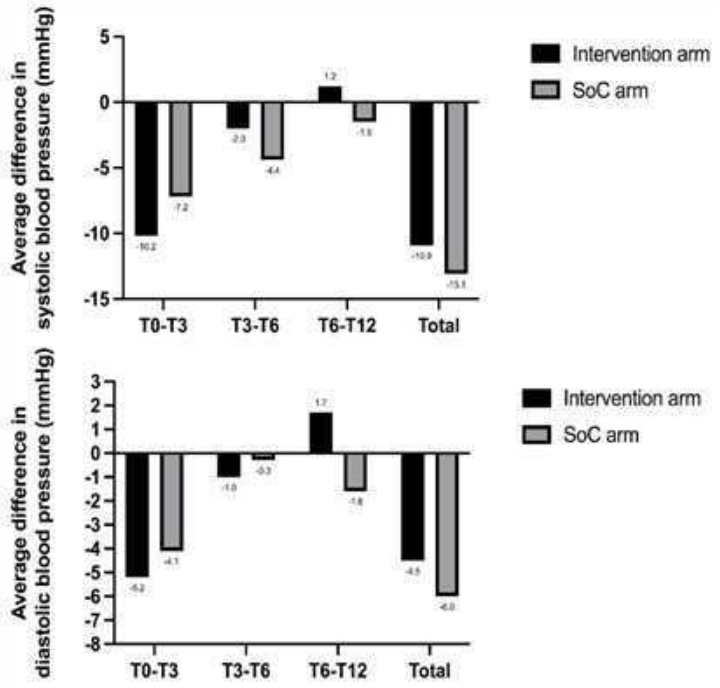
Hawthorne effect

Results from RHYME-RCT

Definition:
The alteration of behavior by the subjects of a study due to their awareness of being observed.

1. *White coat adherence*
2. *Adjustments in lifestyle*

Inevitable while conducting a RCT due to the need for an informed consent.



Systolic and diastolic blood pressure change between the visits divided by the intervention, SoC and standard of care (SoC) arm.

Societal impact of individualized medicine

Less nurses required

Rich data collection

Machine learning

Parent empowerment

Education tools

Privacy?

Erasmus MC

Life in Erasmus MC

Research Group: Clinical Pharmacometrics

NONMEM/Pmetrics

WINNONLIN/PK solver

MWPharm /InsightRx

Erasmus MC

Our group: TDM and Toxicology Lab

Lab: 11 technicians, 5 hospital laboratory pharmacists

6 LC-MS/MS, 1 GC-MS, 2 HPLC-UV , 1 immuno-assay

120 drugs, FDA/EMA validated, ISO-15189

75.000 samples per year

- Diagnostics
- Research

Therapeutic Drug monitoring

Toxicology

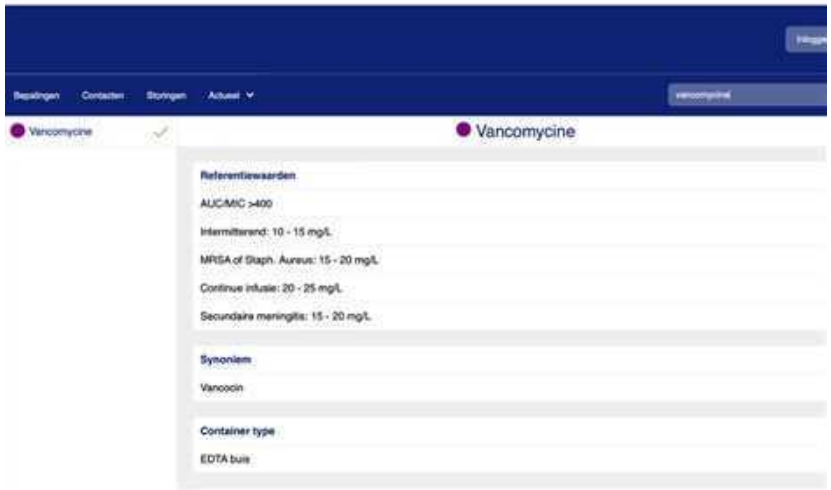
Forensic toxicology

Clinical Practice

Assays: 110 in a weekly schedule

App: smartphone application (Elabgids) and via

Flow



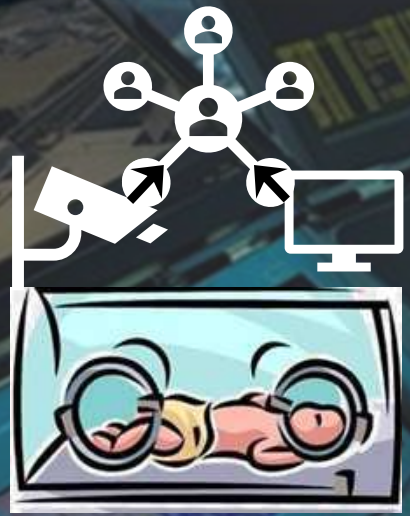
Alternative Sampling

- DBS
- WBC
- Meconium
- ……

Issues with dose optimization (MIPD/TDM)

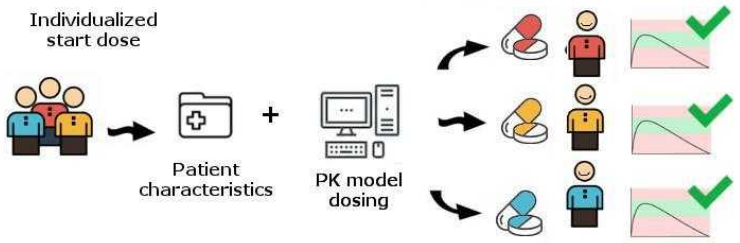
- Collaborations
- Which model to choose?
- Validation of the model
- Can we incorporate all covariates?
- Clinicians resistant to model-based dosing
- Stand-alone
- TDM fast turnaround time
- Time consuming
- Skills available?

Health Care 2030
Computational Medicine



- Risk predictors
- Video imaging
- Machine learning
- Suggestions
  - ‘Observe comfort’
  - ‘Measure CRP’

Summary and future

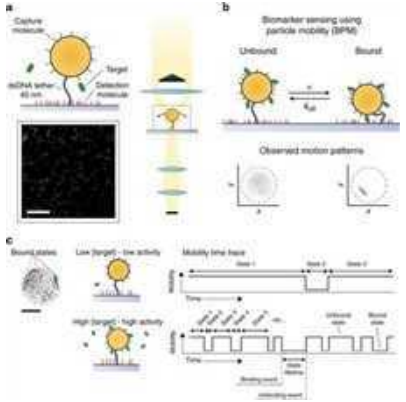


MIPD and TDM

- TDM in the Netherlands

Integration of model-based dosing in clinical practice

- Pediatric Pharmacology
- Anti-infectives



Near future

AI/machine learning

InsightRx integration and collaboration

More formulary, such as pregnancy, obese/anorectic

Dahsboard

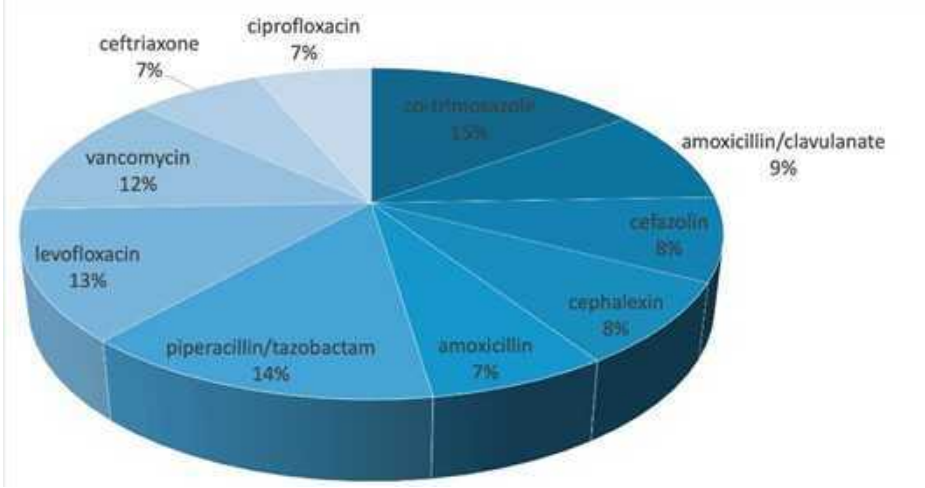
Real-time Biosensors

Erasmus MC

新興工具評估高齡抗生素治療風險—臺灣經驗分享

臺北醫學大學藥學系 陳香吟
Hsiang-Yin Chen, PharmD
Professor and Associate Dean
College of Pharmacy
Taipei Medical University

Adverse reactions associated with antibiotics in Taiwan from 2015 to 2019



表三 2015 至 2019 年抗生素相關案例之不良反應型態統計

所涉及器官系統 (SOC)	總計	症狀分類 (PT)	件次	該類別百分比
Skin and subcutaneous tissue disorders	167 (82.3%)	Stevens Johnson Syndrome	74	44.3%
		Toxic Epidermal Necrolysis	46	27.5%
		Drug reaction with eosinophilia and systemic symptoms	20	12.0%
		Acute generalised exanthematous pustulosis	5	3.0%
		others	22	13.2%
Immune system disorders	14 (6.9%)	Anaphylactic shock	8	57.1%
		Drug hypersensitivity	5	35.7%
		Hypersensitivity	1	7.1%
Hepatobiliary disorders	10 (4.9%)	(Acute) Hepatic failure	4	40.0%
		(Acute) Hepatitis	3	30.0%
		Hepatic function abnormal	2	20.0%
		Drug-induced liver injury	1	10.0%
Nervous system disorders	4 (2.0%)	Encephalopathy	2	50.0%
		Hypoxic-ischaemic encephalopathy	1	25.0%
		Neuropathy peripheral	1	25.0%
Blood and lymphatic system disorders	4 (2.0%)	Agranulocytosis	1	25.0%
		Hypereosinophilic syndrome	1	25.0%
		Thrombocytopenia	1	25.0%
		Pancytopenia	1	25.0%
Cardiac disorders	2 (1.0%)	Arrhythmia	1	50.0%
		Cardiopulmonary failure	1	50.0%
Gastrointestinal disorders	1 (0.5%)	Upper gastrointestinal haemorrhage	1	100.0%
Respiratory thoracic and mediastinal disorders	1 (0.5%)	Acute respiratory failure	1	100.0%
總計	203 *		203	

* 一案件可能涉及 1 種以上之不良反應型態

衛生福利部 藥品不良反應通報表

郵寄地址:100 台北市中正區愛國東路 22 號 10 樓
傳真: (02)2358-4100
通報網址: http://adr.fda.gov.tw
電子信箱: adr@tdrf.org.tw
個案編號（由通報中心填寫）:

- *為必填欄位
- 請勿於通報案件之描述中填入病人身分證字號、地址、電話等得以直接或間接識別該個人之資料。

通報者資料	通報者姓名*	
	電話*	
	電子郵件信箱*	
	通報人員身分*	□醫師 □藥師 □其他醫療人員 □廠商 □民眾(註1) □其他
	服務機構名稱*	
	服務機構地址*	

註1：若通報人員身分為民眾，則無須填寫服務機構名稱；服務機構地址請改為填寫聯絡地址。

案件資料	獲知藥品不良反應日期*	年 月 日
	獲知不良反應最新資訊日期*	年 月 日
	是否為國內案件*	□是；□否 (發生國家:_____)
	是否為文獻通報*(註2)	□否；□是 (文獻名稱:_____)
	獲知藥品不良反應來源*	□醫師 □藥師 □其他醫療人員 □民眾或其他非醫療人員

註2：文獻通報係指藥商主動收集來自醫學文獻報告之疑似藥品不良反應案例而為之通報；若為文獻通報，「獲知藥品不良反應來源」請填寫該文獻之第一作者的身分。

病人資料	識別代號*		原通報單位識別代號	
	性別*	□男 □女 □未知	出生日期(或年齡)*	年 月 日(歲) □未知
	體重	(公斤)	身高	(公分)

不良反應相關資料(一)	不良反應發生日期*	(請填寫年月日，若無法得知請填寫「未知」)
	不良反應嚴重性*	□死亡，日期: 年 月 日，死亡原因：_____ □危及生命 □永久性殘疾 □胎兒、嬰兒先天性畸形 □病人住院或延長病人住院時間 □其他可能導致永久性傷害之併發症(註3) □非嚴重
	不良反應症狀*	

1. Drug Safety Newsletter 2020 JUN Vol . 70 /2.Food and Drug Administration, Ministry of Health and Welfare Website

Clinical Decision Support Systems (CDSS)

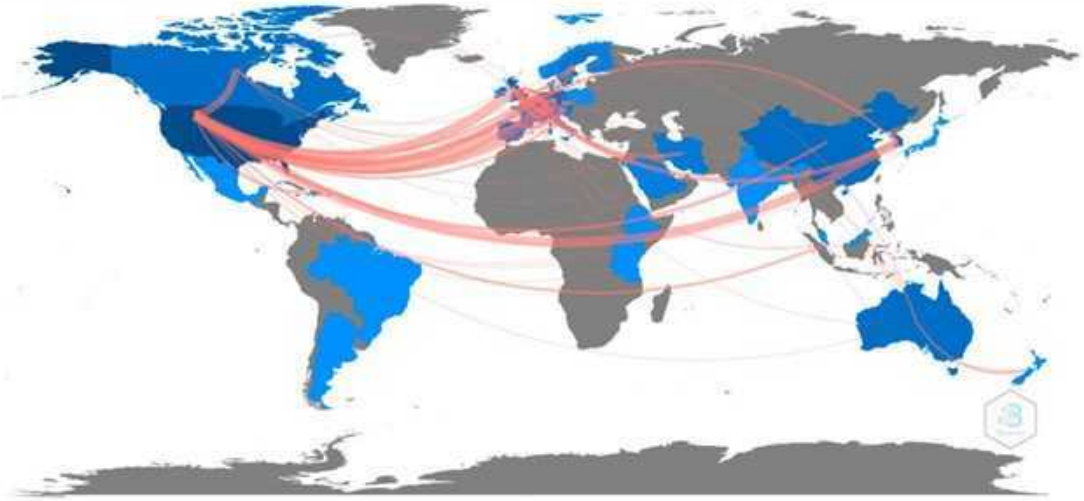


Figure 4. The country collaboration map for CDSS alert studies.

病理報告
藥物資訊
微生物報告
影像學檢查
生化檢驗報告

→ 電子病歷系統

- ✓ 彙整病人分布於電子病歷各子系統之相關臨床資訊，縮短抗生素開立醫師與審查醫師之作業時間。
- ✓ 配合快速診斷工具，加速照護團隊取得檢驗報告與病人接受適當治療之時效。

臨床照護團隊開立抗生素時

- ✓ 依病人相關臨床資訊 (藥物交互作用、培養報告等、肝腎功能危急值等)提供警示訊息。
- ✓ 於醫令套組或臨床路徑導入診治指引。
- ✓ 依病人診斷之適應症預設抗生素品項。

抗生素審核團隊審查抗生素

- ✓ 導入診治指引輔助審查。
- ✓ 依工作時段切換前瞻式審核與回饋以及處方限制與預授權作業模式。

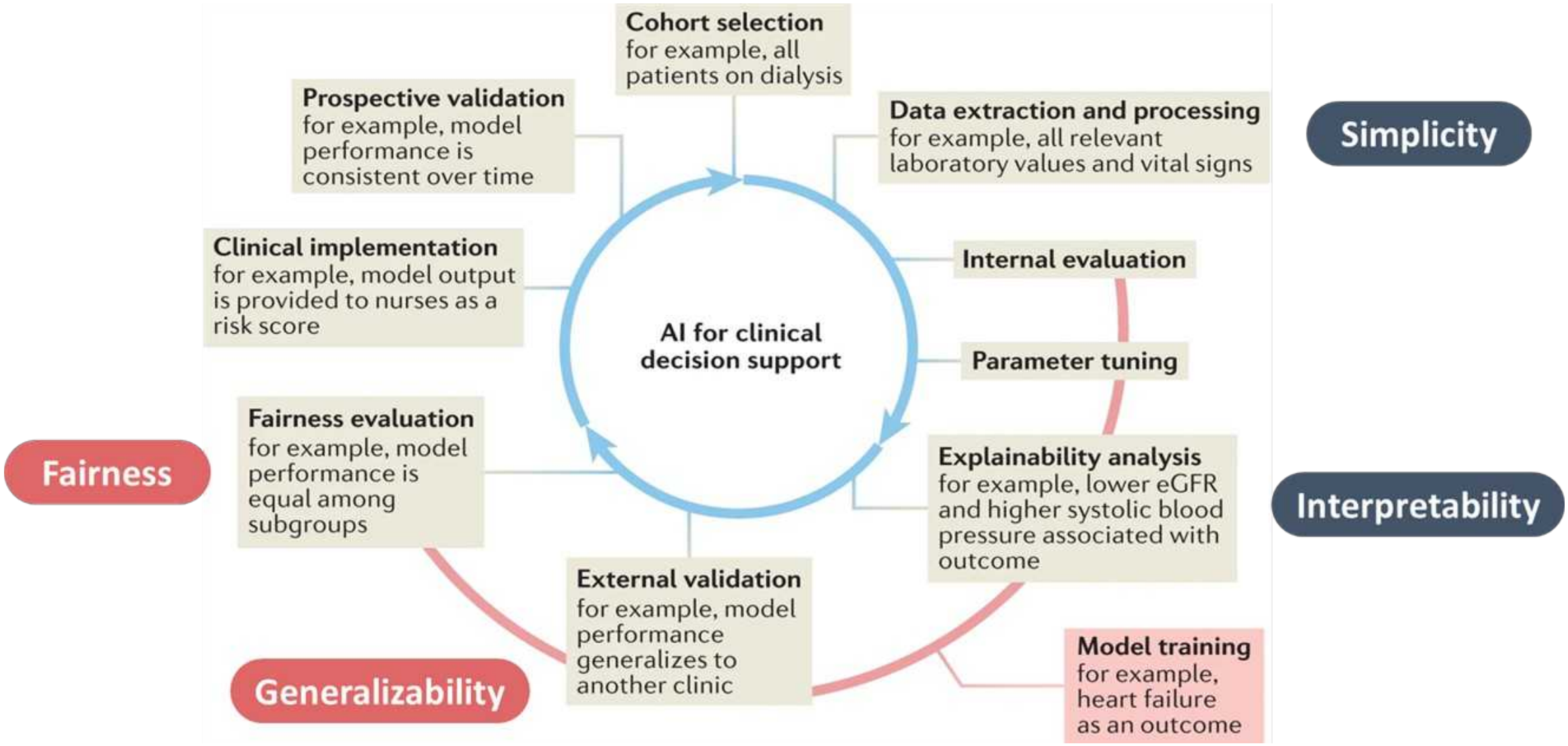
臨床照護團隊開立抗生素後

- ✓ 依病人後續之培養結果或改變之臨床資料提供警示訊息。
- ✓ 以「抗生素暫停」(antimicrobial time-out) 提醒臨床團隊適時重新檢視抗生素開立之適當性。

臨床決策輔助系統 Clinical Decision Support System (CDSS)

1. Chien, et.al (2022). *Healthcare (Basel, Switzerland)*, *10*(4), 601./ 2. Hao-Hsin Wu (2024) *Taiwan Epidemiol Bull,* 10.6524/TEB.202411_40(22).0002

Steps for AI-based clinical decision support

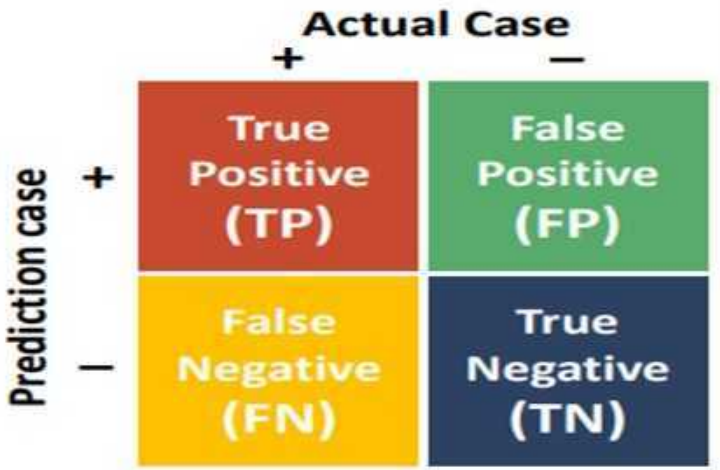


Loftus TJ, et al. (2022) *Nat Rev Nephrol*. Jul;18(7):452-465.

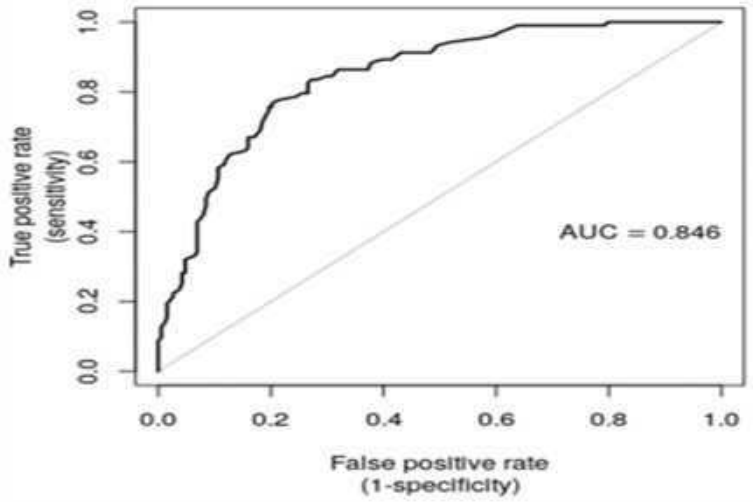
Model Performance Metrics

Evaluation Metrics

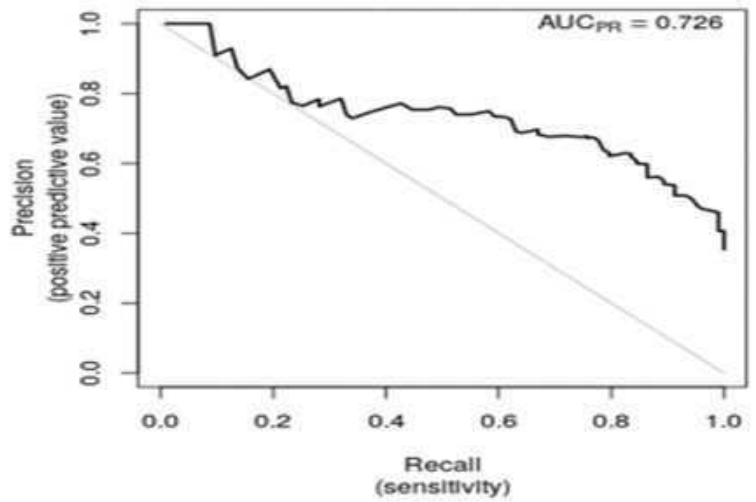
- Accuracy = $\frac{(TP+TN)}{(TP+TN+FP+FN)}$
- Precision = $\frac{TP}{(TP+FP)}$
- Recall = $\frac{TP}{(TP+FN)}$
- F1 score = $\frac{2TP}{(2TP+FP+FN)}$



AUROC



AUPRC

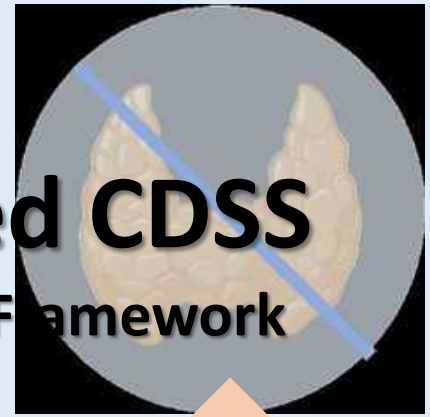


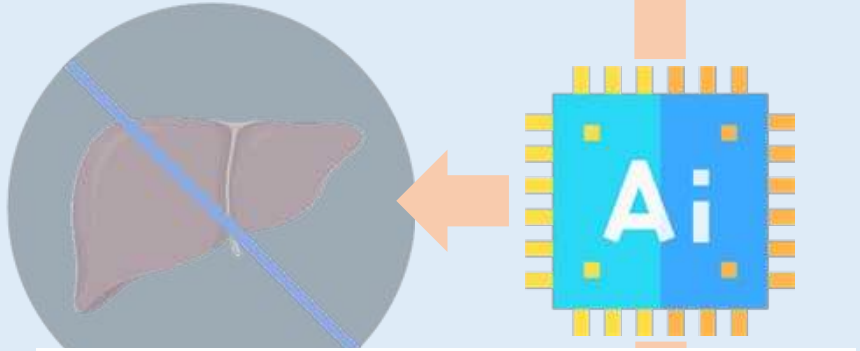
Loftus TJ, et al. (2022) *Nat Rev Nephrol*. Jul;18(7):452-465.

Data collection and preprocessing	Data collection and preprocessing might vary in **format** (eg, unstructured text, structured data, and images) and in **collection methods** (at the individual level, eg, electronic health records, or at the population level (eg, epidemiological surveillance data; table 1).[15,37]	Data availability, accessibility, integration, completeness, timeliness, quality, and standardisation constraints
AI model development and technical validation	AI model development and technical validation involves the selection of appropriate AI techniques and methodologies, depending on **data format** (eg, deep learning for image processing and natural language processing for unstructured text), the **distribution** of available data (eg, applying class imbalance strategies when datasets contain few infected cases compared to controls, or selecting appropriate validation methods), and the **specific task** in infectious disease prevention and management (eg, classification for infection prediction or text extraction for clinical note processing). Model performance is then assessed during technical validation using adequate **performance metrics**, depending on model type and tasks (eg, accuracy, sensitivity, and AUROC).[38]	Bias in AI model selection Algorithm transparency and challenges in explainability
Clinical validation and deployment	Clinical validation and deployment of AI models can take place at different levels. According to previous definitions, **clinical validation** refers to testing an AI solution with real patient data to assess its safety and effectiveness. This includes **retrospective validation** (testing the AI solutions before they are implemented in patient care or using data collected before the start of the study), **prospective validation** (testing the device after it is implemented in patient care or using data collected after the start of the study), and, in its most rigorous and preferred form, **experimental studies** (ie, RCTs).[39]	Lack of clinical validation Challenges in real-world testing
Adoption and continuous monitoring	Adoption and continuous monitoring of AI solutions requires **training and building trust** among health-care professionals, and also ongoing regulations, guidelines and surveillance systems to monitor the performance of AI models and **update** them according to new clinical and technological evidence.	AI literacy and trust among infectious disease clinicians and health-care professionals Regulatory gaps and demand for monitoring
Scaling infrastructure and policy implementation	Scaling of **infrastructure** and **policy implementation** for the adoption AI solutions at the local, national, or global level depends on appropriate policies, including **investment** in technological infrastructure, **interoperability** with existing health-care systems, and strategies to ensure **equitable** access and long-term **sustainability**.[40]	Disparities in technology infrastructure and resources Gaps in normative and policy frameworks

AI-Based CDSS

Theoretical Framework





Artificial Intelligence and Infectious Diseases 1

Artificial intelligence and infectious diseases: an evidence-driven conceptual framework for research, public health, and clinical practice

Anna Odone*, Chiara Barbati*, Silvia Amadasi, Tanja Schultz, David B Resnik

As artificial intelligence (AI) is projected to radically shape health care, its role in infectious disease prevention and management is drawing attention. AI offers promising opportunities to help tackle infectious disease threats and improve clinical management, outbreak detection, and infection control. As part of a dedicated Series on AI and infectious diseases, this paper sets the scene by proposing a conceptual framework that, building upon available AI models and data sources related to pathogens, human hosts, and the environment, comprehensively identifies selected domains where AI can be applied across infectious disease research, public health, and clinical practice. Building on this foundation, the two companion papers in the Series follow with an in-depth exploration of AI applications in diagnostics and antimicrobial resistance. We provide an overview of current and future applications of AI in infectious disease prevention and management, exploring the broad potential, available experimental evidence, real-life implementation examples, and technical normative, ethical, and policy barriers.

Odone A., et al. (2025) *The Lancet. Infectious diseases*, S1473-3099(25)00412-8. Advance online publication.

Shapley Additive exPlanations (SHAP)

變數對模型的影響評估

計算每種特徵組合的權重：
確保無論特徵加入的順序為何，最終結果都是公平的。

Shapley value公式:

- $\phi_j(val) = \sum_{S \subseteq \{x_1,\ldots,x_p\} \setminus \{x_j\}} \frac{|S|!(p-|S|-1)!}{p!} \left(val(S \cup \{x_j\}) - val(S) \right)$

X：所有特徵$x_1, \cdots, x_p$的集合
S :不包含要觀察的特徵 x_j的特徵子集合
例子: X=$\{x_1, x_2, x_3\}$, j=2
$\Rightarrow S$ =$\{\emptyset, \{x_1\}, \{x_3\}, \{x_1, x_3\}\}$

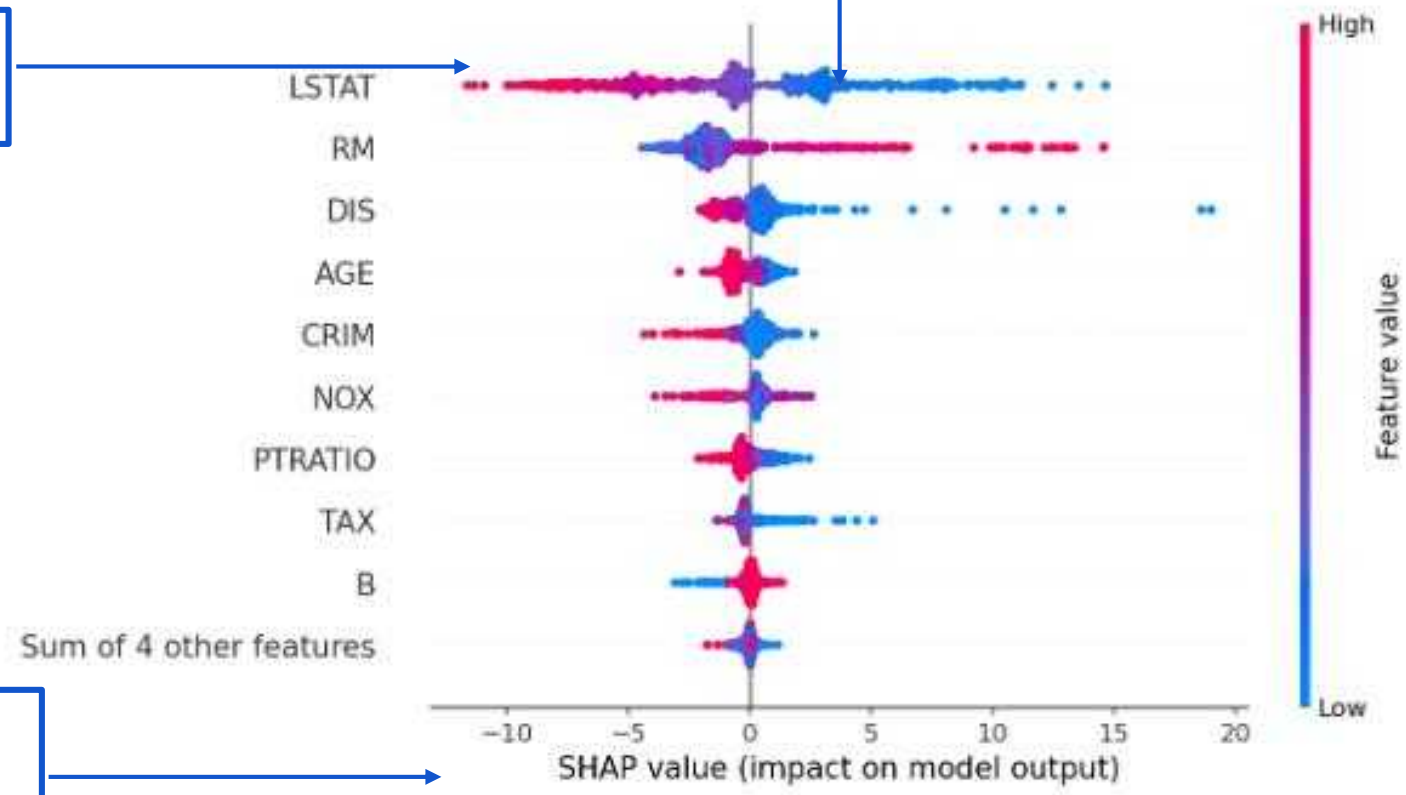
每種排列組合在有無特徵x_j
對模型預測能力帶來的變化

SHAP (SHapley Additive exPlanations)

- Model explanation and interpretation

Shapley value for a feature and an instance

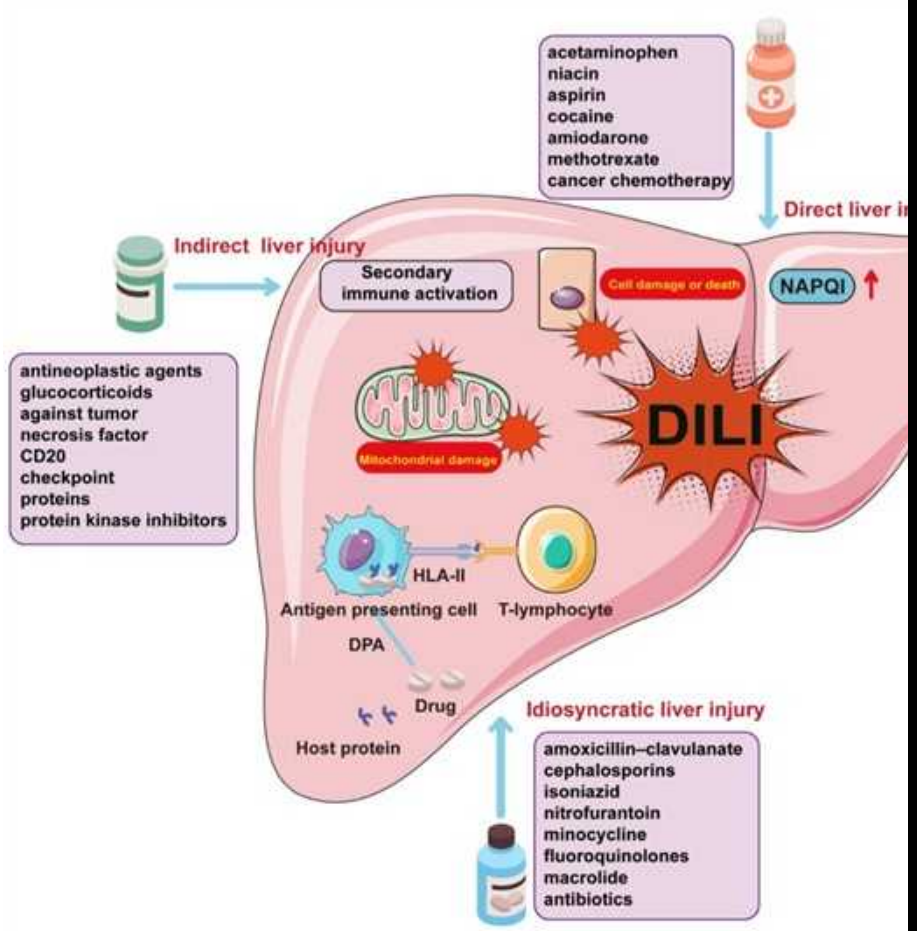
Pink dots: high feature value
Blue dots: low feature value

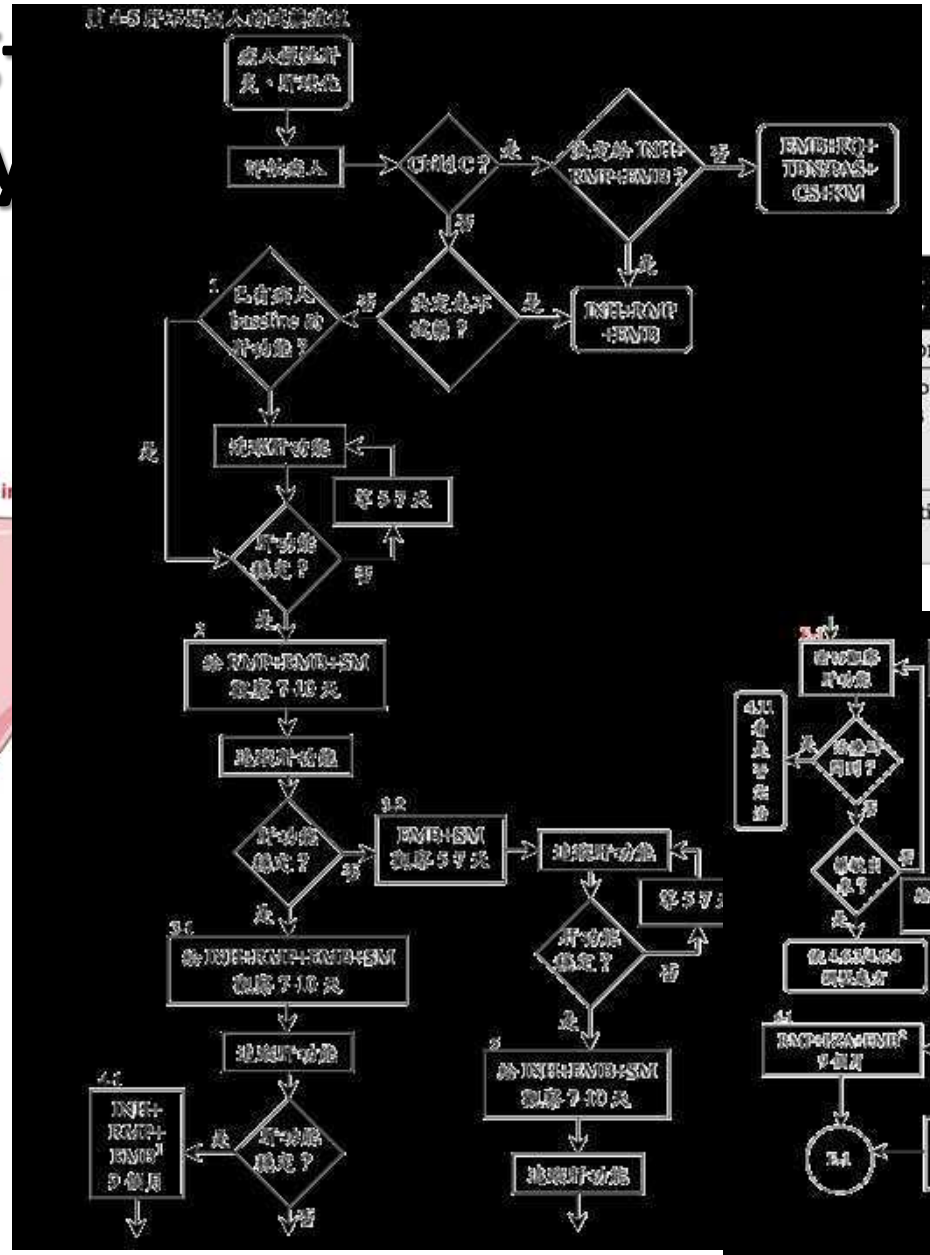


Positive value: positive impact
Negative value: negative impact

Model interpretability does not mean causality !

Anti-tuberculosis drug-induced hepatotoxicity

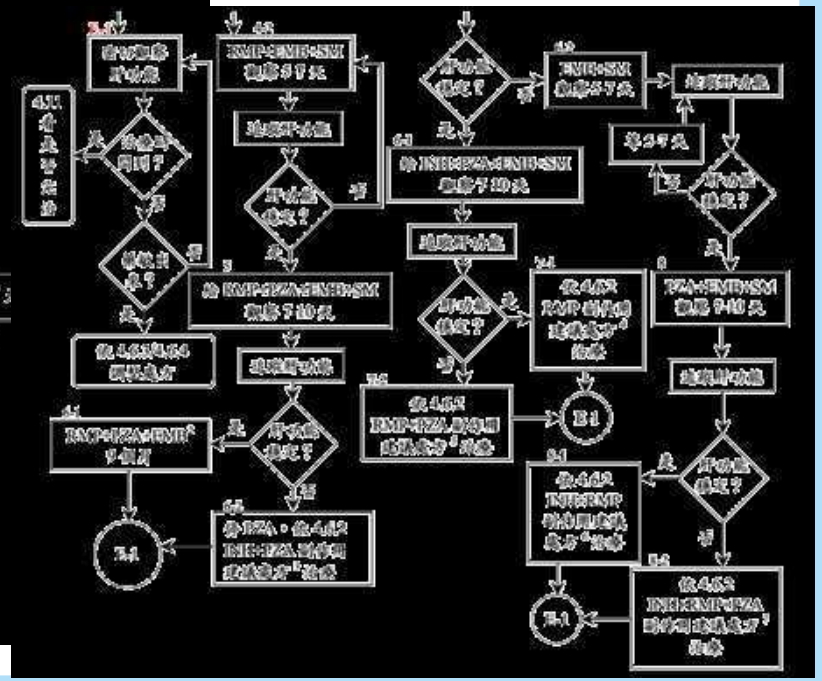




Multivariate analysis of risk factors for in severe ATLI.

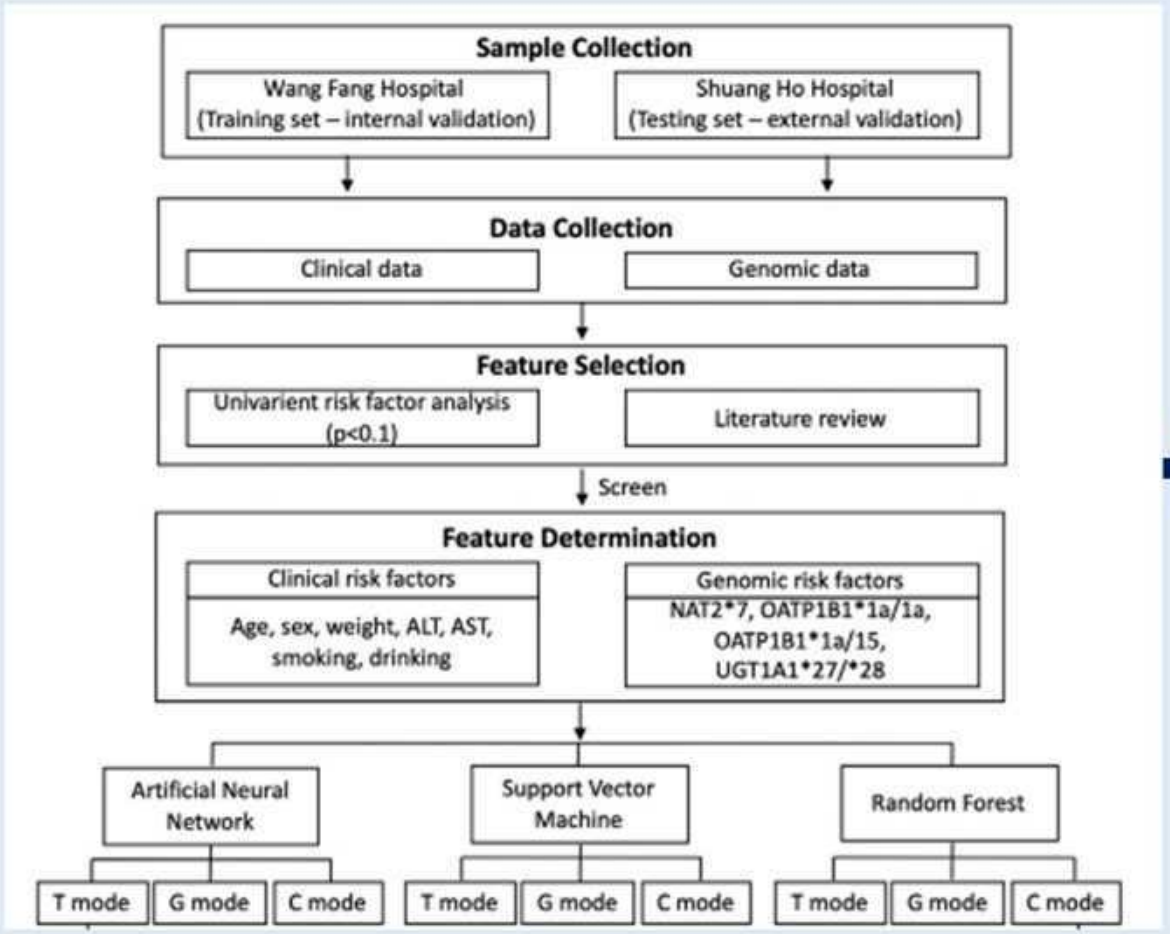
rs	Odds ratio	95% CI	p
oring	8.87	1.32–59.41	0.024
carrier	4.13	0.89–19.10	0.070
	3.71	0.77–17.84	0.102
	1.04	0.99–1.09	0.117

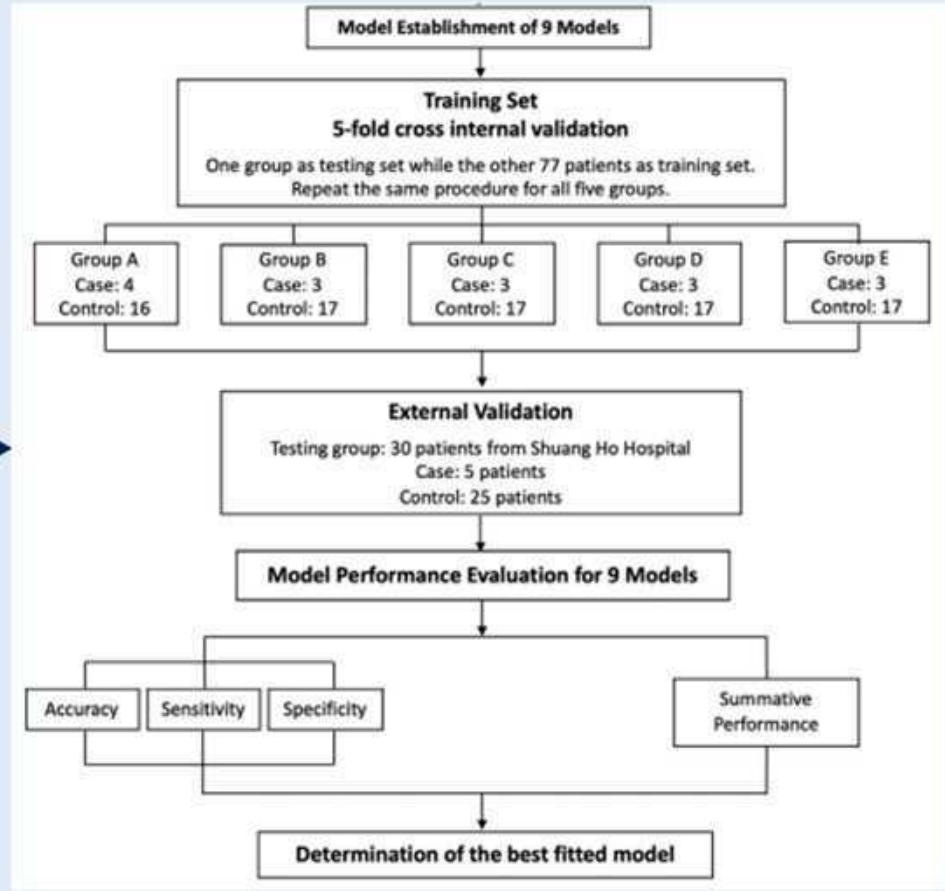
ituberculosis drug-related liver injury; CI = confidence



1.Huang, et al. (2024) *Molecules (Basel, Switzerland)*, *29*(11), 2663./ 2. Centers for Disease Control, Ministry of Health and Welfare, Executive Yuan, Taiwan. Taiwan guidelines for TB diagnosis and treatment. 5th ed./ 3. Chih, et al. (2014) *Journal of food and drug analysis*, *22*(3), 356–362.

Using Machine Learning Algorithm to predict anti-tuberculosis drug-induced hepatotoxicity





*ANN, artificial neural network; SVM, support vector machine; RF, random forest; T, traditional parameters; G, genetic parameters; C, combined parameters.

Lai H., et al. (2022) *Computer methods and programs in biomedicine*, *188*, 105307.

Using Machine Learning Algorithm to predict anti-tuberculosis drug-induced hepatotoxicity

Univariate risk factor analysis.

	No ATDH patients $N = 106$ n (%) or mean±SD	ATDH patients $N = 21$ n (%) or mean±SD	OR (95% CI)	p value
Sex (male/female)	73 (68.9)/33 (31.1)	14 (66.7)/7 (33.3)	1.11 (0.41–3.00)	0.843
Age (years)	55.5 ± 21.4	64.0 ± 17.9	1.02 (1.00–1.05)	0.088*
Weight (kg)	56.7 ± 9.4	51.9 ± 9.7	0.95 (0.90–1.00)	0.035*
Comorbidities				
Hypertension	26 (24.5)	8 (38.1)	1.89 (0.71–5.07)	0.200
Diabetes	31 (29.2)	6 (28.6)	0.97 (0.34–2.73)	0.950
Asthma	4 (3.8)	2 (9.5)	2.68 (0.46–15.71)	0.257
COPD	5 (4.7)	0	-	-
GI-related diseases	14 (13.2)	4 (19.0)	1.55 (0.45–5.27)	0.483
Renal diseases	5 (4.7)	2 (9.5)	2.13 (0.38–11.77)	0.378
Smoking	50 (47)	7 (33.3)	0.56 (0.21–1.50)	0.244
Alcoholics	27 (25.5)	3 (14.3)	0.49 (0.13–1.79)	0.270
Baseline liver function				
AST (U/L) mean±SD	25.0 ± 16.7	31.6 ± 13.9	1.02 (1.00–1.05)	0.083*
ALT (U/L) mean±SD	19.4 ± 8.4	22.3 ± 9.2	1.04 (0.99–1.09)	0.207
Rifampin ≥ 12 mg/kg	17 (16.0)	6 (28.6)	2.09 (0.71–6.76)	0.173
Isoniazid ≥ 8 mg/kg	12 (75.0)	4 (19.0)	1.84 (0.53–6.39)	0.330
Pyrazinamide≥ 25 mg/kg	17 (16.0)	4 (19.0)	1.23 (0.37–4.12)	0.734

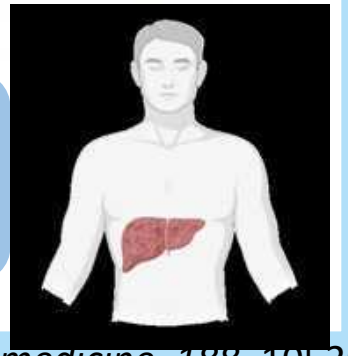
* $p<0.1$.ATDH, anti-tuberculosis drug-induced hepatotoxicity; OR, odds ratio; CI, confidence interval; SD standard deviation; COPD, chronic obstructive pulmonary disease; AST, aspartate aminotransferase; ALT, alanine aminotransferase.

The area under the receiver operating characteristic curve (AUC) calculated for the training and test sets for the nine models.

Model	Internal validation from the training set	External validation from the test set
ANN_T	0.705	0.768
ANN_G	0.828	0.843
ANN_C	0.894	0.898
SVM_T	0.718	0.689
SVM_G	0.783	0.710
SVM_C	0.801	0.728
RF_T	0.694	0.688
RF_G	0.709	0.701
RF_C	0.724	0.718

ANN, artificial neural network; SVM, support vector machine; RF, random forest; T traditional mode containing only clinical variables; G, gene mode containing only genomic variable; C, combination mode containing all variables.

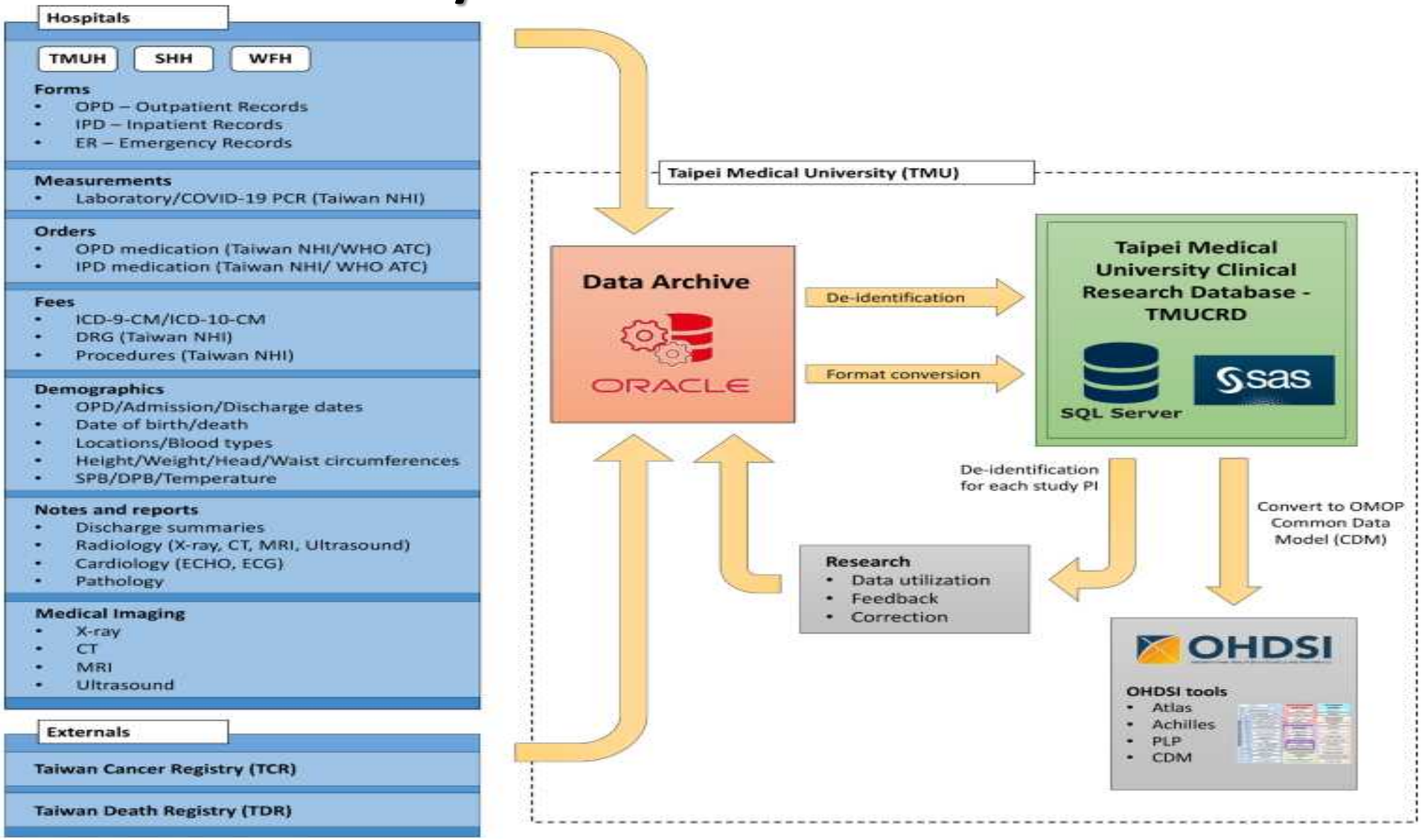
The present ANN combined model would be an innovation to predict ATDH, decrease TB treatment failure and potentially save healthcare resources and expenses on public health.



*ANN, artificial neural network; SVM, support vector machine; RF, random forest; T, traditional parameters; G, genetic parameters; C, combined parameters.

Lai H., et al. (2022) *Computer methods and programs in biomedicine*, *188*, 105307.

Taipei Medical University Clinical Research Database



Nguyen P, et al.(2024) *BMJ health & care informatics*, *31*(1), e100890.

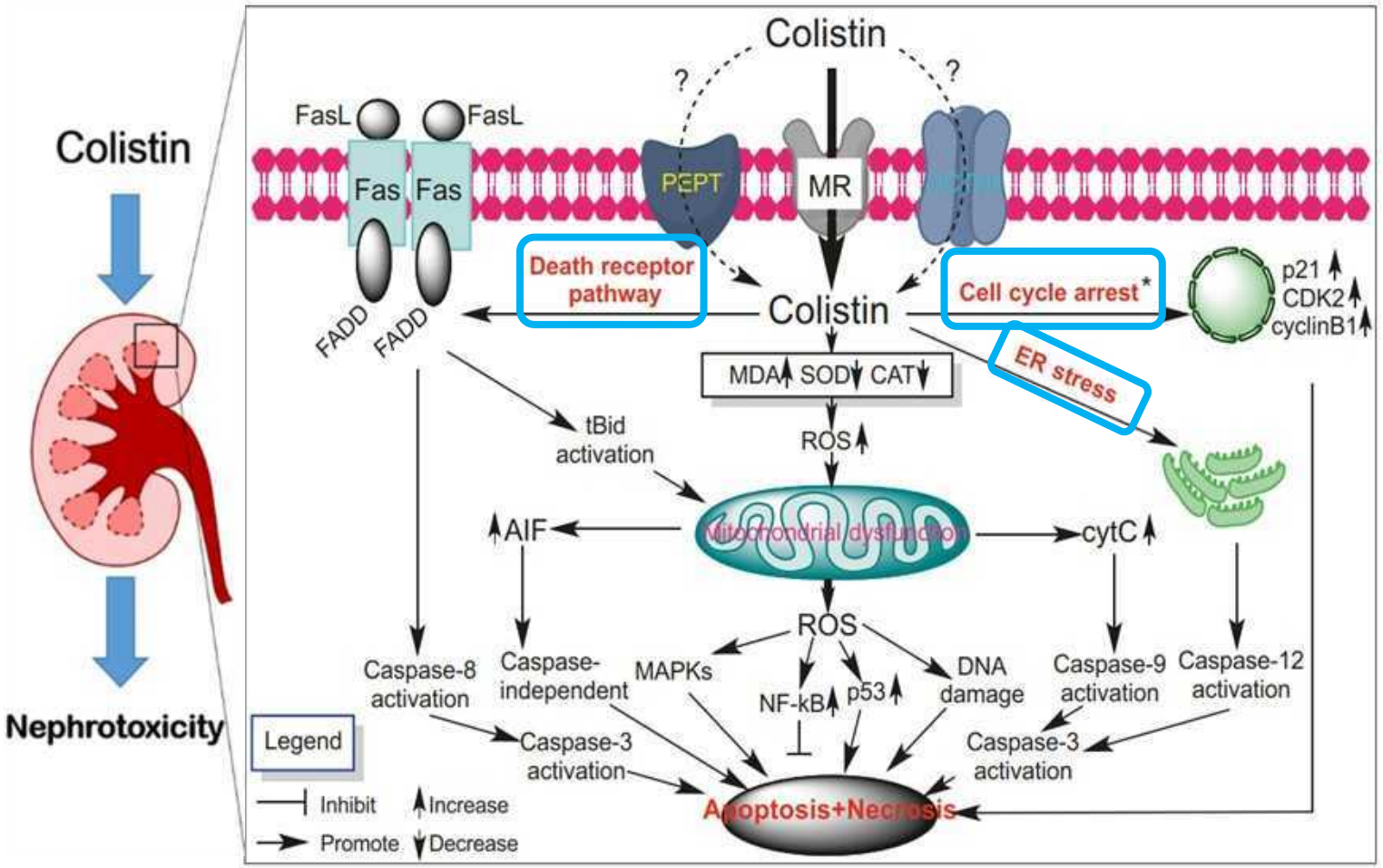
Drug-induced nephrotoxicity:
Drugs and Risk factors

Patient - related	Kidney - related	Drug-related
		
Old age (≥ 60-65 years)	Underlying kidney insufficiency with GFR < 60 mL/min/1.73m^2	Use of high doses and prolonged dosing periods
Female sex	True or effective volume depletion (kidney hypoperfusion)	Potent direct nephrotoxic drug effects
Altered pharmacogenetics - genetic variations in hepatic CYP450 system and kidney transporters	Biotransformation of drugs to nephrotoxic metabolites and reactive oxygen species	Exposure to multiple nephrotoxic agents
Comorbidities: cirrhosis, diabetes, hypertension, heart failure, sepsis, metabolic perturbations (hypokalemia, hypomagnesemia, hypercalcemia, urine pH disturbances), active cancers	High metabolic rate of tubular cells within a hypoxic environment	Pharmacokinetic and / or pharmacodynamic interactions between drugs that increase the free fraction, interfere with biotransformation or impair the excretion of drugs and their metabolites
	Proximal tubular uptake of drugs: apical via endocytosis or pinocytosis with drug accumulation or basolateral drug transport via hOATs or hOCTs	

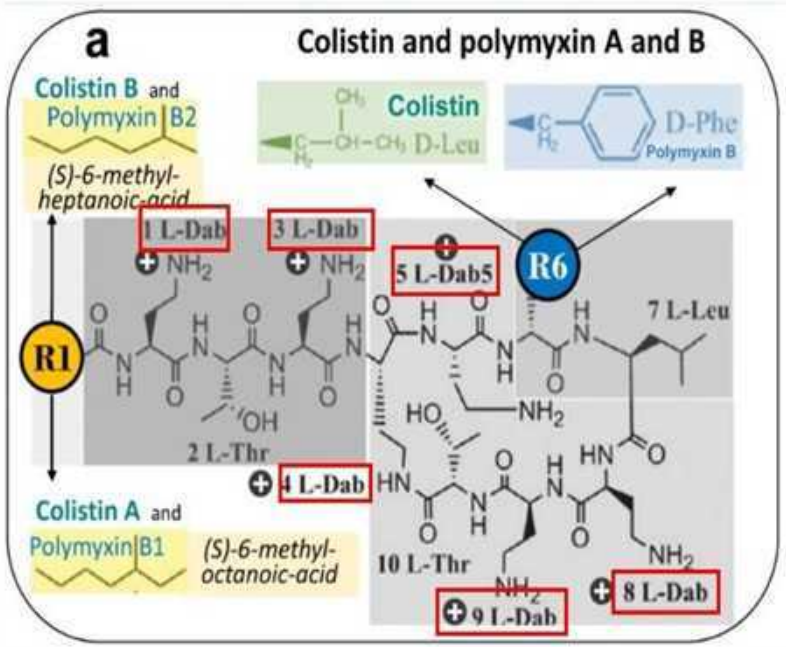
- Antibiotics: Aminoglycosides, cephalosporin, Beta-lactams penicillin, sulfonamides, Amphotericin B, Vancomycin
- Chemotherapy: Platinum
- Antiviral Medication: Acyclovir
  NSAID: Diclofenac, Ibuprofen,Celecoxib, Naproxen

Dobrek L. (2023). *Life (Basel, Switzerland)*, 13(2), 325.

Colistin-induced nephrotoxicity

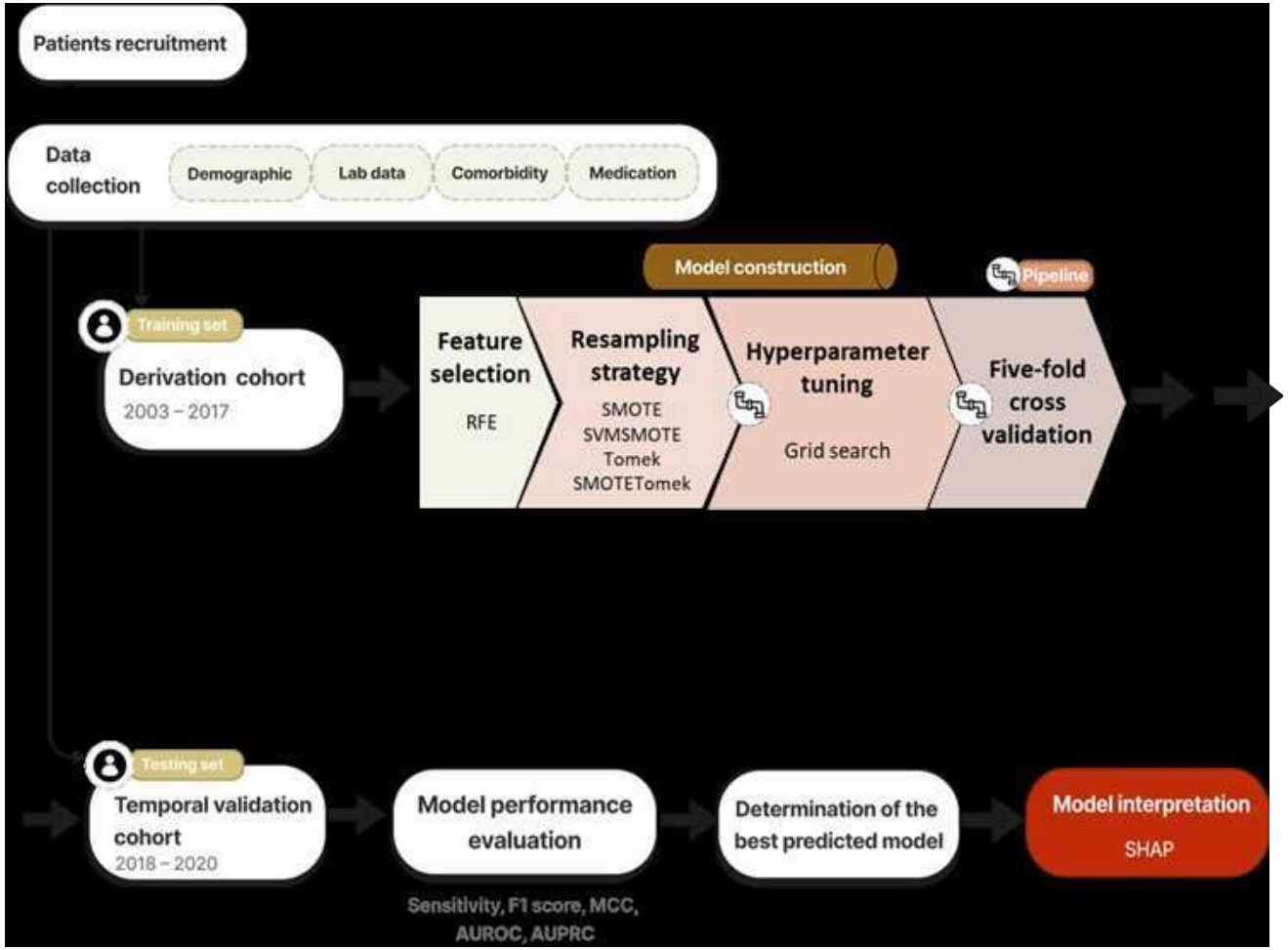


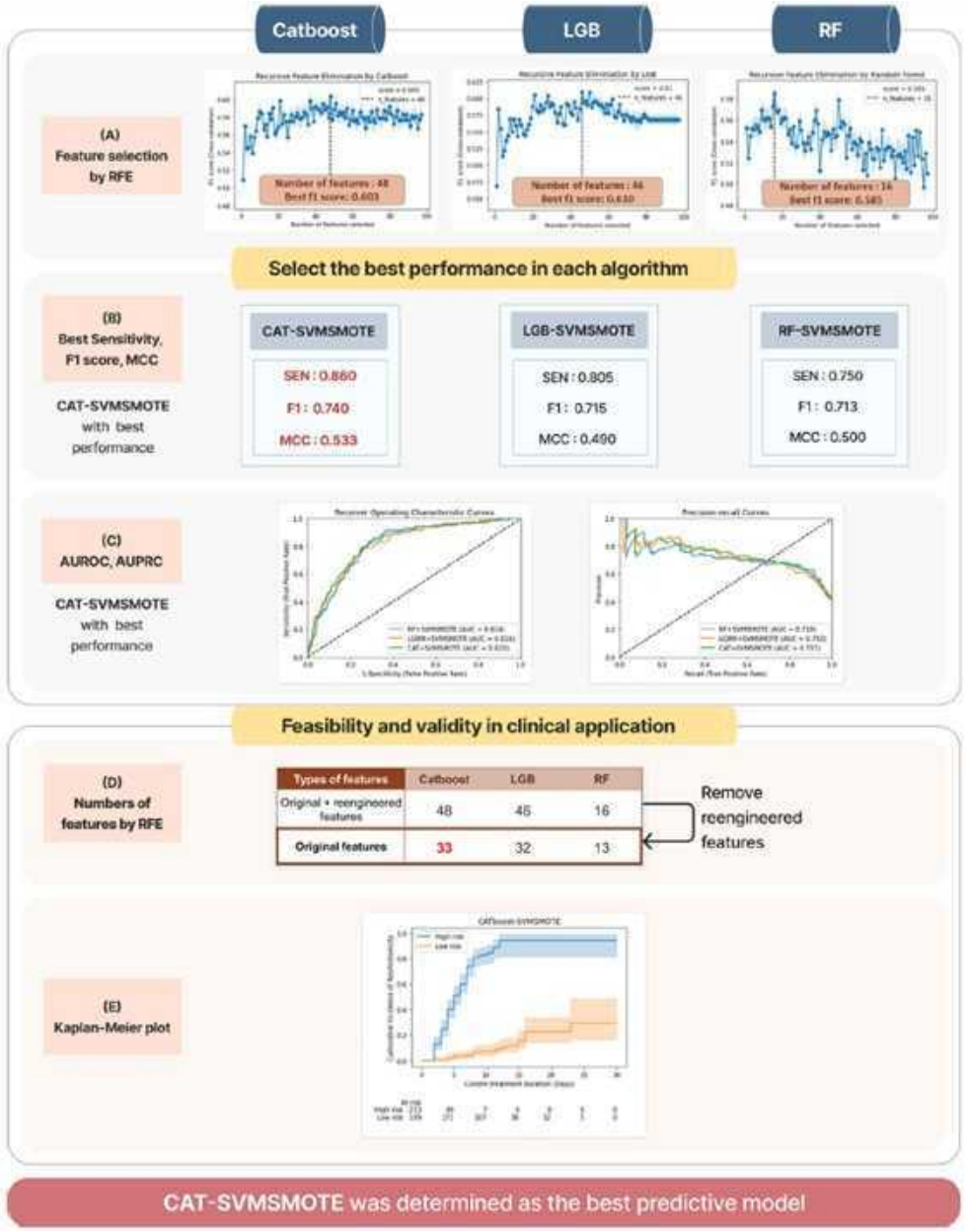
MR: Megalin receptor
PEPT2 :Peptide transporter 2
OCTN2:Organic cation transporter 2



1.Dai C., et al. *Antimicrob Agents Chemother* 58:4075–4085 / 2. Zhu, Y.,et al. *Pharmacokinetics and Perspectives. Microorganisms*, 9(6), 1154.

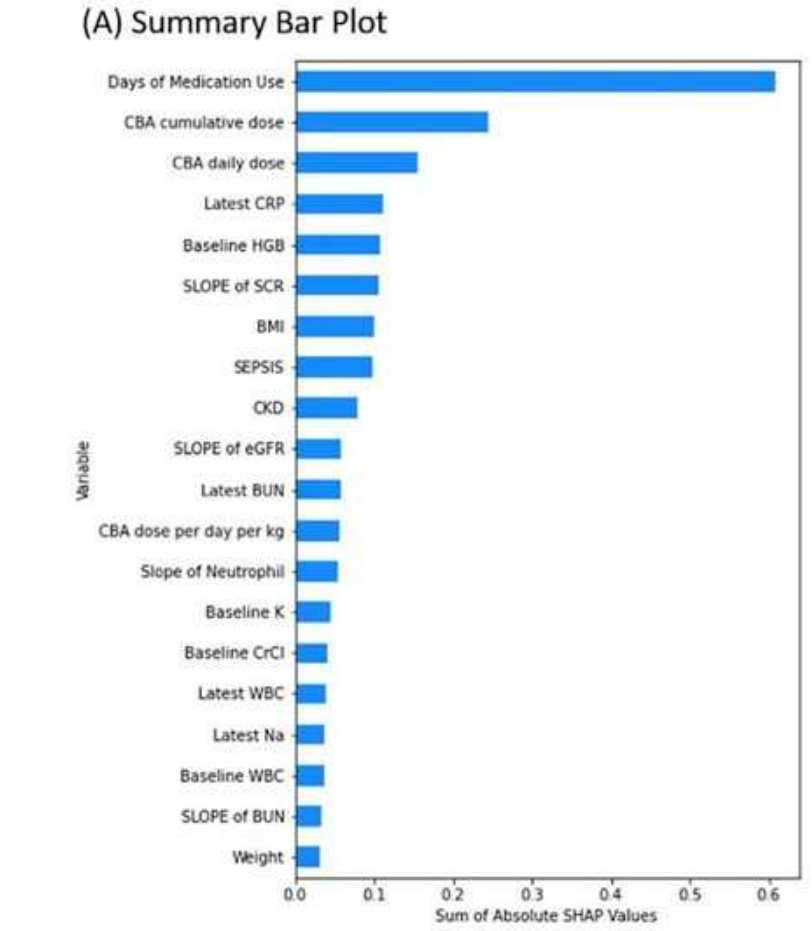
Using Machine Learning Algorithm to predict colistin-induced nephrotoxicity

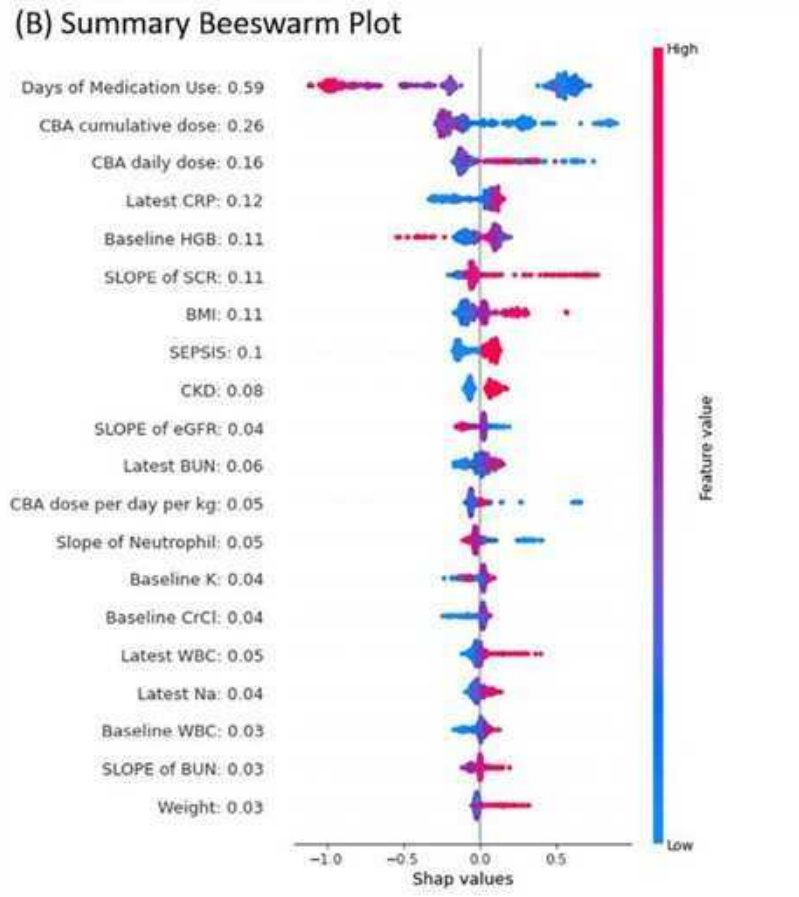




Chiu, et al. (2024) *International journal of antimicrobial agents*, *64*(1), 107175.

Interpretation of the best predictive model

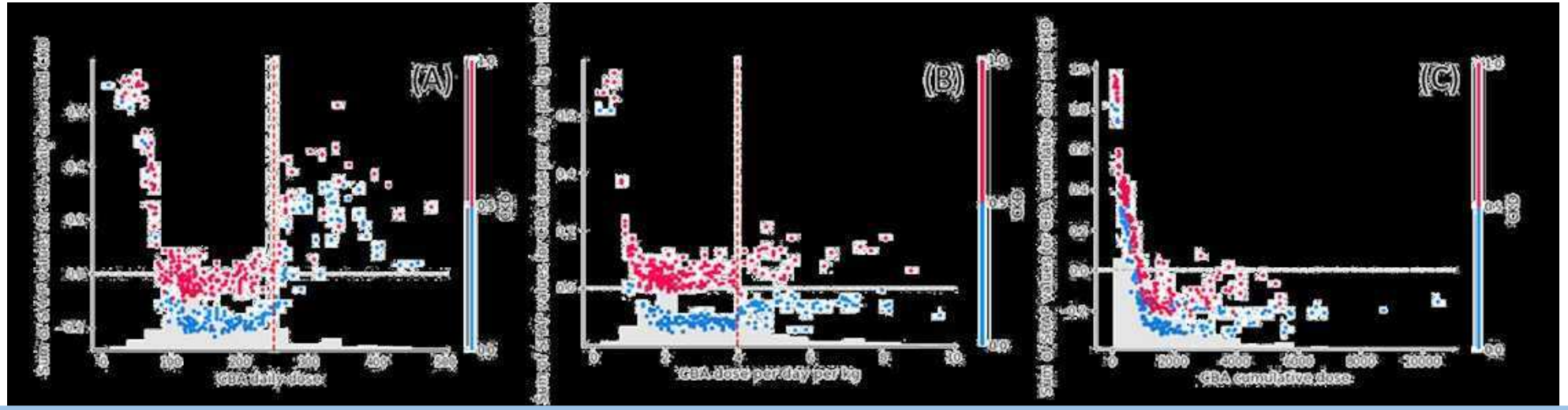




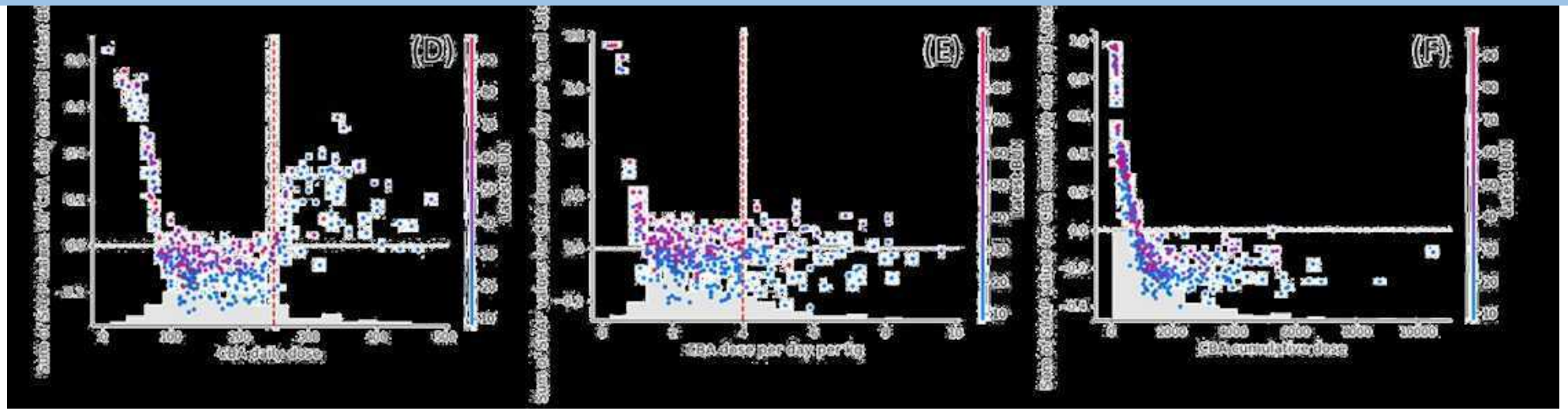
Most important features: the number of days, cumulative dose, and daily dose of colistin

Chiu, et al. (2024) *International journal of antimicrobial agents*, *64*(1), 107175.

Interpretation of the best predictive model

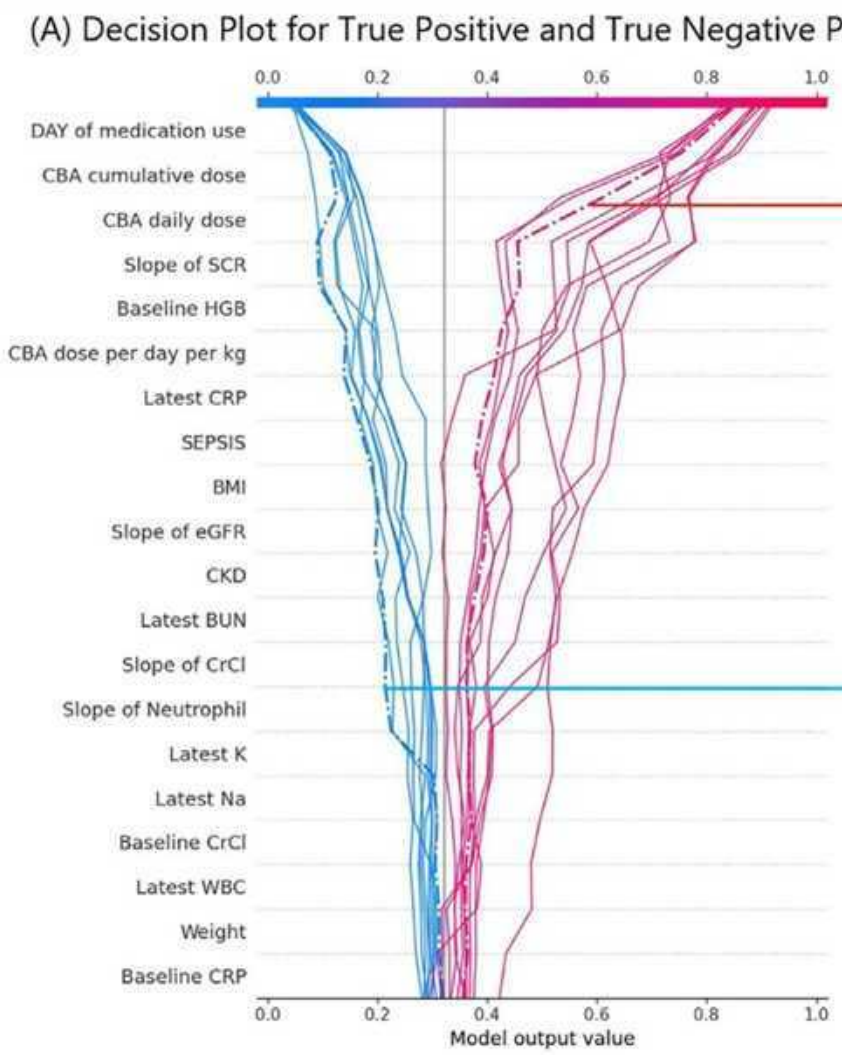


A cutoff dose of 4.0 mg/kg body weight/d for patients with a higher risk of colistin-induced AKI



Chiu, et al. (2024) *International journal of antimicrobial agents*, *64*(1), 107175.

Interpretation of the best predictive model



True Positive Patient 8: SHAP value 0.85

A cumulative colistin dose of 210.8 mg, daily dose of 52.7 mg, 4 d of colistin use, a haemoglobin level of 8.9 g/dL, and the latest CRP level of 17.3 mg/dL

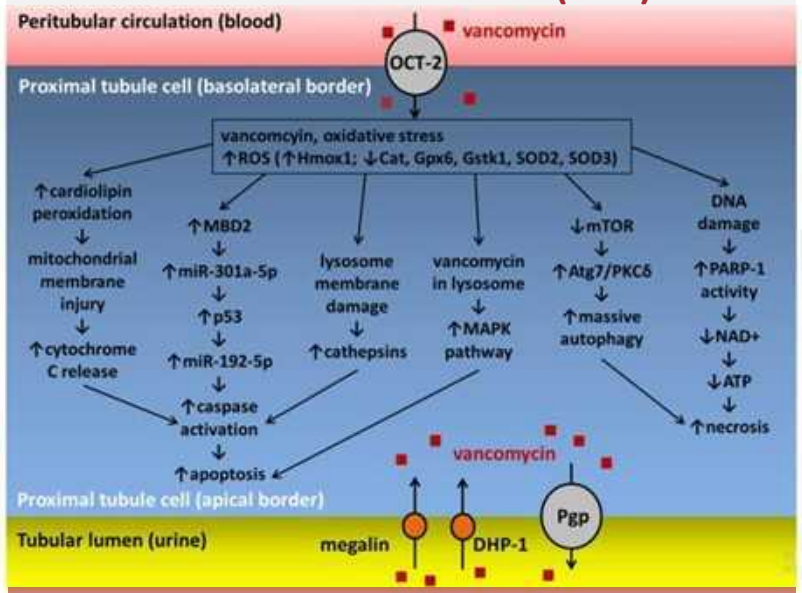
True Negative Patient 159: SHAP 0.05

15 d of colistin use, a haemoglobin level of 15.1 g/dL, a potassium level of 2.4 mEq/L, the latest CRP level of 0.7 mg/dL, no sepsis, and high accumulative colistin dose of 4409 mg

Chiu, et al. (2024) *International journal of antimicrobial agents*, *64*(1), 107175.

Vancomycin-induced nephrotoxicity

Acute tubular necrosis (ATN)



Oxidative stress

- High intracellular drug concentration within the renal tubules

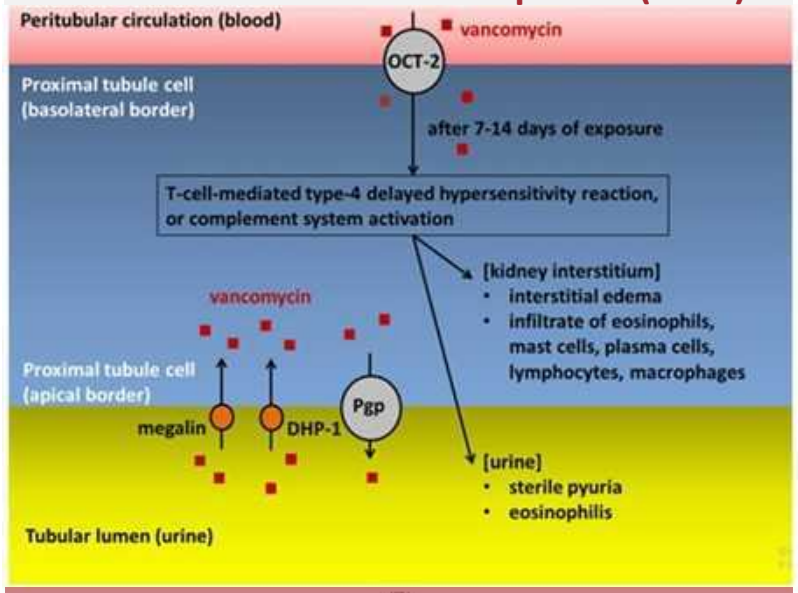
→ generation of reactive oxygen species

→ oxidative stress

→ mitochondrial dysfunction

→ cellular apoptosis

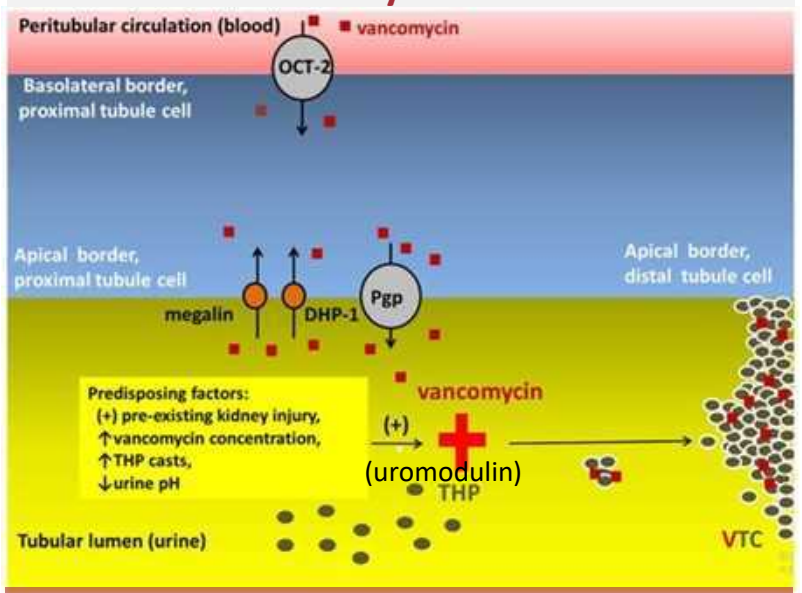
Acute tubulointerstitial nephritis (ATIN)



Allergic reactions

- T-cell-mediated type-4 delayed hypersensitivity reaction or complement system activation

Intratubular crystal obstruction



Tubular casts

- Vancomycin-associated tubular casts

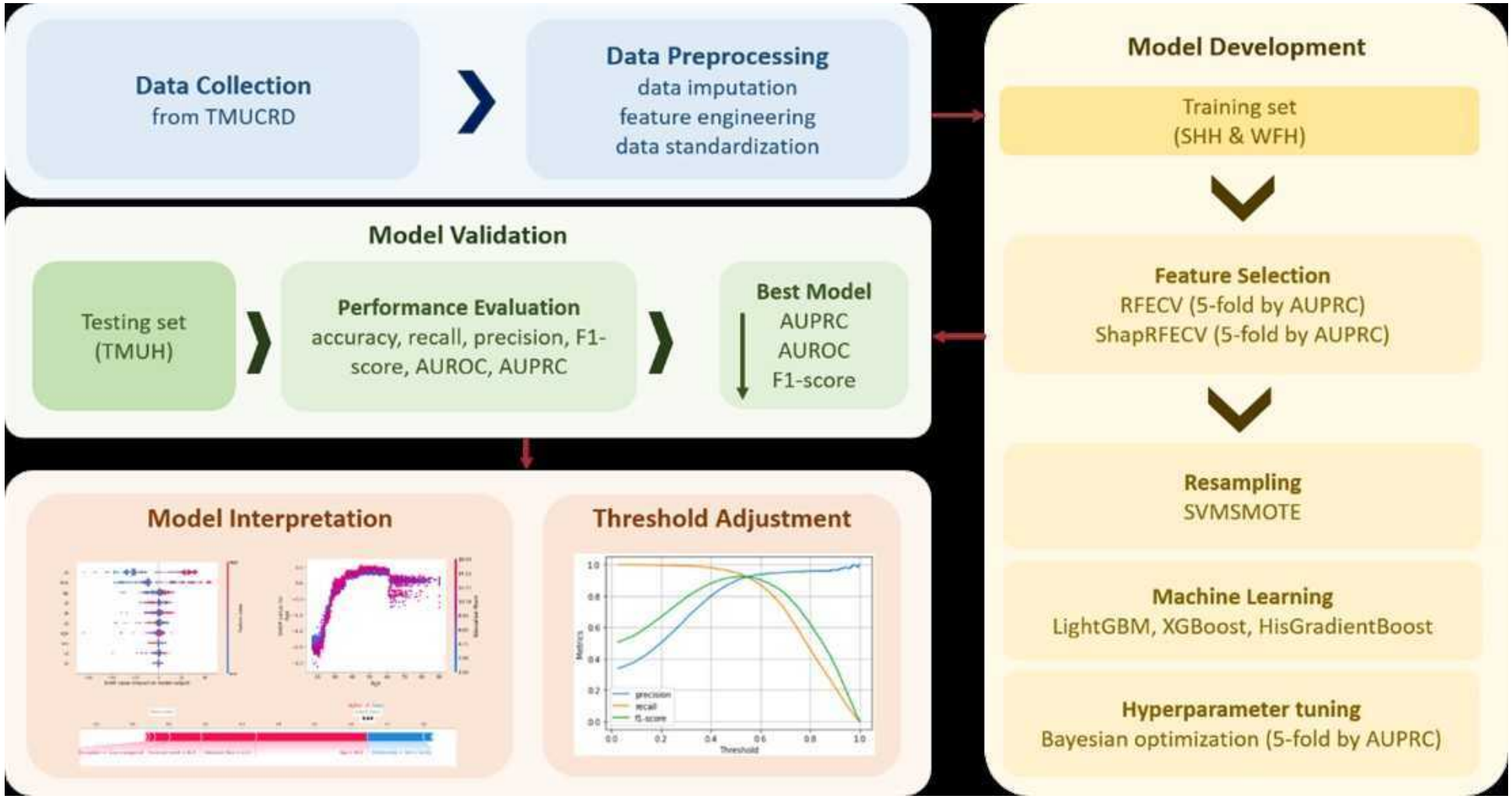
→ obstruct distal tubular lumens

→ block urine flow

→ trigger inflammation

1. Kan WC, et al. *Int J Mol Sci*. 2022;23(4):2052. / 2. Perazella MA. *Curr Opin Crit Care*. 2019;25(6):550-557. / 3. Perazella MA, et al. *Clin J Am Soc Nephrol*. 2022;17(8):1220-1233.

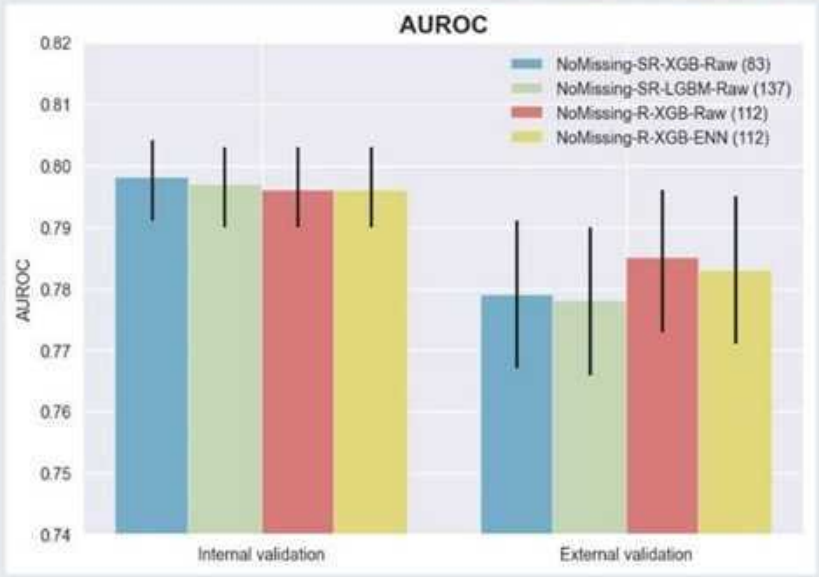
Using Machine Learning Algorithm to predict vancomycin- and teicoplanin-associated acute kidney injury

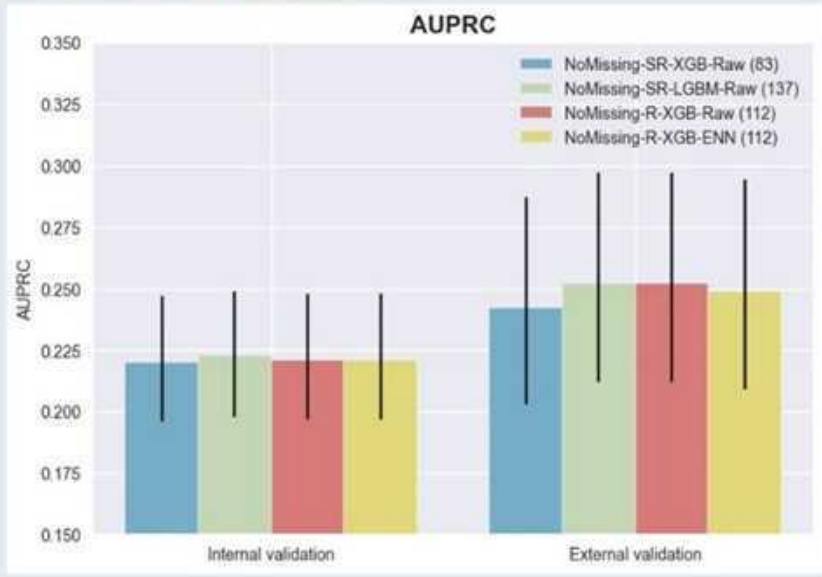


Unpublished (under revision)

Using Machine Learning Algorithm to predict vancomycin- and teicoplanin-associated acute kidney injury

Select models based on AUPRC in internal validation



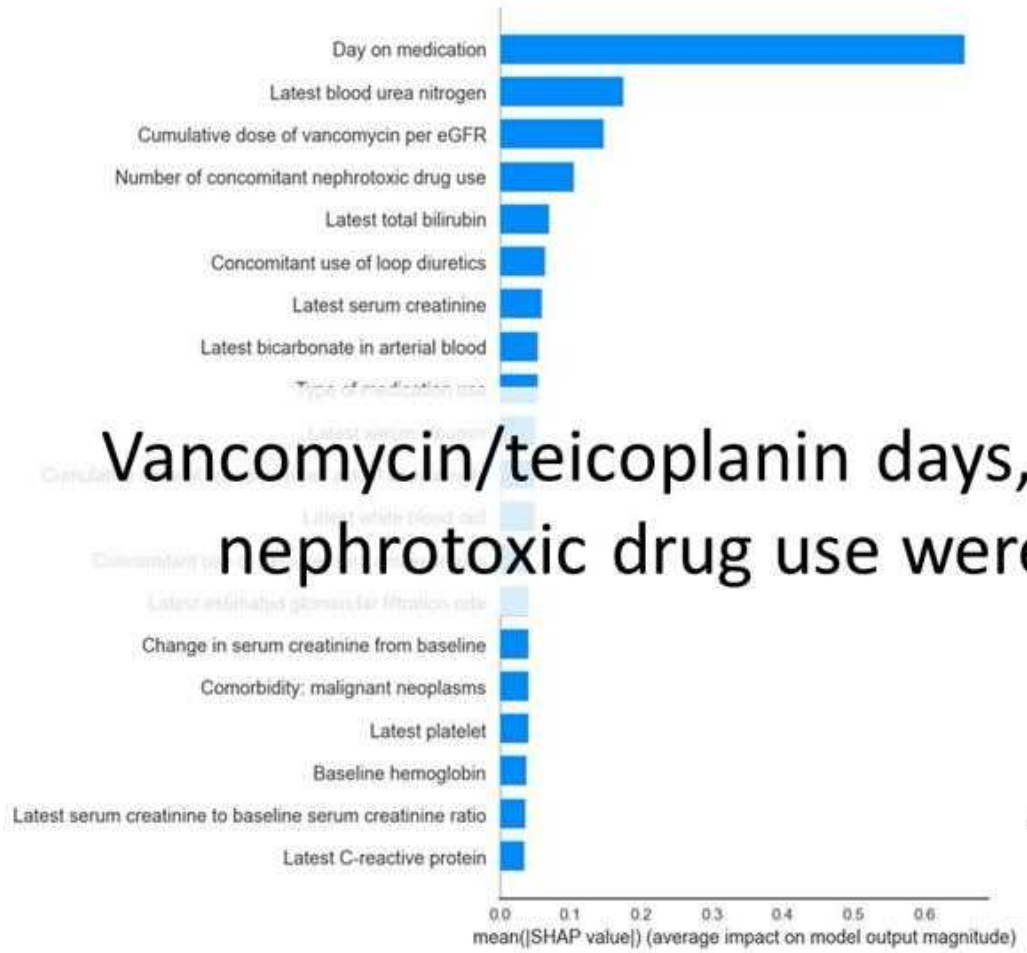


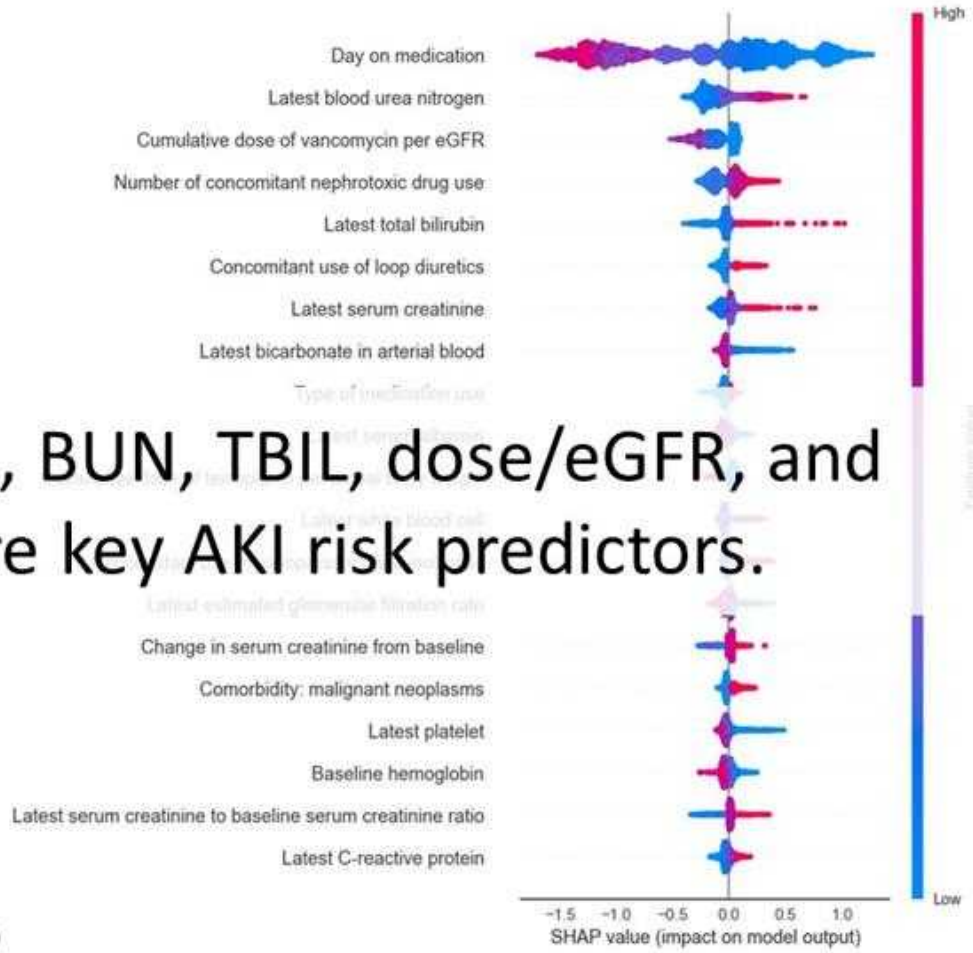
Strike a balance between model performance and feasibility in clinical applications

	NoMissing-SR-XGB-Raw	NoMissing-SR-LGBM-Raw	NoMissing-R-XGB-Raw	NoMissing-R-XGB-ENN
No. of features	83	137	112	112
Internal validation AUROC	0.798 (0.791-0.804)	0.797 (0.790-0.803)	0.796 (0.790-0.803)	0.796 (0.790-0.803)
Internal validation AUPRC	0.220 (0.196-0.247)	0.223 (0.198-0.249)	0.221 (0.197-0.248)	0.221 (0.197-0.248)

Unpublished (under revision)

Interpretation of the best predictive model

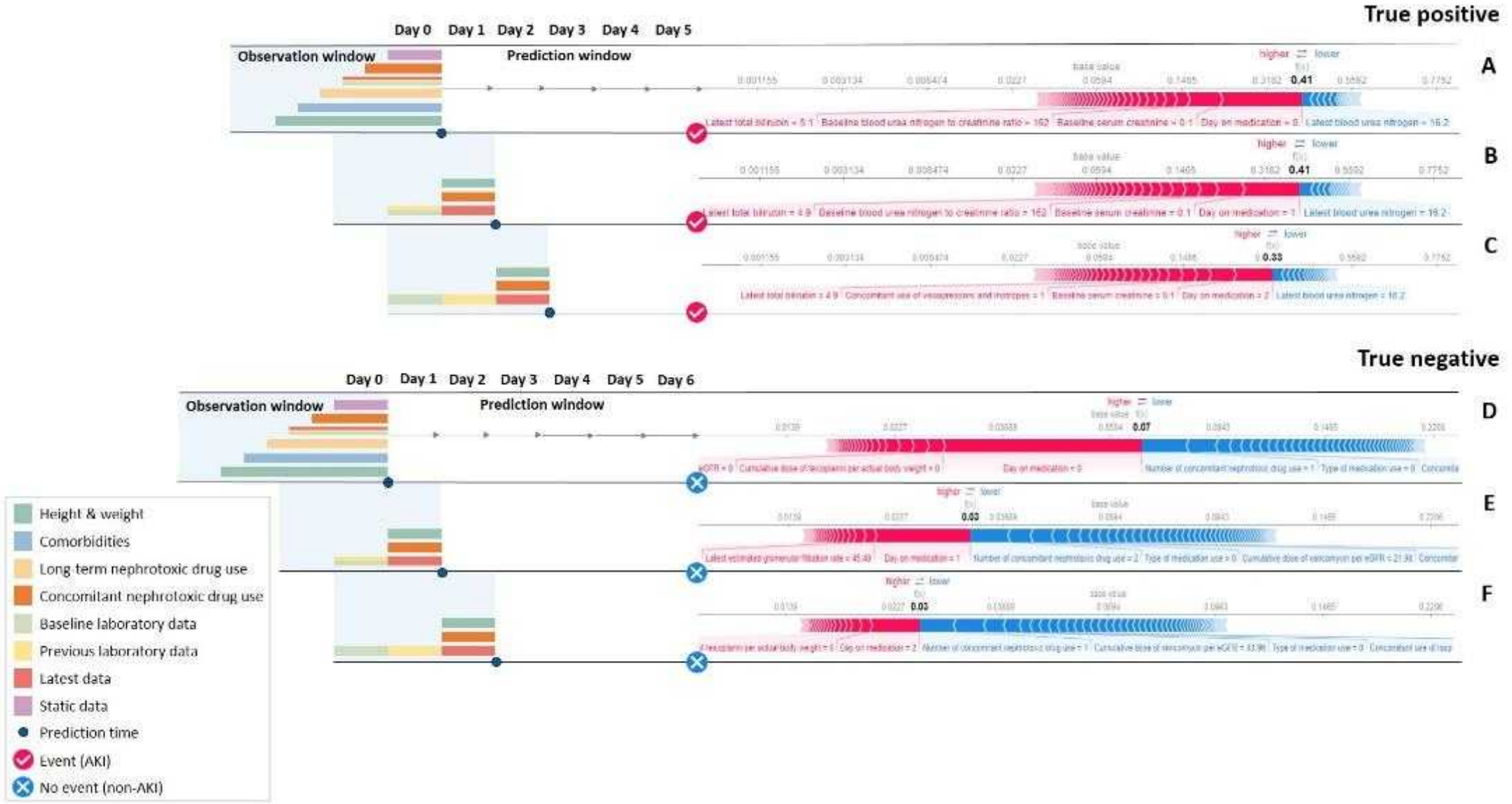




Vancomycin/teicoplanin days, BUN, TBIL, dose/eGFR, and nephrotoxic drug use were key AKI risk predictors.

Unpublished (under review)

Interpretation of the best predictive model



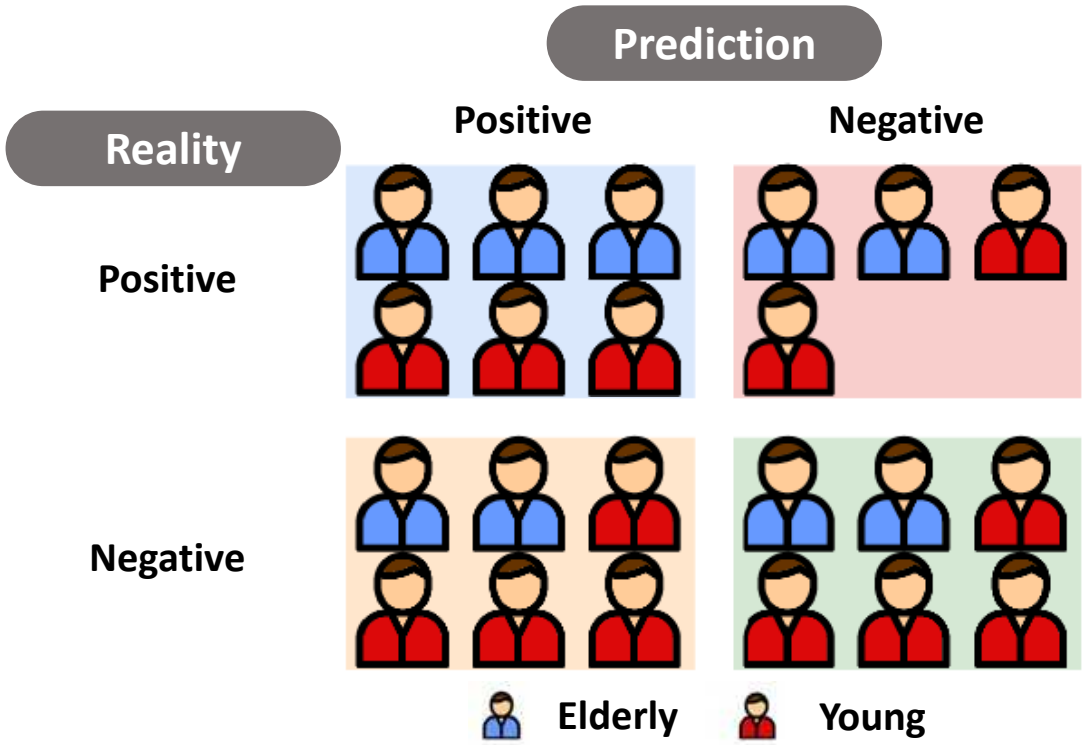
Unpublished (under review)

Equality of Odds (EO) Metric

Fairness

Equalized odds (EO) metric

- Minimize false positives and obtain equal performance across sensitive attribute classes
- EO was achieved if: **Not more/less than 0.1**
  - TPR not be significantly lower than the average &
  - FPR not be significantly higher than the average
- Using the 1st threshold for the sensitive attributes group: age, sex, race, insurance, language, and marital status
- Threshold optimization from fairlearn
  - the post-processing thresholdoptimizer method with the balanced accuracy objective and either the EO, FPR parity or TPR parity constraint



$$TPR = \frac{TP}{TP + FN} \qquad FPR = \frac{FP}{FP + TN}$$

	Overall	Elderly	Young
TPR (True positive Rate)	0.6	0.6	0.6
FPR (False positive Rate)	0.5	0.5	0.5
EO (Equalized odds)	-	✓	✓

Xu Z, et al. (2024) *NPJ Digit Med*. Oct 17;7(1):286.

Equality of Odds (EO) Metric

		Short model				Long model			
Sensitive attribute	Group	AUROC	TPR	FPR	EO	AUROC	TPR	FPR	EO
—	All patients	0.78 (SD 0.02)	0.80 (SD 0.05)	0.25 (SD 0.02)	—	0.80 SD (0.01)	0.85 SD (0.04)	0.25 SD (0.04)	—
Sex	Female	0.74 (SD 0.18)	0.79 (SD 0.35)	0.29 (SD 0.13)	✓	0.80 SD (0.15)	0.85 SD (0.34)	0.25 SD (0.10)	✓
	Male	0.80 (SD 0.08)	0.82 (SD 0.22)	0.23 (SD 0.06)	✓	0.80 SD (0.16)	0.84 SD (0.33)	0.23 SD (0.08)	✓
Age	20	0.73 (SD 0.08)	0.74 (SD 0.15)	0.27 (SD 0.06)	✓	0.76 SD (0.09)	0.77 SD (0.16)	0.24 SD (0.05)	✓
	30	0.80 (SD 0.02)	0.86 (SD 0.06)	0.26 (SD 0.04)	✓	0.72 SD (0.03)	0.64 SD (0.09)	0.20 SD (0.05)	✗
	40	0.78 (SD 0.04)	0.81 (SD 0.08)	0.25 (SD 0.03)	✓	0.77 SD (0.02)	0.80 SD (0.06)	0.26 SD (0.06)	✓
	50	0.76 (SD 0.04)	0.78 (SD 0.09)	0.25 (SD 0.04)	✓	0.80 SD (0.04)	0.87 SD (0.08)	0.26 SD (0.05)	✓
	60	0.79 (SD 0.02)	0.82 (SD 0.04)	0.23 (SD 0.04)	✓	0.80 SD (0.03)	0.84 SD (0.03)	0.24 SD (0.05)	✓
	70	0.73 (SD 0.08)	0.69 (SD 0.19)	0.23 (SD 0.07)	✓	0.81 SD (0.06)	0.86 SD (0.12)	0.23 SD (0.05)	✓
	80	0.77 (SD 0.02)	0.81 (SD 0.04)	0.26 (SD 0.03)	✓	0.81 SD (0.01)	0.85 SD (0.06)	0.23 SD (0.05)	✓
	90	0.78 (SD 0.03)	0.79 (SD 0.07)	0.23 (SD 0.02)	✗	0.78 SD (0.02)	0.78 SD (0.04)	0.22 SD (0.04)	✓
Race	Asian	0.79 (SD 0.08)	0.83 (SD 0.12)	0.24 (SD 0.11)	✓	0.80 SD (0.11)	0.84 SD (0.18)	0.24 SD (0.08)	✓
	Black	0.78 (SD 0.04)	0.83 (SD 0.07)	0.27 (SD 0.05)	✓	0.80 SD (0.04)	0.85 SD (0.07)	0.24 SD (0.06)	✓
	Hispanic	0.80 (SD 0.07)	0.85 (SD 0.12)	0.25 (SD 0.08)	✓	0.80 SD (0.08)	0.84 SD (0.16)	0.25 SD (0.08)	✓
	Native	0.78 (SD 0.17)	0.97 (SD 0.07)	0.43 (SD 0.35)	✗	0.82 SD (0.13)	1.00 SD (0.00)	0.35 SD (0.23)	✓
	Other	0.76 (SD 0.06)	0.72 (SD 0.10)	0.19 (SD 0.05)	✓	0.79 SD (0.07)	0.77 SD (0.09)	0.20 SD (0.09)	✓
	Unknown	0.79 (SD 0.05)	0.83 (SD 0.11)	0.25 (SD 0.03)	✓	0.82 SD (0.03)	0.87 SD (0.06)	0.23 SD (0.05)	✓
	White	0.77 (SD 0.02)	0.79 (SD 0.06)	0.24 (SD 0.03)	✓	0.80 SD (0.02)	0.84 SD (0.04)	0.24 SD (0.05)	✓
Insurance	Medicaid	0.72 (SD 0.07)	0.69 (SD 0.17)	0.26 (SD 0.06)	✗	0.76 SD (0.08)	0.77 SD (0.16)	0.26 SD (0.05)	✓
	Medicare	0.78 (SD 0.03)	0.81 (SD 0.06)	0.25 (SD 0.02)	✓	0.81 SD (0.02)	0.85 SD (0.04)	0.24 SD (0.05)	✓
	Other	0.78 (SD 0.02)	0.80 (SD 0.05)	0.24 (SD 0.03)	✓	0.80 SD (0.02)	0.84 SD (0.05)	0.23 SD (0.04)	✓
Language	English	0.77 (SD 0.04)	0.79 (SD 0.09)	0.25 (SD 0.04)	✓	0.81 SD (0.06)	0.85 SD (0.11)	0.24 SD (0.05)	✓
	Other	0.78 (SD 0.02)	0.80 (SD 0.05)	0.25 (SD 0.02)	✓	0.77 SD (0.01)	0.78 SD (0.04)	0.24 SD (0.04)	✓
Marital status	Divorced	0.78 (SD 0.04)	0.80 (SD 0.10)	0.24 (SD 0.03)	✓	0.79 SD (0.05)	0.82 SD (0.09)	0.24 SD (0.05)	✓
	Married	0.77 (SD 0.03)	0.77 (SD 0.06)	0.22 (SD 0.02)	✓	0.81 SD (0.01)	0.83 SD (0.05)	0.22 SD (0.05)	✓
	Single	0.78 (SD 0.02)	0.84 (SD 0.05)	0.28 (SD 0.03)	✓	0.79 SD (0.03)	0.84 SD (0.06)	0.27 SD (0.04)	✓
	Widowed	0.79 (SD 0.04)	0.82 (SD 0.08)	0.24 (SD 0.02)	✓	0.81 SD (0.03)	0.85 SD (0.07)	0.24 SD (0.06)	✓
	Unknown	0.77 (SD 0.05)	0.83 (SD 0.09)	0.29 (SD 0.05)	✓	0.84 SD (0.04)	0.93 SD (0.06)	0.24 SD (0.07)	✓

Post-processing threshold optimization

Short model

		Original results				Threshold optimisation results			
Sensitive attribute	Group	AUROC	TPR	FPR	EO	AUROC	TPR	FPR	EO
Age	20	0.73	0.74	0.27	✓	0.63	0.86	0.61	✗
	30	0.80	0.86	0.26	✓	0.72	0.73	0.28	✓
	40	0.78	0.81	0.25	✓	0.76	0.82	0.31	✓
	50	0.76	0.78	0.25	✓	0.81	0.86	0.25	✓
	60	0.79	0.82	0.23	✓	0.79	0.87	0.29	✓
	70	0.73	0.69	0.23	✓	0.78	0.87	0.31	✓
	80	0.77	0.81	0.26	✓	0.80	0.87	0.26	✓
	90	0.78	0.79	0.23	✗	0.78	0.86	0.3	✓
Race	Asian	0.79	0.83	0.24	✓	0.71	0.81	0.38	✓
	Black	0.78	0.83	0.27	✓	0.79	0.86	0.28	✓
	Hispanic	0.80	0.85	0.25	✓	0.76	0.84	0.31	✓
	Native	0.78	0.97	0.43	✗	0.75	0.93	0.43	✗
	Other	0.76	0.72	0.19	✓	0.78	0.84	0.29	✓
	Unknown	0.79	0.83	0.25	✓	0.81	0.86	0.23	✓
	White	0.77	0.79	0.24	✓	0.78	0.87	0.31	✓
Insurance	Medicaid	0.72	0.69	0.26	✗	0.74	0.82	0.34	✓
	Medicare	0.78	0.81	0.25	✓	0.77	0.88	0.33	✓
	Other	0.78	0.80	0.24	✓	0.79	0.9	0.33	✓

Long model

		Origional results				Threshold optimisation results			
Sensitive attribute	Group	AUROC	TPR	FPR	EO	AUROC	TPR	FPR	EO
Age	20	0.76	0.77	0.24	✓	0.69	0.63	0.24	✗
	30	0.74	0.64	0.20	✗	0.78	0.88	0.31	✓
	40	0.77	0.8	0.26	✓	0.76	0.76	0.23	✓
	50	0.8	0.87	0.26	✓	0.81	0.88	0.25	✓
	60	0.8	0.84	0.24	✓	0.81	0.86	0.24	✓
	70	0.81	0.86	0.23	✓	0.81	0.88	0.25	✓
	80	0.81	0.85	0.23	✓	0.82	0.89	0.25	✓
	90	0.78	0.78	0.22	✓	0.78	0.81	0.25	✓

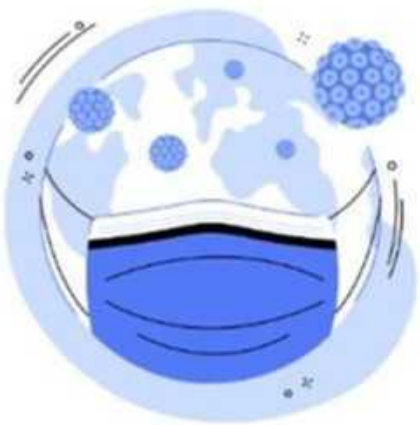
Bolton, W.J., et al. (2024) *Nat Commun* **15**, 506

Optimizing Antibiotic Use in Older Adults Through Digital Health Initiatives

INPATIENT
In hospital environments, electronic health records (EHRs) integrated with clinical decision support systems (CDSS) assist clinicians in selecting the appropriate antibiotics, dosages, and treatment durations. Real-time alerts help prevent overprescribing and ensure adherence to guidelines, reducing the risk of antimicrobial resistance.

NURSING HOME & LTC
In nursing homes and LTC facilities, digital tools enable staff to monitor residents' health statuses and antibiotic regimens more effectively. Telemedicine services provide access to infectious disease specialists, aiding in accurate diagnoses and appropriate antibiotic use without the need for hospital transfers.

OUTPATIENT
For outpatient care, digital platforms facilitate e-prescribing with built-in stewardship protocols that alert providers to potential antibiotic overuse. Mobile health apps educate patients on proper antibiotic usage and adherence, promoting responsible consumption and reducing unnecessary prescriptions.



SURVEILLANCE
Digital health technologies enhance surveillance by aggregating data on antibiotic prescribing patterns and resistance trends. Advanced analytics and machine learning can predict outbreaks and identify areas of concern, enabling timely public health interventions.

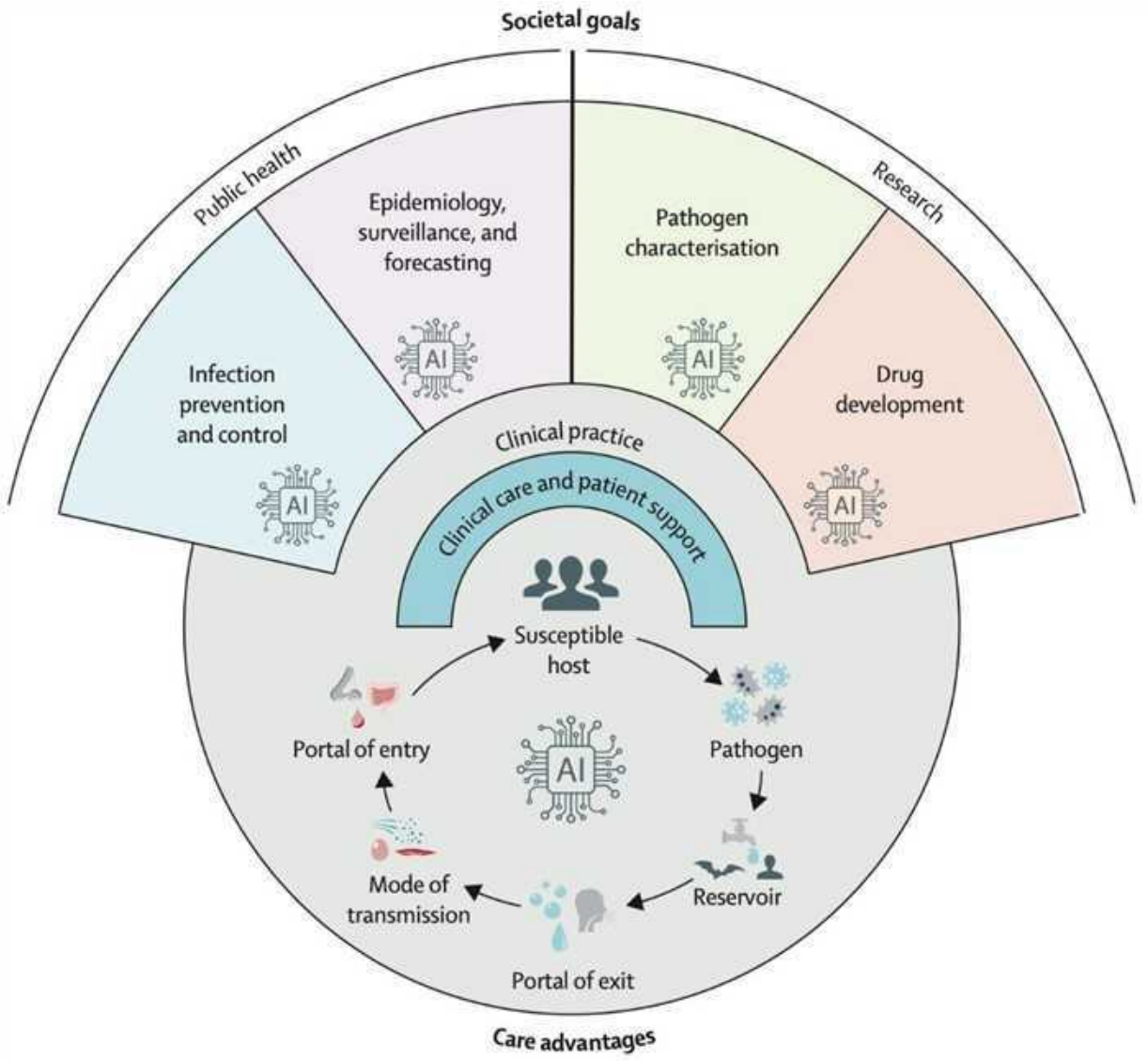
ABX STEWARDSHIP
Across all settings, digital tools support antibiotic stewardship programs by providing actionable insights into prescribing behaviors and resistance data. This empowers healthcare teams to implement targeted strategies, monitor outcomes, and continuously improve antibiotic management practices.

Bear, M. et al. (2025) *Curr Infect Dis Rep* 27, 7

AI in Infectious Disease

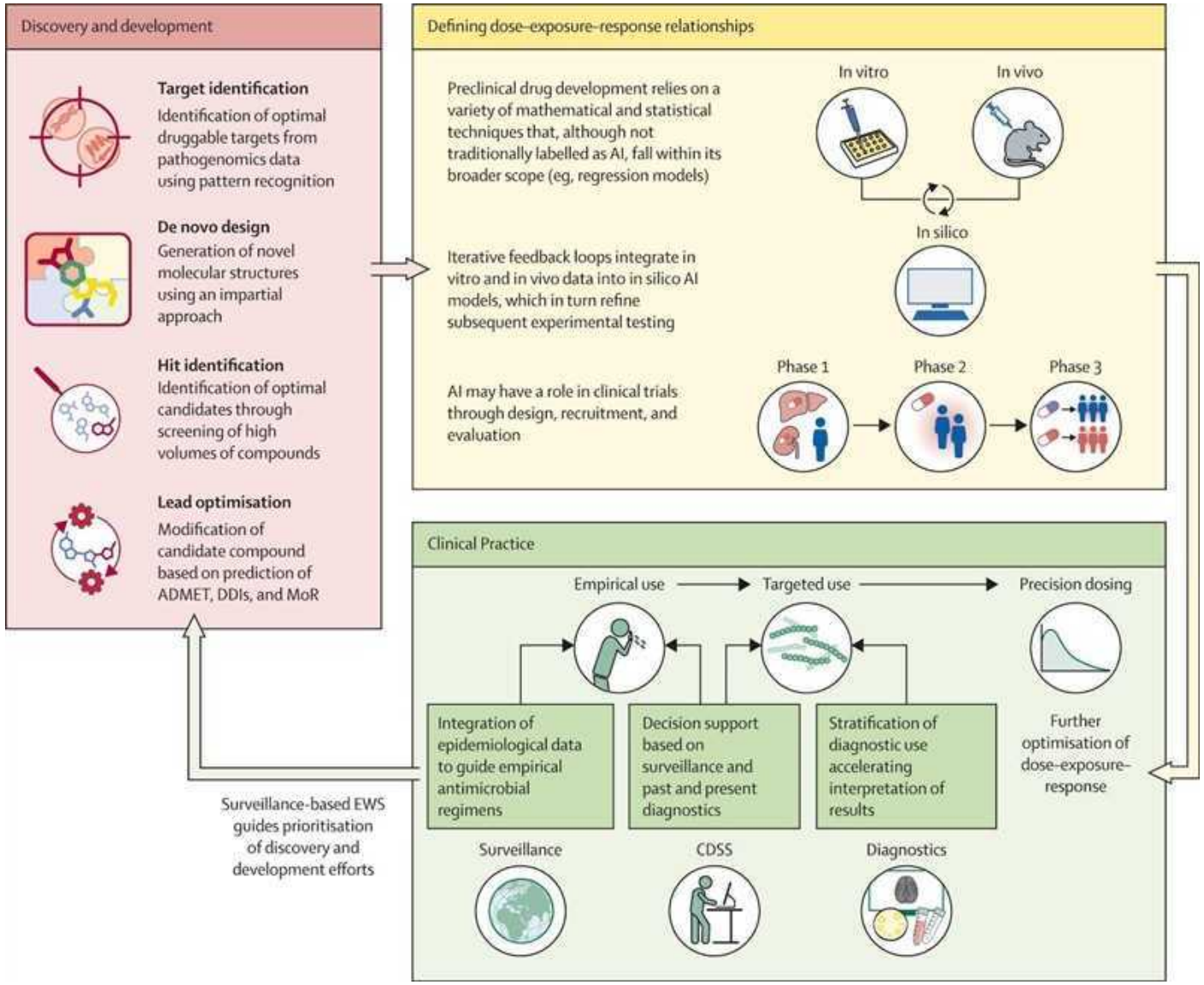
	Data source	Data examples
Pathogen		
Pathogen surveillance data	Surveillance systems	Case notifications, outbreak alerts, and strain prevalence
Genomic and sequencing data	Genomic databases	Whole genome sequencing, variant tracking, and mutational profiles
Molecular and antimicrobial resistance data	Surveillance networks and laboratory systems	Resistance profiles and molecular typing
Host		
Clinical reports	Clinical information systems	Clinical notes, hospital admissions, discharge summaries, and emergency visits
Biomarker data	Laboratory information systems	Blood tests, imaging reports, microbiological cultures, PCR and serological tests, and cytology and histology reports
Patient monitoring data	Remote monitoring systems	Wearable and implantable devices and symptom trackers
Epidemiological data	Public health surveillance systems	Vaccination records, mortality data, and disease registries
Administrative data	Administrative databases	Drug prescriptions, hospital bed occupancy, and absenteeism records
Digital behavioural and mobility data	Mobile network operators and tracking systems	Mobility patterns and contact tracing app data
Public perception data	Social media platforms and search engines	Social media activity and web search trends
Environment		
Climate and environmental data	Meteorological and environmental monitoring systems	Temperature, humidity, rainfall, and air quality
Water and wastewater surveillance data	Environmental health agencies	Pathogen detection in sewage and potable water
Vector and zoonotic surveillance data	Veterinary and entomological surveillance systems	Animal reservoirs and vector density monitoring

Table 1: **Available types of data, data sources, and examples supporting artificial intelligence models in infectious disease prevention and management, categorised according to the components of the epidemiologic triad**



1. Odone A., et al. (2025) *The Lancet. Infectious diseases*, S1473-3099(25)00412-8. Advance online publication. */ 2. Howard, A., et al. (2025). The Lancet Infectious Diseases.*

AI in Infectious Disease



Artificial Intelligence and Infectious Diseases 2

Artificial intelligence and infectious disease diagnostics: state of the art and future perspectives

Luca Miglietta, Timothy M Rawson, Ronald Galiwango, Alex Tasker, Damien K Ming, Darlington Akogo, Cecilia Ferreyra, Eric O Aboagye, N Claire Gordon, Carolina Garcia-Vidal, Jesus Rodriguez-Manzano, Alison H Holmes

Artificial intelligence (AI) is reshaping infectious disease diagnostics by supporting clinical decision making, optimising laboratory and clinical workflows, and enabling real-time disease surveillance. AI approaches improve pathogen detection, antimicrobial stewardship, and treatment monitoring, enhancing diagnostic accuracy, efficiency, and scalability. The role of AI in combating antimicrobial resistance is particularly significant, enabling rapid pathogen identification and personalised treatment. Despite progress over the past two decades, widespread AI adoption in infectious disease diagnostics faces challenges. In high-income countries, fragmented data ecosystems, incomplete datasets, and algorithmic bias hinder clinical integration. Meanwhile, low-income and middle-income countries contend with limited digital infrastructure, unstandardised data, and financial constraints, exacerbating disparities in diagnostic access. Further barriers include concerns over interoperability, data privacy, cybersecurity, and the regulation of AI implementation. This paper examines the role of AI in infectious disease diagnostics, highlighting both opportunities and limitations. It underscores the need for coordinated investments in digital infrastructure, harmonised data-sharing frameworks, and clinician engagement to support equitable, sustainable adoption. Addressing these challenges will enable health-care systems to harness the potential of AI to improve infectious disease detection, prevention, and management of infectious diseases, thereby strengthening global health resilience.

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See Online/Comment https://doi.org/10.1016/S1473-3099(25)00507-X, https://doi.org/10.1016/S1473-3099(25)00498-0, and https://doi.org/10.1016/S1473-3099(25)00497-9
This is the second in a Series of three papers about artificial intelligence and infectious diseases. All papers in the Series are available at https://www.

Artificial Intelligence and Infectious Diseases 3

Artificial intelligence and infectious diseases: tackling antimicrobial resistance, from personalised care to antibiotic discovery

Alex Howard, Nada Reza, Peter L Green, Mo Yin, Erin Duffy, Henry C Mwandumba, Alessandro Gerada, William Hope

Antimicrobial resistance (AMR) is an intractable problem that has the potential to significantly limit advances in human health. Recently, the UN General Assembly (UNGA) High-Level Statement on AMR defined targets for addressing the impact of resistance on human, animal, and environmental health. For human health, the discovery and development of new antibiotics, antimicrobial stewardship programmes, antimicrobial surveillance, and infection control and prevention are all key areas. Artificial intelligence (AI) is ideally placed to help achieve the UNGA targets via its role in revealing patterns in data that are clinically indiscernible, and using that information to build clinical decision support systems. However, significant barriers remain in terms of necessary infrastructure, know-how, and the implementation of AI approaches. In this Series paper, we consider the potential applications of AI in combatting the AMR problem through drug discovery and development, antimicrobial stewardship, diagnostics, and surveillance, and their use in public health. We then discuss the technical, infrastructure, regulatory, ethical, and policy challenges that affect these domains.

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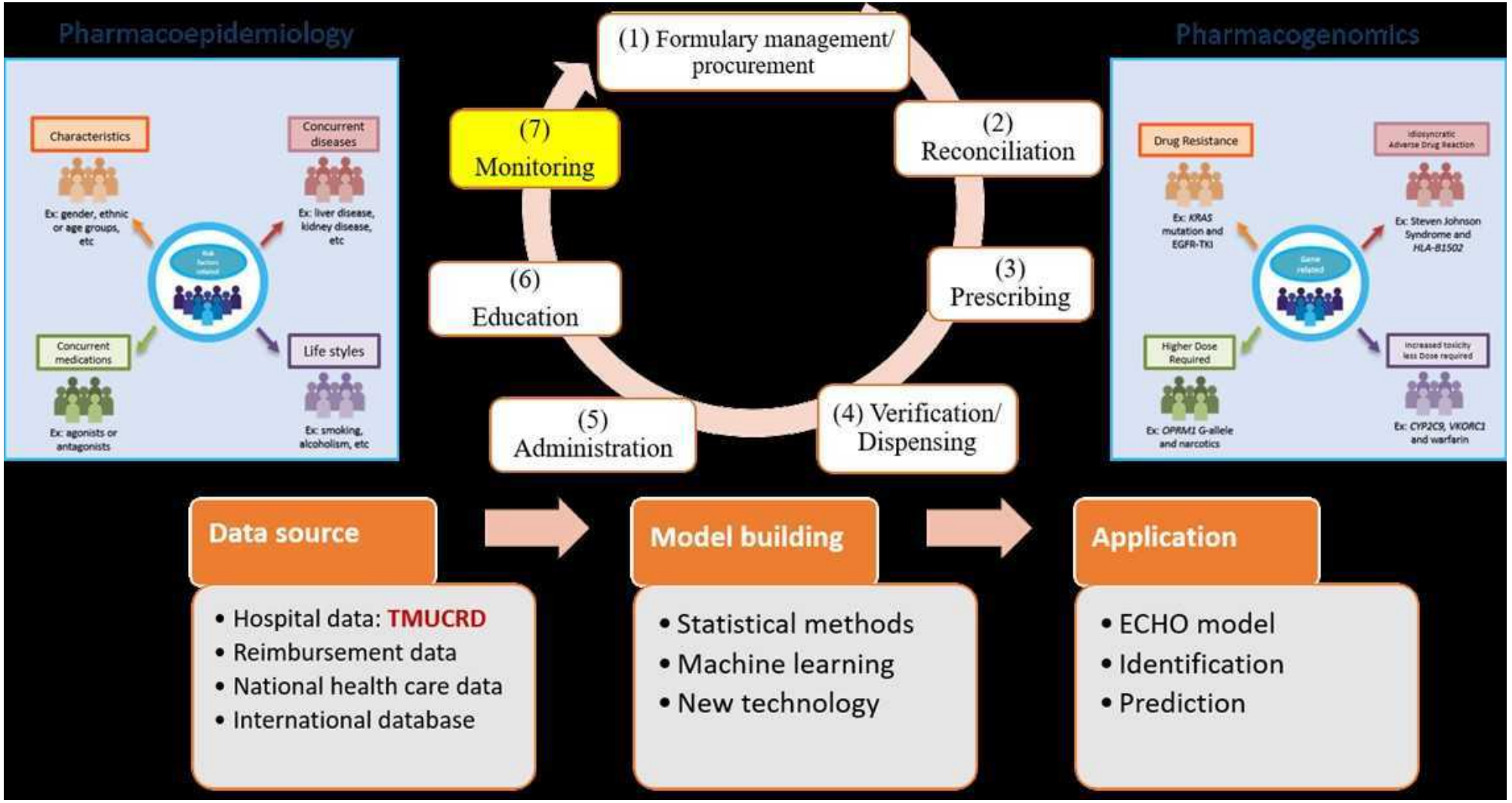
See Online/Comment https://doi.org/10.1016/S1473-3099(25)00501-X, https://doi.org/10.1016/S1473-3099(25)00498-0, and https://doi.org/10.1016/S1473-3099(25)00497-9
This is the third in a Series of

1. Odone A., et al. (2025) *The Lancet. Infectious diseases*, S1473-3099(25)00412-8. Advance online publication. */ 2. Howard, A., et al. (2025). The Lancet Infectious Diseases.*

Big Data Analysis for Monitoring Pharmacotherapy

From Rule-based techniques to AI computation



Thank you for listening!

shawn@tmu.edu.tw

藥害救濟制度介紹&
抗生素相關藥害案例分析

簡美夷 組長

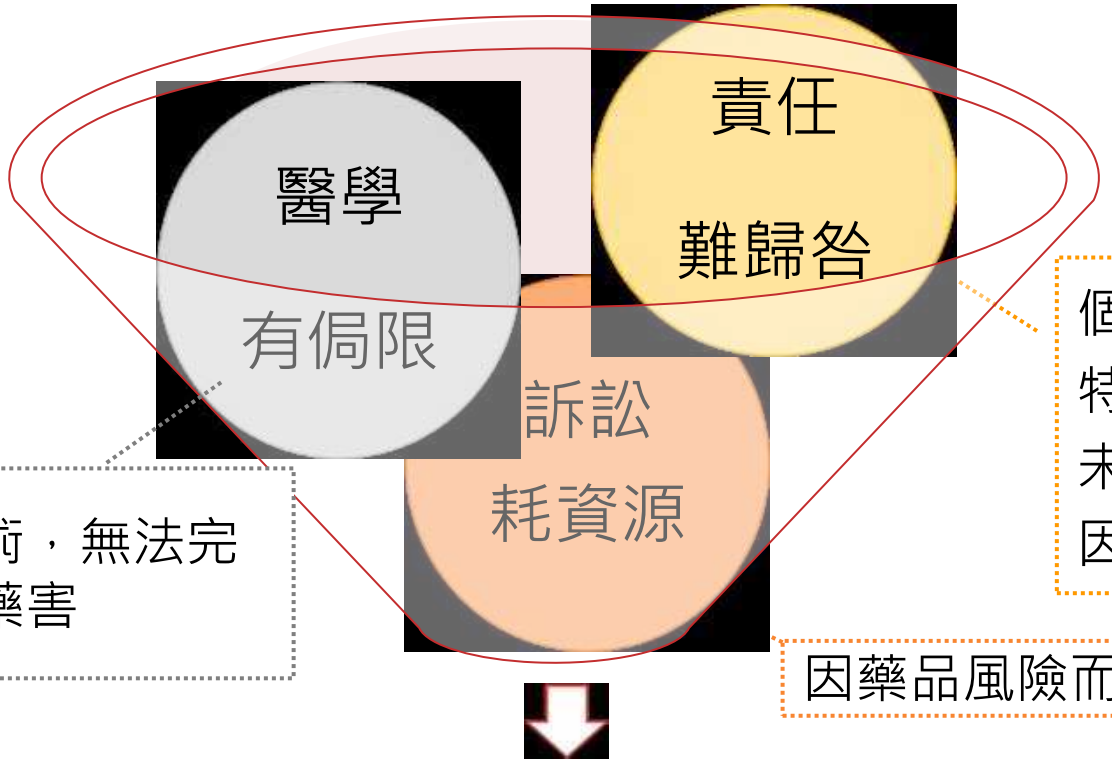
2025年9月26日

大綱

- 藥害救濟制度及藥害救濟法
- 藥害救濟申請及作業流程
- 藥害救濟業務
- 審議案例分析
- 結語

藥品傷害之發生

No drug is 100% safe for all people in all circumstances.



已知的科學技術，無法完全避免或預防藥害

個別體質狀況
特殊生理反應
未必有人應負責
因果關係難以證明

因藥品風險而興訟，曠日費時

病人無辜受害?

藥害救濟制度及藥害救濟法

藥害救濟法

89年5月31日公布實施
100年5月4日修正

沿革

88年：
實施「藥害救濟要點」

89年：
總統公布施行「藥害救濟法」

90年：
成立**藥害救濟基金會**

100年：
藥害救濟法修正

藥害救濟法

89年5月31日公布實施
100年5月4日修正

目的

- 使正當使用合法藥物而受害者，獲得及時救濟
- 避免不必要訴訟浪費社會成本
- 維護廠商及醫療機構名譽
- 避免事件過度渲染，健全醫藥產業發展

原則

- 人道救濟補償制度，非過失賠償

藥害救濟法適用範圍

藥害救濟法第3-4條

✓ 正當使用合法藥物

- 正當使用-依醫藥專業人員之指示或藥物標示使用
- 合法藥物-領有衛生福利部核發藥物許可證，依法製造、輸入及販賣的藥物

(不含中藥、試驗用藥、醫療器材)

✓ 藥害

符合身心障礙者保護法令所定障礙類別、等級者

因藥物不良反應致死亡、障礙或嚴重疾病(住院)

104.12.7衛福部公告：
限於因藥物不良反應致危及生命、導致病人住院、延長病人住院時間且需作處置以防止永久性傷害者

⇨ **可申請藥害救濟給付**

藥害救濟法

- 申請時效(第14條) ：知有藥害之日起三年內
- 申請類別與資格(第12條) ：

嚴重疾病(住院)
由受害人本人或
法定代理人申請

身心障礙(身心障礙證明)
由受害人本人或
法定代理人申請

死亡
法定繼承人申請

衛生福利部　公告

114年2月11日　發文字號衛授食字第1141410859號

- 主旨：公告財團法人藥害救濟基金會為辦理114年度藥害救濟業務之受託單位。
- 依據：藥害救濟法**第6條**第1項、行政程序法第16條第1項及第2項
- 公告事項：本部114年度委託「財團法人藥害救濟基金會」

1. 受理藥害救濟案件之申請
2. 藥害救濟金之給付
3. 藥害救濟徵收金之收取及管理
4. 藥害救濟審議之先行及後續作業，

包含向**醫療機構調閱申請個案之完整病歷資料或醫療費用**等相關資料。

藥害救濟法 - 資料提供及保密

- 為辦理藥害救濟及其相關業務，主管機關得向財稅機關、醫療機構及其他相關機關(構)或團體要求提供有關資料，被要求者不得拒絕、規避或妨礙。《第10條》
- 辦理本法所定藥害救濟相關業務之人員，因執行業務而知悉、持有藥物製造業者、輸入業者或藥害受害人之秘密者，不得無故洩漏，並不得為自己利益而使用。《第11條》

- 醫療機構或其他相關機關(構)或團體違反第10條規定者，處新台幣2萬元以上10萬元以下罰鍰，並得按次處罰。《第23條》
- 違反第11條規定者，處新台幣6千元以上3萬元以下罰鍰。《第24條》

藥害救濟法–基金來源

藥害救濟法第5條

- **藥物製造業者及輸入業者繳納之徵收金**
- 罰鍰、滯納金
- 藥害救濟徵收金調高金額

  (每單一案例給付救濟金額的25%
- 代位求償之所得
- 捐贈收入
- 其他有關收入
- **（102年度公告調整藥害救濟徵收金之比率為千分之0.5）**

徵收金: 一定比例[註]之前一年度藥物銷售額

註:一定比例-

1. 基金總額<3億→0.1%
2. 基金總額>3億→0.02%~0.2%　藥害救濟法第7條

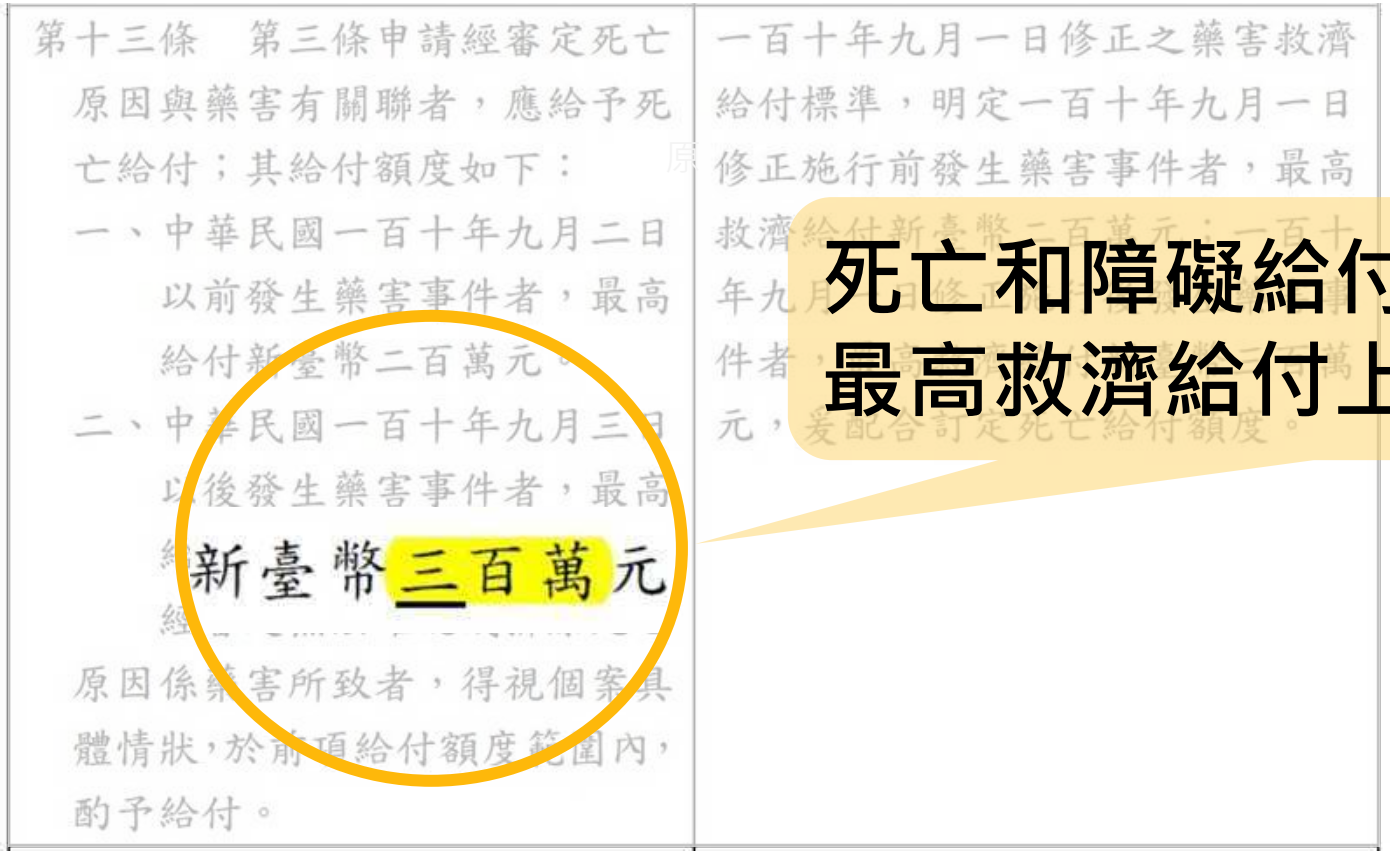
西藥製劑

最新條文修正

發布日：112年6月15日

《藥害救濟申請及審議委員會審議辦法》第十三條、第十四條規定

110年9月3日後發生藥害事件者適用新標準



第十三條　第三條申請經審定死亡原因與藥害有關聯者，應給予死亡給付；其給付額度如下：

一、中華民國一百十年九月二日以前發生藥害事件者，最高給付新臺幣二百萬元。

二、中華民國一百十年九月三日以後發生藥害事件者，最高給付新臺幣三百萬元。

原因係藥害所致者，得視個案具體情狀，於前項給付額度範圍內，酌予給付。

一百十年九月一日修正之藥害救濟給付標準，明定一百十年九月一日修正施行前發生藥害事件者，最高救濟給付新臺幣二百萬元；一百十年九月一日修正施行後發生藥害事件者，最高救濟給付新臺幣三百萬元，爰配合訂定死亡給付額度。

死亡和障礙給付
最高救濟給付上限調升至三百萬

藥害救濟給付計算裁量表 修正

1. 適用於 110 年 9 月 2 日以前發生之藥害事件：

藥害救濟給付（點數）＝ 基本給付（點數）＋ 附加給付（點數）

每點折合新臺幣五萬元

救濟項目	基本給付（單位：點）	附加給付 （單位：點）		給付金額範圍（單位：新臺幣萬元）
死亡給付	32	受害人有下列親屬之一者，得另計附加給付： 一、 配偶 二、 未成年子女或領有殘障手冊之子女 三、 父母	給付點數	160-200
		其他：無法確認或排除死亡原因係藥害所致者，視個案具體情狀暨其死亡與使用藥品產生不良反應之關聯程度，另行酌予給付。		

救濟項目	基本給付（單位：點）		附加給付 （單位：點）		給付金額範圍（單位：新臺幣萬元）
	障礙等級	給付點數	受害人有下列親屬之一者，得另計附加給付： 一、配偶 二、未成年子女或領有殘障手冊之子女 三、父母	給付點數	
障礙給付	極重度	30		10	150—200
	重度	22		8	110—150
	中度	20		6	100—130
	輕度	19		4	95—115
	其他：無法確認或排除障礙原因係藥害所致者，視個案具體情狀暨障礙與使用藥品產生不良反應之關聯程度，另行酌予給付。				

藥害救濟給付計算裁量表 修正

2. 適用於 110 年 9 月 3 日以後發生之藥害事件：

救濟給付種類	藥品與藥害之關聯程度	給付金額範圍（單位：新臺幣萬元）	備註
死亡給付	極高	225-300	
	高	150-225	
	中	75-150	
	低	最高 75	
障礙給付	重度 極高	225-300	依受害人之受害醫療處置及自身既有疾病與危險因子，視藥品與藥害之關聯程度，審定給付金額。
	重度 高	150-225	
	重度 中	75-150	
	重度 低	最高 75	
	中度 極高	170-225	
	中度 高	115-170	
	中度 中	55-115	
	中度 低	最高 55	
	輕度 極高	145-195	
	輕度 高	100-145	
	輕度 中	50-100	
	輕度 低	最高 50	
	極輕度 極高	130-175	
	極輕度 高	90-130	
	極輕度 中	45-90	
	極輕度 低	最高 45	

110年9月3日前、後發生之藥害事件適用不同給付標準

適用於110年9月2日以前發生之藥害事件

藥害救濟給付計算裁量表　　修正

1. 適用於 110 年 9 月 2 日以前發生之藥害事件：

藥害救濟給付（點數）＝ 基本給付（點數）＋ 附加給付（點數）

每點折合新臺幣五萬元

救濟項目	基本給付（單位：點）	附加給付　（單位：點）		給付金額範圍（單位：新臺幣萬元）
死亡給付	32	受害人有下列親屬之一者，得另計附加給付： 一、 配偶 二、 未成年子女或領有殘障手冊之子女 三、 父母	給付點數 8	160-200
	其他：無法確認或排除死亡原因係藥害所致者，視個案具體情狀暨其死亡與使用藥品產生不良反應之關聯程度，另行酌予給付。			最高 100 萬元

救濟項目	基本給付（單位：點）		附加給付　（單位：點）		給付金額範圍（單位：新臺幣萬元）
	障礙等級	給付點數	受害人有下列親屬之一者，得另計附加給付： 一、配偶 二、未成年子女或領有殘障手冊之子女 三、父母	給付點數	
障礙給付	極重度	30		10	150—200
	重度	22		8	110—150
	中度	20		6	100—130
	輕度	19		4	95—115
	其他：無法確認或排除障礙原因係藥害所致者，視個案具體情狀暨障礙與使用藥品產生不良反應之關聯程度，另行酌予給付。				

救濟項目	給付金額範圍	給付金額範圍
嚴重疾病給付	於醫療機構住院期間或延長住院期間，所支出並具有正式收據之必要醫療費用。	最高 60 萬元
	無法確認或排除嚴重疾病原因係藥害所致者，視個案具體情狀暨其嚴重疾病與使用藥品產生不良反應之關聯程度，另行酌予給付。	
	因病情需要住入加護病房或燒燙傷病房者，得酌予增加救濟給付。	

適用於110年9月3日以後發生之藥害事件 (1)

藥害救濟給付計算裁量表　　修正

2. 適用於 110 年 9 月 3 日以後發生之藥害事件：

救濟給付種類		藥品與藥害之關聯程度	給付金額範圍（單位：新臺幣萬元）	備註
死亡給付		極高	225-300	
		高	150-225	
		中	75-150	
		低	最高 75	
障礙給付	極重度	極高	225-300	依受害人之受害醫療處置及自身既有疾病與危險因子，視藥品與藥害之關聯程度，審定給付金額。
		高	150-225	
		中	75-150	
		低	最高 75	
	重度	極高	170-225	
		高	115-170	
		中	55-115	
		低	最高 55	

適用於110年9月3日以後發生之藥害事件 (2)

藥害救濟給付計算裁量表　　修正

2. 適用於 110 年 9 月 3 日以後發生之藥害事件：

救濟給付種類		藥品與藥害之關聯程度	給付金額範圍（單位：新臺幣萬元）	備註
障礙給付	極重度	極高	225-300	依受害人之受害醫療處置及自身既有疾病與危險因子，視藥品與藥害之關聯程度，審定給付金額。
		高	150-225	
		中	75-150	
		低	最高 75	
	重度	極高	170-225	
		高	115-170	
		中	55-115	
		低	最高 55	
	中度	極高	145-195	
		高	100-145	
		中	50-100	
		低	最高 50	
	輕度	極高	130-175	
		高	90-130	
		中	45-90	
		低	最高 45	

適用於110年9月3日以後發生之藥害事件 (3)

藥害救濟給付計算裁量表　　修正

2. 適用於 110 年 9 月 3 日以後發生之藥害事件：

救濟給付種類	藥品與藥害之關聯程度	給付金額範圍（單位：新臺幣萬元）	備註
嚴重疾病給付	有關聯	1-60	(1) 給付受害人於醫療機構住院期間或延長住院期間，所支出並具有正式收據之必要醫療費用。 (2) 經審定無法確認或排除嚴重疾病原因係藥害所致者，視個案具體情狀暨其嚴重疾病與藥品之關聯程度酌予給付。 (3) 因病情需要住入加護病房或燒燙傷病房者，得酌予增加救濟給付。

藥害救濟給付原則 為人道救濟而非過失賠償

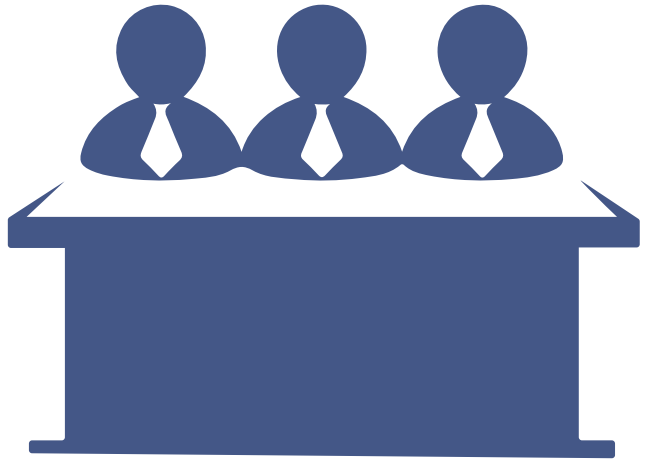
死亡給付、障礙給付、嚴重疾病給付

- 可合理認定係因藥品之不良反應致死亡/障礙者，依給付裁量表之金額範圍給付。無法排除其相關性者，於最高額度內酌予給付
- 嚴重疾病類別，給付其至醫療機構診療所支出並具有正式收據之必要醫療費用
- 給付內容並不包含：

  精神賠償、看護費用、工作賠償、其他：如交通費用等

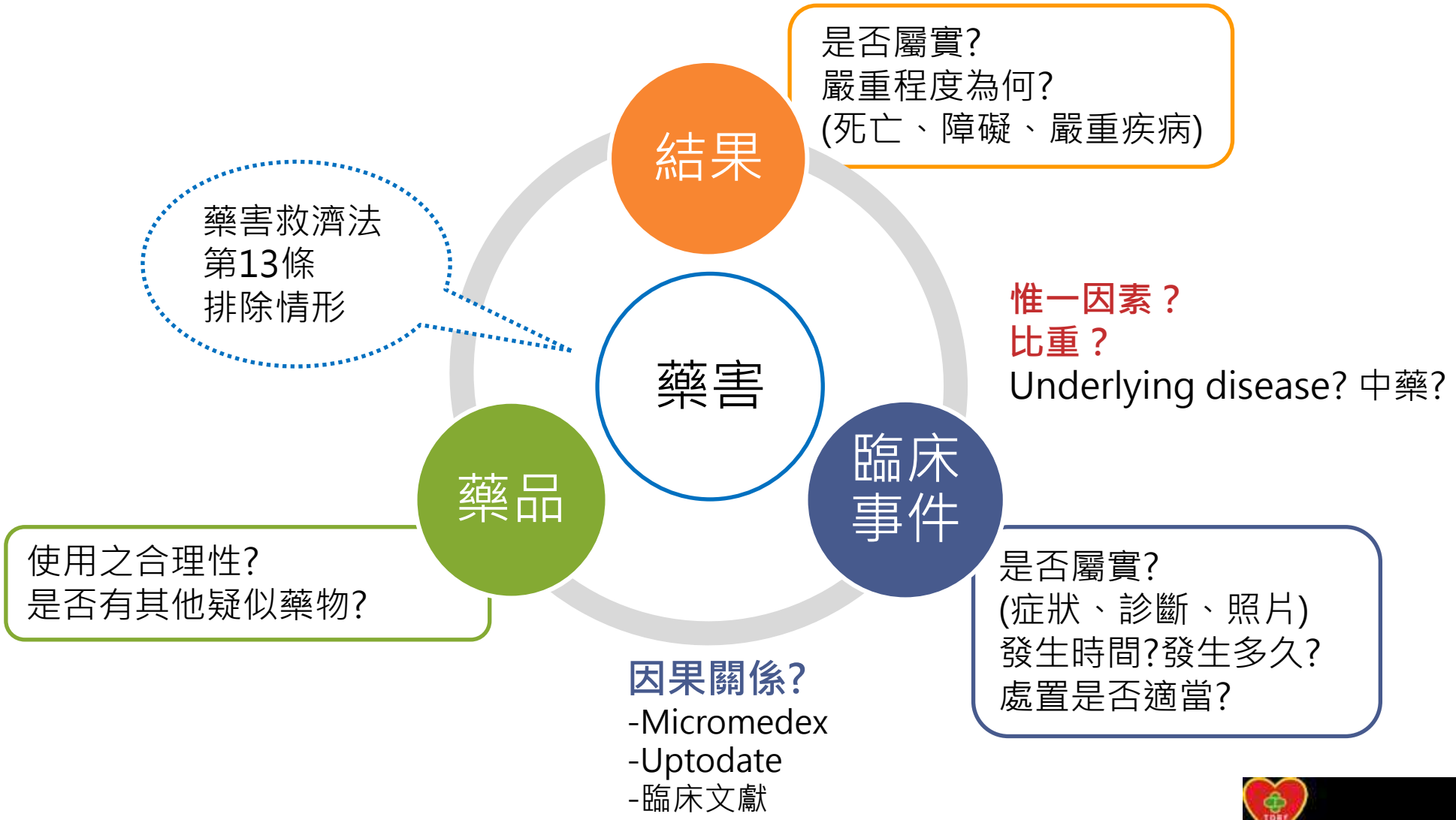
藥害救濟審議組織

藥害救濟法第15條



- 主管機關為辦理藥害救濟及給付金額之審定，應設藥害救濟審議委員會；其組織及審議辦法，由主管機關定之。
- 藥害審議委員會置委員11至17人，由主管機關遴聘醫學、藥學、法學專家及社會公正人士擔任之，其中法學專家及社會公正人士不得少於三分之一。

藥害救濟審議原則（通則）


是否屬實?
嚴重程度為何?
(死亡、障礙、嚴重疾病)
結果
藥害救濟法
第13條
排除情形
藥害
惟一因素？
比重？
Underlying disease? 中藥?
藥品
臨床事件
使用之合理性?
是否有其他疑似藥物?
是否屬實?
(症狀、診斷、照片)
發生時間?發生多久?
處置是否適當?
因果關係?
-Micromedex
-Uptodate
-臨床文獻

為什麼藥害救濟申請不通過?

本法施行前

已獲賠償

適應症外使用

臨床試驗用藥物

其他經
主管機關公告
之情形

人為過失

打疫苗受害

輕微的不良反應

常見且可預期

申請不一定會通過救濟

註：
包含所有《藥害救濟法》
第13條項目

為什麼藥害救濟申請不通過?

人為過失

有人應對藥害負責

如.吃錯藥、開錯藥...

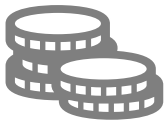
打疫苗受害

依傳染病防治法申請

預防接種受害救濟

本法施行前

本法施行前已發見之藥害



已獲賠償

同一原因事實已獲賠償，

但不含人身保險給付在內

*藥害救濟法第13條參照


藥害救濟 VS.
預防接種受害救濟
制度內容不相同，自身權益一次搞懂
藥害救濟
預防接種受害救濟
制度
中央主管機關
衛生福利部（食品藥物管理署）
衛生福利部（疾病管制署）
救濟金來源
國庫：藥害救濟基金
國庫：預防接種受害救濟基金
適用藥物範圍
領有中央主管機關核發藥物許可證之藥物
領有中央主管機關核發許可證或專案核准進口，並經檢驗或書面審查合格之疫苗
給付種類
死亡、障礙或嚴重疾病給付
死亡、障礙、嚴重疾病或其他不良反應給付
向誰申請
財團法人藥害救濟基金會
接種地所屬地方衛生局
向誰諮詢
財團法人藥害救濟基金會
諮詢專線：02-2358-4097
地方衛生局或
疾病管制署諮詢專線：1922
申請期限
自請求權人知有藥害時起3年內
自請求權人知有受害情事日起2年內；或自受害發生日起5年內
廣告
FDA 衛生福利部食品藥物管理署
財團法人藥害救濟基金會

為什麼藥害救濟申請不通過?

輕微的不良反應
未達死亡、障礙或嚴重疾病(住院)程度

臨床試驗用藥物
急救時超量藥物

適應症外使用
符合當時醫學原理及用藥適當性者，不在此限

常見且可預期
WHO定義發生率≧1%為common[常見]

其他經主管機關公告之情形

*藥害救濟法第13條參照

適應症外使用藥品之審議原則

（100.09.28行政院衛生署令）

- 藥害救濟法第十三條第八款所稱「符合當時醫學原理及用藥適當性者不在此限」，其審議原則如下：

  一. 有「藥品查驗登記審查準則」所稱十大醫藥先進國家已經核准之適應症，而我國尚未核准之情形，列為符合醫學原理之參考文獻之一。

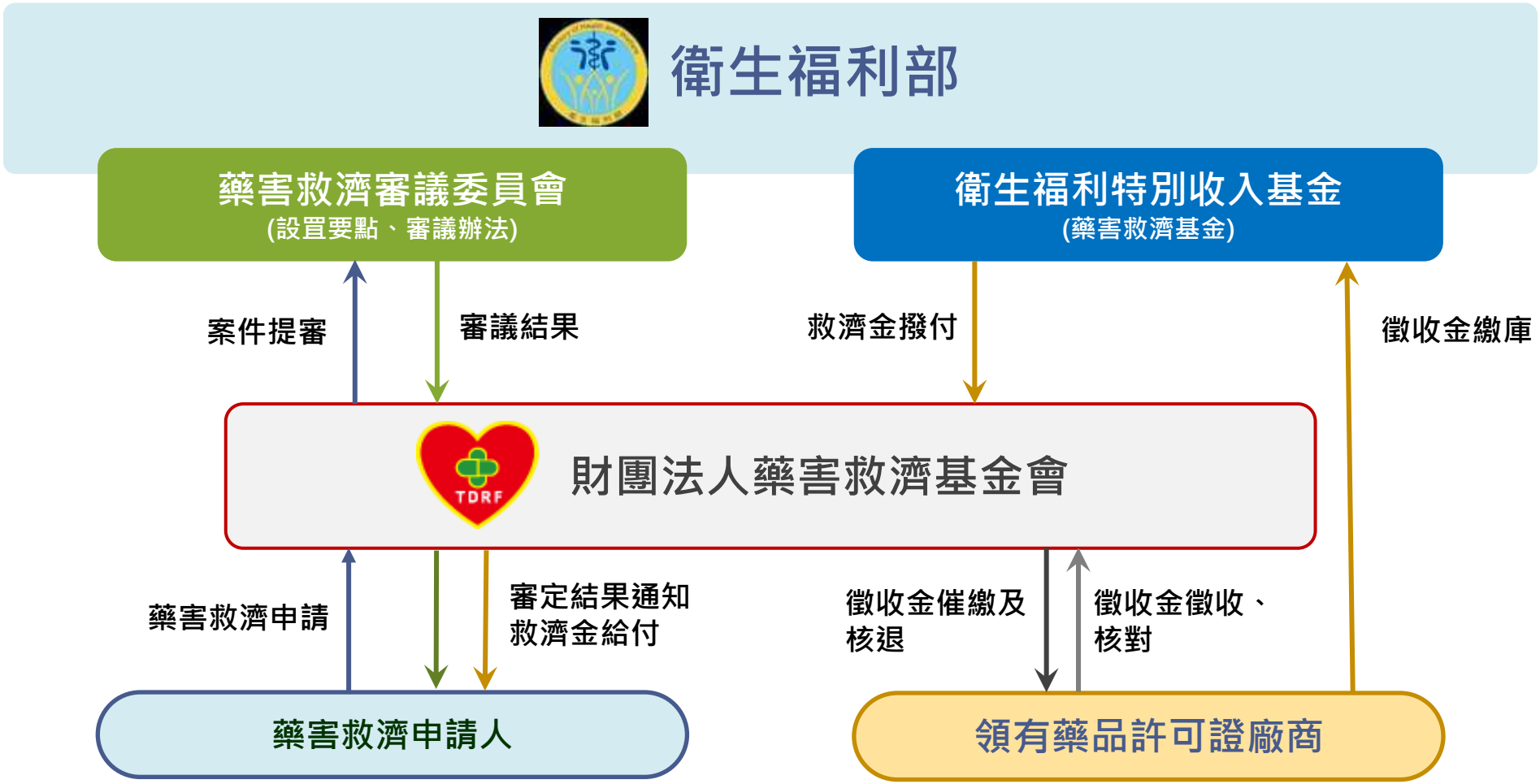
  二. 所治療疾病已收載於國內外專科醫學會或政府機關出版之臨床診治指引。

  三. 屬於傳統治療方法，且已廣為臨床醫學教學書籍收載列為治療可選用藥物（drugs of choice），並符合目前醫學常規等。另，必要時可由本署藥害救濟審議委員會請相關專科醫學會提供專業治療指引。

- 符合前項原則之案件，仍應由行政院衛生署藥害救濟審議委員會視整體個案情形判斷之。

藥害救濟申請及作業流程

藥害救濟業務運作圖


衛生福利部
藥害救濟審議委員會
(設置要點、審議辦法)
衛生福利特別收入基金
(藥害救濟基金)
案件提審
審議結果
救濟金撥付
徵收金繳庫
財團法人藥害救濟基金會
藥害救濟申請
審定結果通知
救濟金給付
徵收金催繳及
核退
徵收金徵收、
核對
藥害救濟申請人
領有藥品許可證廠商

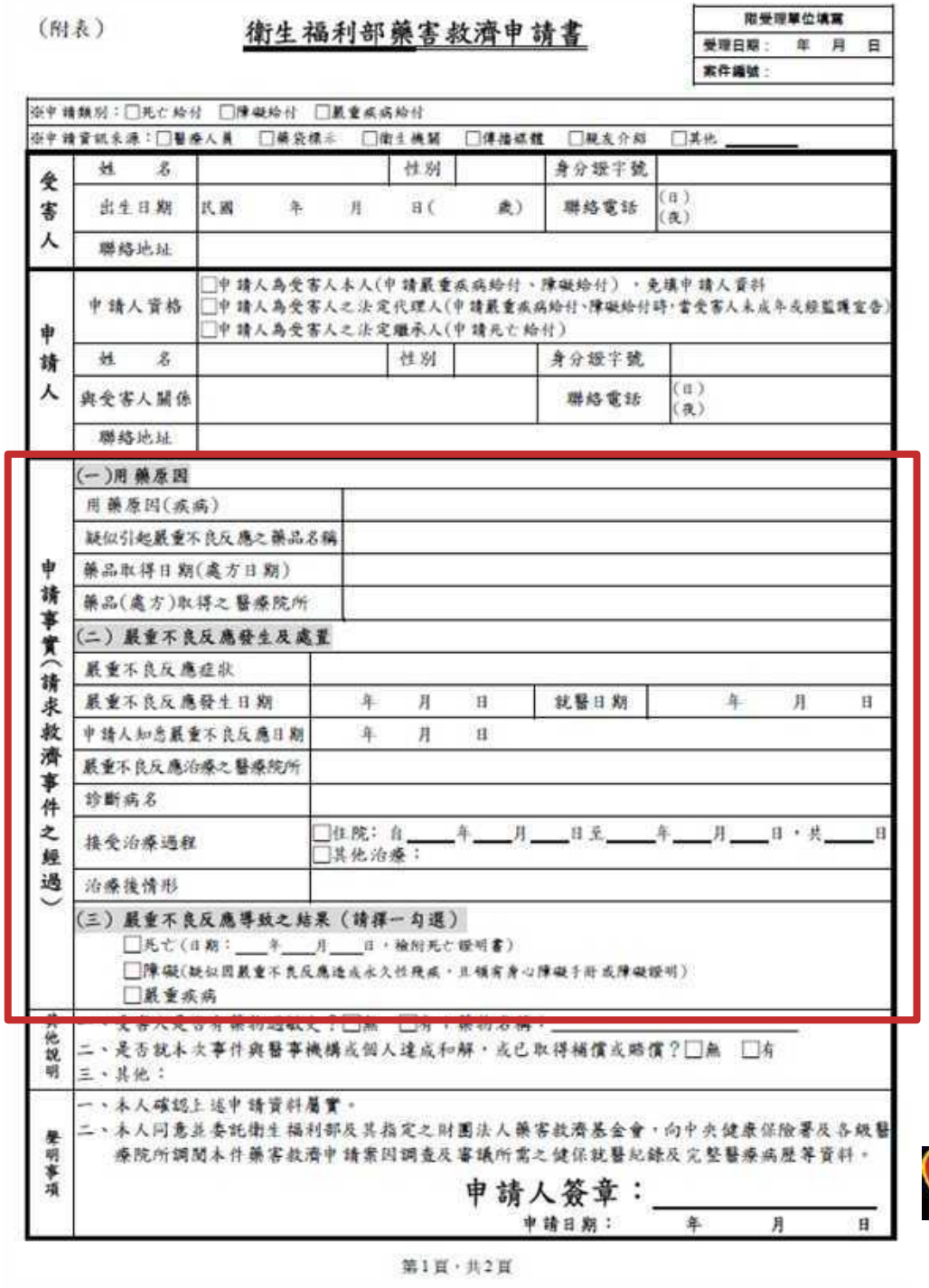
藥害救濟申請書

第一頁

受害人

申請人

申請事實



（附表）

衛生福利部藥害救濟申請書

由受理單位填寫
受理日期：　年　月　日
案件編號：

由申請類別：□死亡給付　□障礙給付　□嚴重疾病給付

由申請資訊來源：□醫療人員　□藥袋標示　□衛生機關　□傳播媒體　□親友介紹　□其他＿＿＿＿

受害人	姓　名		性別	身分證字號	
	出生日期	民國　年　月　日（　歲）		聯絡電話	（日） （夜）
	聯絡地址				
申請人	申請人資格	□申請人為受害人本人（申請嚴重疾病給付、障礙給付），免填申請人資料 □申請人為受害人之法定代理人（申請嚴重疾病給付、障礙給付時，當受害人未成年或經監護宣告） □申請人為受害人之法定繼承人（申請死亡給付）			
	姓　名		性別	身分證字號	
	與受害人關係			聯絡電話	（日） （夜）
	聯絡地址				
申請事實（請求救濟事件之經過）	（一）用藥原因				
	用藥原因（疾病）				
	疑似引起嚴重不良反應之藥品名稱				
	藥品取得日期（處方日期）				
	藥品（處方）取得之醫療院所				
	（二）嚴重不良反應發生及處置				
	嚴重不良反應症狀				
	嚴重不良反應發生日期	年　月　日	就醫日期	年　月　日	
	申請人知悉嚴重不良反應日期	年　月　日			
	嚴重不良反應治療之醫療院所				
	診斷病名				
	接受治療過程	□住院：自＿＿年＿＿月＿＿日至＿＿年＿＿月＿＿日，共＿＿日 □其他治療：			
	治療後情形				
	（三）嚴重不良反應導致之結果（請擇一勾選）				
	□死亡（日期：＿＿年＿＿月＿＿日，檢附死亡證明書）				
	□障礙（疑似因嚴重不良反應造成永久性殘疾，且領有身心障礙手冊或障礙證明）				
	□嚴重疾病				
其他說明	一、是否人是否有藥物過敏史？□無　□有，藥物名稱：＿＿＿＿				
	二、是否就本次事件與醫事機構或個人達成和解，或已取得補償或賠償？□無　□有				
	三、其他：				
聲明事項	一、本人確認上述申請資料屬實。				
	二、本人同意並委託衛生福利部及其指定之財團法人藥害救濟基金會，向中央健康保險署及各級醫療院所調閱本件藥害救濟申請案因調查及審議所需之健保就醫紀錄及完整醫療病歷等資料。				
	申請人簽章：＿＿＿＿＿＿				
	申請日期：　年　月　日				

第1頁，共2頁

藥害救濟申請書

第一頁

申請需檢附資料

申請藥害救濟應注意事項

申請需檢附資料：

請寄：100台北市中正區愛國東路22號10樓　財團法人藥害救濟基金會 收

申請死亡給付	申請障礙給付	申請嚴重疾病給付
1. 申請書正本 2. 受害前後病歷摘要 3. 受害後診斷證明書 4. 死亡證明 5. 解剖報告影本(若有，請檢附) 6. 申請人身分證正反面影本 7. 戶口名簿影本	1. 申請書正本 2. 受害前後病歷摘要 3. 診斷證明書 4. 身心障礙手冊或障礙證明正反面影本 5. 身分證正反面影本 6. 戶口名簿影本(申請人為法定代理人時檢附)	1. 申請書正本 2. 受害前後病歷摘要 3. 診斷證明書 4. 醫療費用收據影本 5. 身分證正反面影本 6. 戶口名簿影本(申請人為法定代理人時檢附)

申請藥害救濟應注意事項：

一、藥害救濟之請求權人如下：
（一）死亡給付：受害人之法定繼承人。
（二）障礙給付或嚴重疾病給付：受害人本人或其法定代理人。
二、藥害救濟之申請，請求權人應自知有藥害時起，三年內為之。
三、有下列各款情事之一者，不得申請藥害救濟：
（一）有事實足以認定藥害之產生應由藥害受害人、藥物製造業者或輸入業者、醫師或其他之負其責任。
（二）本法施行前已發現之藥害。
（三）因接受預防接種而受害，而得依其他法令獲得救濟。
（四）同一原因事實已獲賠償或補償，但不含人身保險給付在內。
（五）藥物不良反應未達死亡、身體障礙或嚴重疾病之程度。
（六）因急救使用超量藥物致生損害。
（七）因使用試驗用藥物而受害。
（八）未依藥物許可證所載之適應症或效能而為藥物之使用，但符合當時醫學原理及用藥適者，不在此限。
（九）常見且可預期之藥物不良反應。
（十）其他經主管機關公告之情形
四、藥害救濟申請人檢附之資料不合程式者，主管機關或其所委託之機關（構）、團體得通知正。藥害救濟申請人應於接獲通知後三十日內補正，逾期不補正者，不予受理。前項補正有正當理由，藥害救濟申請人得於三十日補正期間屆滿前，申請延期一次。但延長期間不逾三十日。
五、藥害救濟請求權人對救濟給付之審定如有不服，須於處分到達次日起三十日內，提起訴願
六、藥害救濟審議結果僅作為判定救濟與否之依據，其是否成立其他民、刑事責任，應以司法關裁判為準。
七、已領取藥害救濟給付而基於同一原因事實取得其他賠償或補償者，於取得賠償或補償之內，應返還其領取之藥害救濟給付。但自人身保險所取得之給付不在此限。

以上規定，本人均已知悉，並願意遵守

此致　衛生福利部

申請人簽章：_____

藥害救濟申請應檢附文件

嚴重疾病類別	障礙類別	死亡類別
申請書正本	申請書正本	申請書正本
受害前後病歷摘要	受害前後病歷摘要	受害前後病歷摘要
診斷證明書	診斷證明書	受害後診斷證明書
醫療費用收據影本	**障礙證明正反面影本**	**死亡證明**
身分證正反面影本	身分證正反面影本	解剖報告影本(若有)
戶口名簿影本（申請人為法定代理人時檢附）	戶口名簿影本（申請人為法定代理人時檢附）	申請人身分證正反面影本
		戶口名簿影本

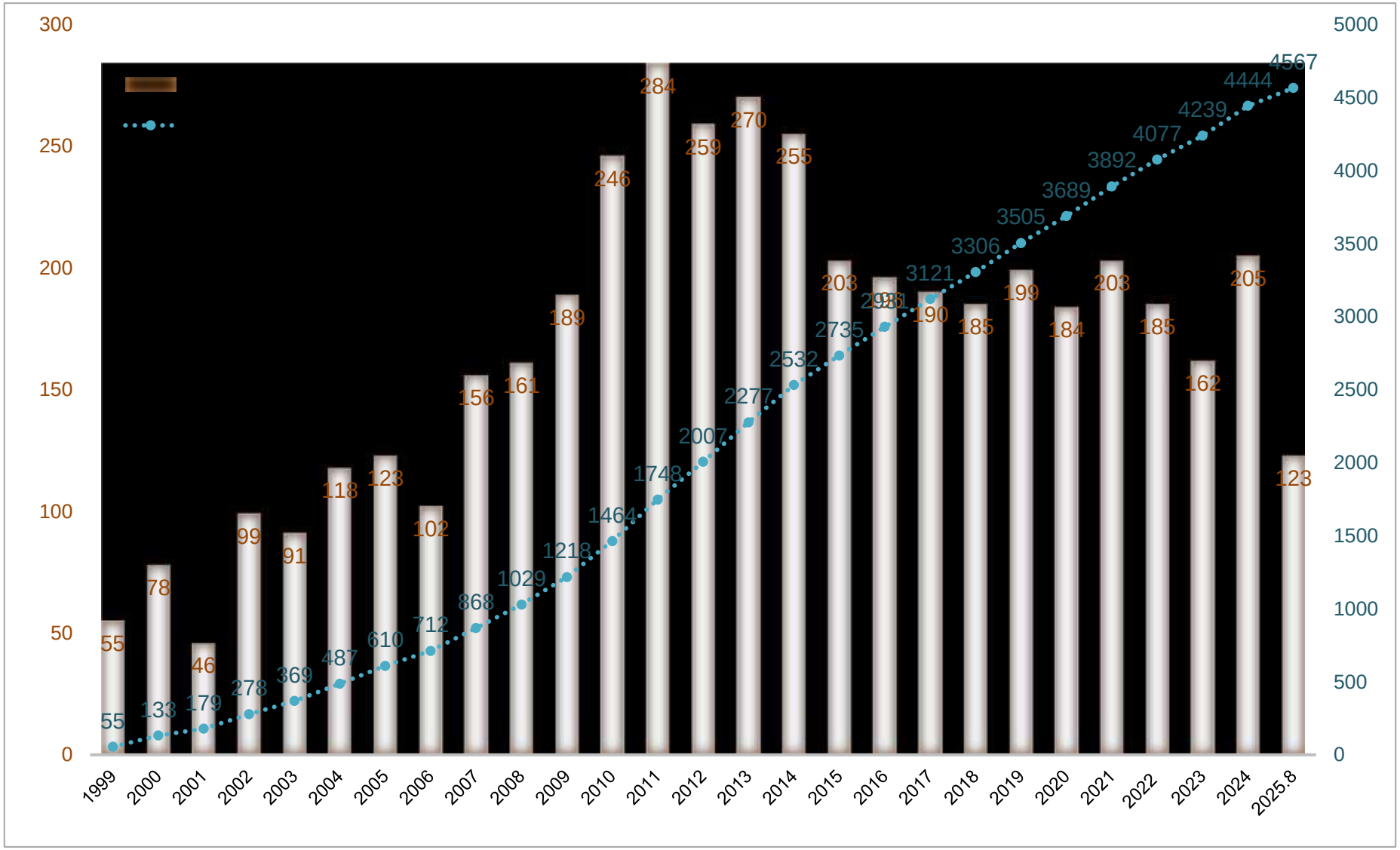
申請書需簽名正本，其餘文件檢附影本

藥害救濟申請作業

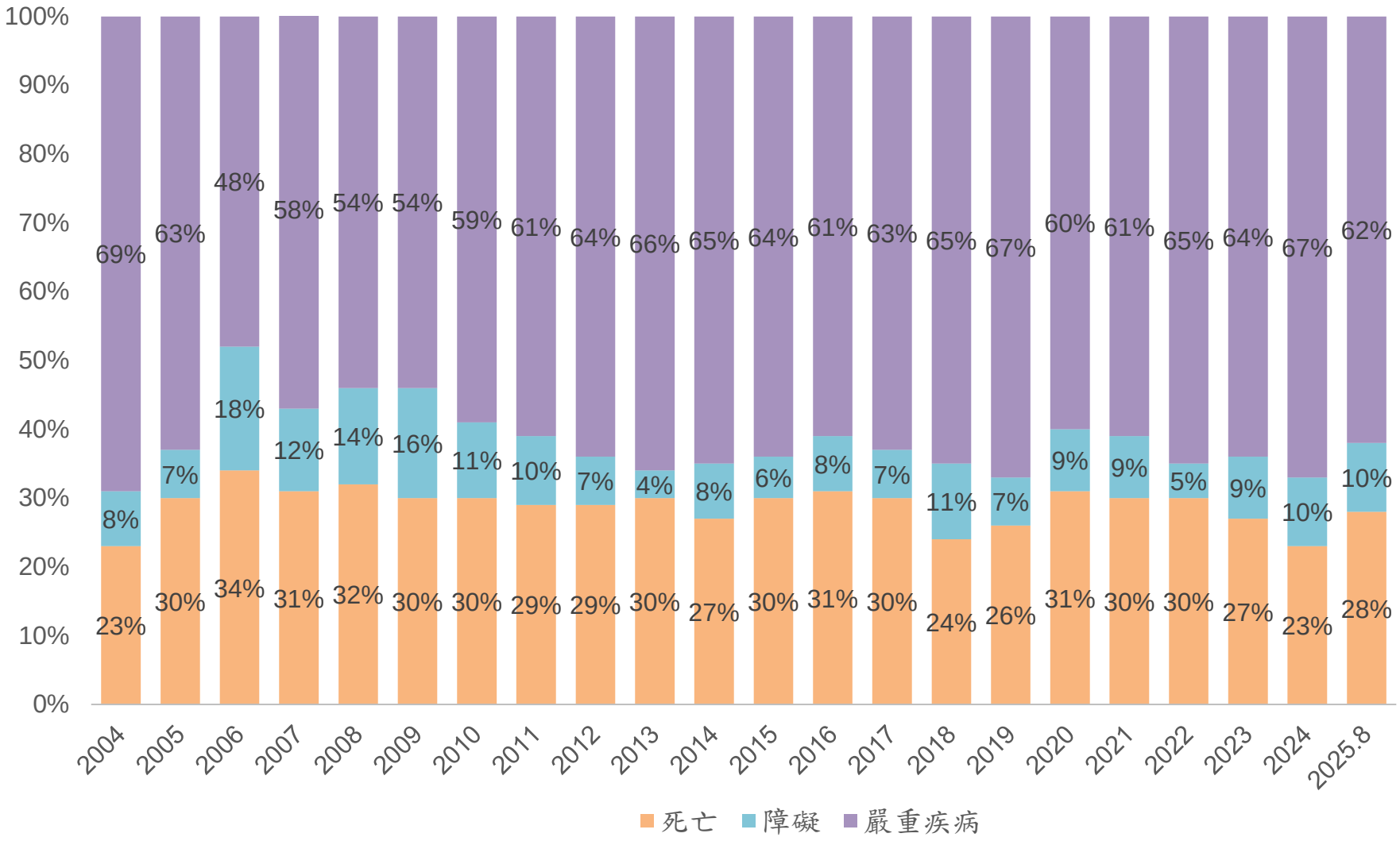
依據個案案情複雜程度不同，
從**受理通知**到**審議結果**一般需費時6~9個月不等

藥害救濟業務

歷年藥害救濟申請案件數統計



歷年藥害救濟受理案件申請類別統計圖



*不含預防接種受害救濟案件

歷年給付類別及金額之性別差異統計

*不含預防接種受害救濟案件

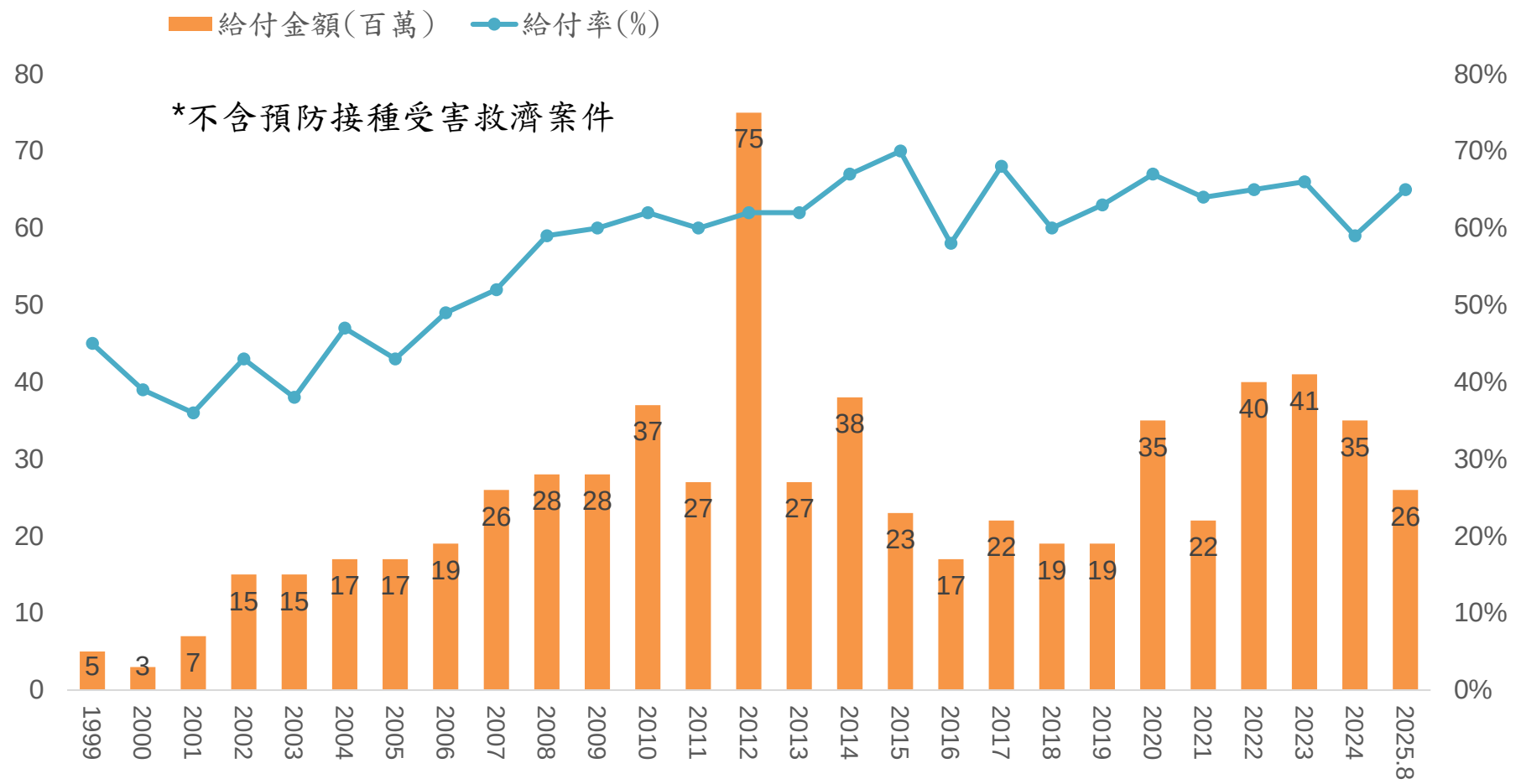
(1999 –2025.8)

給付類別	性別		案件數	性別		總金額(元)
	女	男		女	男	
死亡給付	294	424	718	NT$208,947,500	NT$297,903,750	NT$506,851,250
障礙給付	66	56	122	NT$63,750,542	NT$53,616,588	NT$117,367,130
嚴重疾病給付	946	764	1710	NT$39,532,665	NT$31,271,006	NT$70,803,671
總計	1306	1244	2550	NT$312,230,707	NT$382,791,344	NT$695,022,051

第1～389次審議會

歷年通過救濟之金額與給付率

(1999 –2025.8)



總給付金額為$6億9,502萬2,051元 ；

平均獲得救濟比率為 59.85%

藥害救濟給付案之前五大藥品不良反應統計 (1)

(1999 –2025.8)

*不含預防接種受害救濟案件

不良反應類別	性別		總計	症狀分類	小計
	女	男			
Skin and subcutaneous tissue disorders 皮膚及皮下組織疾患	885	813	1698 (66.59%)	Stevens Johnson Syndrome 史蒂文生氏-強生症候群	873
				Toxic Epidermal Necrolysis 毒性表皮壞死溶解症(包含SJS/TEN overlap)	326
				Drug reaction with Eosinophilia and Systemic Symptoms 藥物疹合併嗜伊紅血症及全身症狀	218
				Other 其他	281
Hepatobiliary disorders 肝膽疾患	95	127	222 (8.71%)	Hepatitis (急性)肝炎	87
				Hepatic failure (急性)肝衰竭	56
				Drug-induced liver injury 藥物性肝傷害	26
				Fulminant Hepatitis 猛爆性肝炎	24
				Other 其他	29
Immune system disorders 免疫系統疾患	94	107	201 (7.88%)	Anaphylactic shock 過敏性休克	158
				Drug hypersensitivity 藥物過敏	26
				Other 其他	17

第1～389次審議會

藥害救濟給付案之前五大藥品不良反應統計 (2)

(1999 –2025.8)

*不含預防接種受害救濟案件

不良反應類別	性別 女	性別 男	總計	藥品不良反應	小計
Blood and lymphatic system disorders 血液及淋巴系統疾患	77	31	108 (4.24%)	Agranulocytosis 顆粒性白血球減少症	36
				Pancytopenia 全血球減少症	28
				Thrombocytopenia 血小板減少症	12
				Neutropenia 嗜中性球減少症	10
				Leukopenia 白血球低下症	7
				Other 其他	15
Nervous system disorders 神經系統疾患	42	46	88 (3.45%)	Neuroleptic malignant syndrome 抗精神病藥物惡性症候群	18
				Encephalopathy 腦病變	7
				Cerebral infarction腦梗塞	6
				Hypoxic-ischaemic encephalopathy 缺氧性腦病變	5
				Other 其他	52

第1～389次審議會

藥害救濟給付案之可疑藥品前十名

(1999 –2025.8)

排名	藥品成分	案例數
1	Allopurinol	283
2	Rifampin/Isoniazid/Pyrazinamide (單方或複方)	162
3	Phenytoin	160
4	Carbamazepine	146
5	Diclofenac	110
6	Co-trimoxazole	93
7	Lamotrigine	70
8	Ibuprofen	68
9	Sulfasalazine	66
10	Mefenamic acid	63

第1～389次審議會

審定結果不予救濟之理由分析

排名	不予救濟給付原因	性別		總計
		女	男	
1	與藥品無相關	312	355	667
2	常見且可預期之藥物不良反應	206	228	434
3	未依藥物許可證所載之適應症或效能而為藥物之使用	176	122	298
4	有事實足以認定藥害之產生應由藥害受害人、藥物製造業者或輸入業者、醫師或其他之人負其責任	45	55	100
5	藥物不良反應未達死亡、障礙或嚴重疾病之程度	46	51	97
6	藥害救濟之請求權，自請求權人知有藥害時起，因三年間不行使而消滅	18	11	29
7	非屬藥害救濟法第3條第1款所稱因藥物不良反應致死亡、障礙或嚴重疾病之藥害	15	7	22
8	同一原因事實已獲賠償或補償。但不含人身保險給付在內	13	5	18
9	本法施行前已發見之藥害	8	6	14
9	非屬現行藥害救濟法第3條第2款所稱領有主管機關核發藥物許可證，依法製造、輸入或販賣之藥物	7	7	14
9	其他經主管機關公告之情形	7	7	14
10	退件或請求權人資格不符	2	0	2
11	因接受預防接種而受害，而得依其他法令獲得救濟	0	1	1
11	因使用試驗用藥物而受害	0	1	1
	總計	855	856	1711

第1～389次審議會

抗生素相關案例之疑似藥品類別 Top 5

(1999 –2024)

排名	藥物類別	ATC編碼	筆數	百分比
1	**Combinations of penicillins, incl. beta-lactamase inhibitors** *（例如: Amoxicillin/Clavulanate、Piperacillin/Tazobactam）*	J01CR	136	14.66%
2	**First-generation cephalosporins** *（例如: Cephalexin、Cefazolin、Cefadroxil）*	J01DB	121	13.04%
3	**Fluoroquinolones** *（例如: Levofloxacin、Ciprofloxacin、Moxifloxacin）*	J01MA	118	12.72%
4	**Combinations of sulfonamides and trimethoprim, incl. derivatives** *（例如: Co-trimoxazole）*	J01EE	91	9.81%
5	**Third-generation cephalosporins** *（例如: Ceftriaxone、Ceftazidime）*	J01DD	85	9.16%

第1～381次審議會

抗生素相關案例之不良反應類型 Top 3

(1999 –2024)

不良反應類型	總計	症狀分類	件次	該類別百分比
Skin and subcutaneous tissue disorders 皮膚及皮下組織疾患	534 (78.65%)	Stevens Johnson Syndrome 史蒂文生氏-強生症候群	255	47.75%
		Toxic Epidermal Necrolysis 毒性表皮壞死溶解症(包含SJS/TEN overlap)	147	27.53%
		Drug reaction with Eosinophilia and Systemic Symptoms 藥物疹合併嗜伊紅血症及全身症狀	48	8.99%
		Other 其他	84	15.73%
Immune system disorders 免疫系統疾患	66 (9.72%)	Anaphylactic shock 過敏性休克	55	83.33%
		Drug hypersensitivity 藥物過敏	9	13.64%
		Other 其他	2	3.03%
Hepatobiliary disorders 肝膽疾患	22 (3.24%)	Hepatitis (急性)肝炎	7	31.82%
		Hepatic failure (急性)肝衰竭	5	22.73%
		Drug-induced liver injury 藥物性肝傷害	4	18.18%
		Other 其他	6	27.27%

第1～381次審議會

結語

預防藥害的超前部署

1. **重視藥品安全資訊**

   –藥品仿單（說明書）與最新藥物安全警訊

3. **處方前後監測追蹤**

   –藥品過敏史

   –定期安排追蹤檢查（e.g., 肝腎功能、血液檢查、視力追蹤）

3. **告知、提醒及溝通**

   –可能發生的不良反應、症狀與因應方法

   –off-label use

結語

- **藥物傷害**

  可預防的應儘量避免

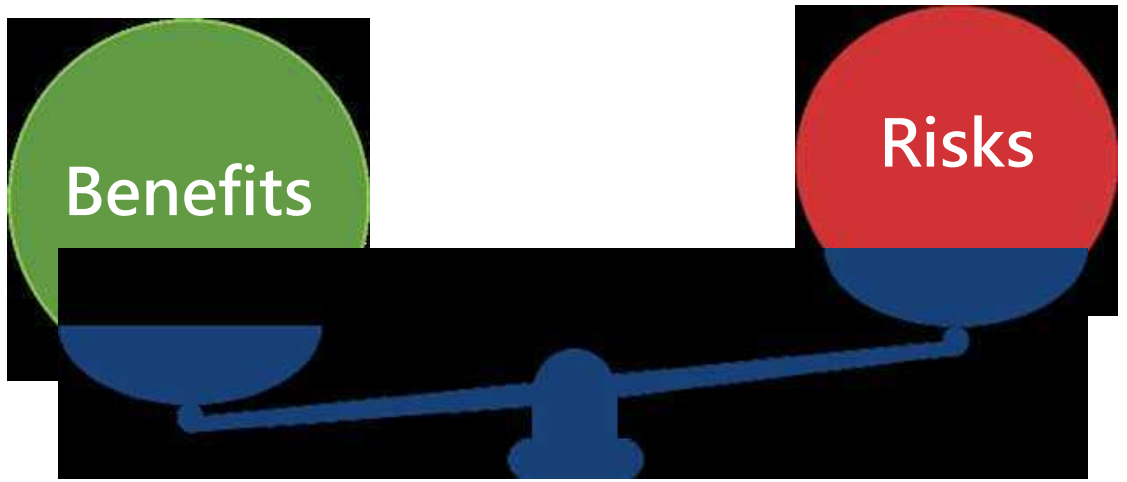
  不可預防的應謹慎監測

- **藥害救濟制度**

  使受害民眾獲得及時救濟

  減少不必要的訴訟

  從事後救濟到事前預防



效益　V.S　風險

就診時，擔心過敏藥物資訊不完整?

健保醫療資訊雲端查詢系統可查詢及登錄保險對象之過敏藥物及症狀

瞭解更多

健保醫療資訊

雲端查詢系統

藥害救濟基金會【醫識能藥識能】：用藥安全資訊，強化醫病正確用藥溝通

財團法人藥害救濟基金會
Taiwan Drug Relief Foundation

關於基金會　最新消息　藥物安全　藥害救濟　醫療關懷　健康醫療知識庫

健康醫療知識庫

- 醫識能藥識能
  - 用藥安全資訊
  - 醫病關懷溝通
- 藥害救濟案例分享
- 用藥安全圖文插畫
- 媒體影音
- 出版刊物
- 衛教文宣下載

首頁 / 健康醫療知識庫 / 醫識能藥識能 / 用藥安全資訊

【醫識能·藥識能】抗生素錯誤認知，小心害了你！

2025/6/2

抗生素的發明與應用，成為數十年來挽救人類生命的重要利器，然而錯誤使用抗生素將可能煉成超級細
不良反應發生，民眾要如何趨吉避凶，藥害救濟基金會整理坊間流傳之抗生素錯誤認知，幫助民眾正確

你的抗生素好像很有效 給我試試看?!

因每個人的體質、病況、生理狀況等都不盡相同，無論使用任何藥品，都須經過醫師或藥師等醫療專業
使用，皆不建議私相授受。抗生素的使用須考量的層面甚廣，如菌株對抗生素的感受性(antimicrobial
染部位、病患的肝腎功能、發生藥品不良反應之風險因子等，醫學文獻即指出[1,2]，氟喹諾酮(fluoroquir
(macrolides)抗生素對女性、年老者、先天性QT延長、心肌梗塞或患有其他心臟相關疾病等族群，可能
長(此為嚴重心律不整的前兆)，且以上風險因子越多，發生機率越高。

藥害救濟基金會提醒，若是隨意拿別人或與他人交換抗生素服用，除了易產生抗藥性之外，將無法預估
風險；此外，若因吃別人的藥品而發生嚴重藥品不良反應，因藥品非正當合法使用，將無法申請藥害救
益，民眾應於就診後取得藥品服用，以免賠了夫人又折兵。

《透視藥害危機》新書推薦

— 臨床、法務與社工人員的實務應對指南 —

《透視藥害危機：臨床案例解析及關鍵50問》聚焦於**藥品風險**、**臨床案例**、**制度運作與實務經驗**，是一本深入淺出的專業書籍。

無論你是醫療人員、法務、社工，或是關心公共健康的讀者，都值得一讀。歡迎各界索取參閱。

本書於博客來、誠品等各大網路書店上架販售，請上網搜尋《透視藥害危機》

書中涵蓋：

- 藥害事件的臨床案例與分析
- 臨床風險辨識的重點與盲點
- 藥害救濟制度的適用條件與申請流程
- 民眾常見用藥誤解與風險觀念釐清

【書籍索取資訊】

開放機關團體申請索取，依申請數量酌收圖書處理費。
(郵資另計)

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