

ICU-acquired complications

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Attributable mortality of an ICU-acquired complication?

Are there specific (immune system) pathways leading to an ICU-acquired complication?

ICU-acquired complications in MARS

- Infections HAP / VAP
- ARDS
- Acute Kidney Injury
- Thromboses/clots
- Bedsores
- Myocardial infarction
- Delirium

Appropriate quantification of the impact and burden of these complications are imperative to understanding its severity and the importance of additional preventive measures and timely treatment.

All these complications are all associated with increased ICU mortality, but....the well-known mantra "correlation does not imply causation" dictates that a considerable number of patients die with, but not necessarily from, the complication.

Causal inference – counterfactual interpretation

Counterfactual:

If I could theoretically prevent a ICU-acquired complication, how many lives are saved?

Solution: create a pseudo-ICU-population that has exactly the same trajectory (severity of disease, sepsis, treatments etc) towards ICU-acquired complication, but then it was prevented (in theory).

Full definition of our counterfactual model ICU-acquired complications (1)

Estimation of ICU mortality due to ICU-acquired complication, which expresses the proportion of preventable death cases in the ICU in the absence of a ICU-acquired complication.

This (inherently causal) effect measure involves:

the nonobservable counterfactual incidence of ICU death that would have been observed if, counter to the fact, a ICU-acquired complication had been avoided in all considered patients.

	Definition	Formula
Attributable mortality (AM)	Increase or decrease in death (D) if a patient presents an exposure (E) at the time (t).	AM(t) = P[D(t) = 1 E(t) = 1] - P[D(t) = 1 E(t) = 0]
Attributable fraction (AF)	 Proportion of deaths (D) that are attributable to an exposure (E) at the time (t). Proportion of deaths (D) that would not have occurred if no patient presented the exposure (E) at the time (t). 	$AF(t) = \{(P[D(t) = 1] - P[D(t) = 1 E(t) = 0]\}/P[D(t) = 1]$

Original Investigation | Caring for the Critically Ill Patient

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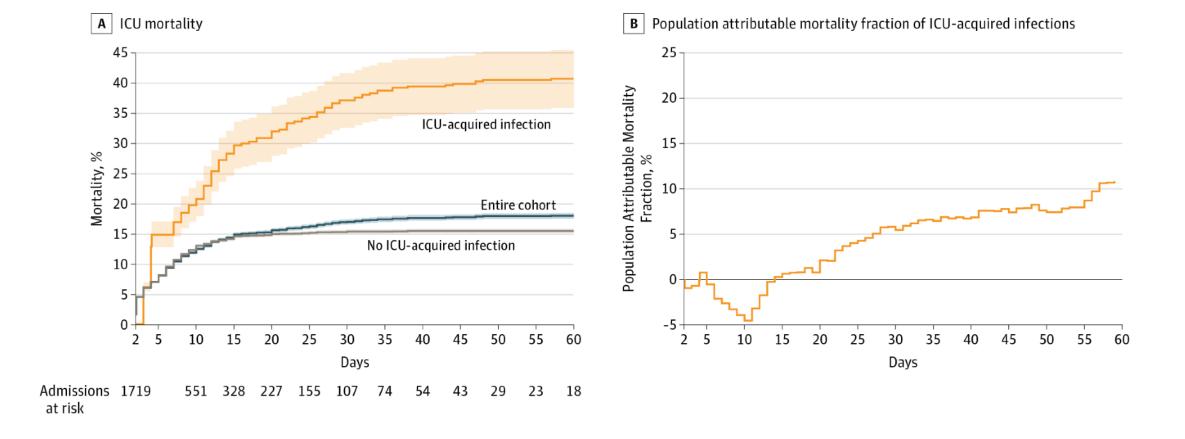
April 12, 2016

Incidence, Risk Factors, and Attributable Mortality of Secondary Infections in the Intensive Care Unit After Admission for Sepsis

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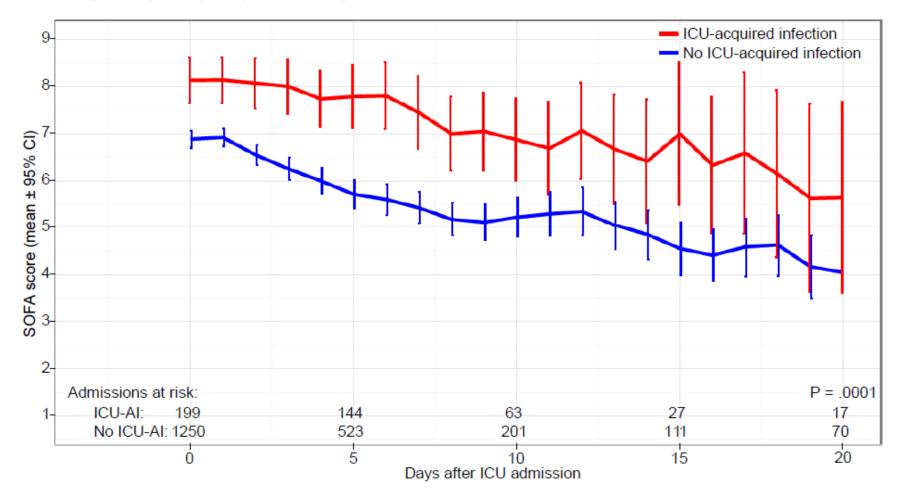
JAMA. 2016;315(14):1469-1479. doi:10.1001/jama.2016.2691



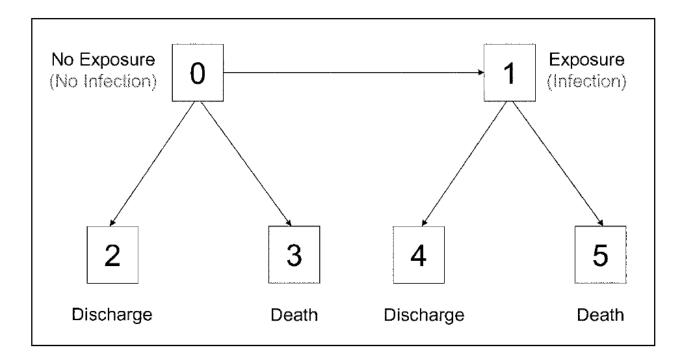
A, Estimated intensive care unit (ICU)-mortality calculated using the multistate model (see the Methods section in the Supplement). Shaded areas represent 95% CIs. B, Population attributable ICU mortality fraction over time adjusted for quartiles of Acute Physiology and Chronic Health Evaluation IV score and quartiles of age. The population attributable mortality fraction was expressed as the percentage of ICU mortality caused by the ICU-acquired infections. The negative values of attributable mortality fraction in the first 14 days after ICU

admission are most likely driven by the most severely ill patients encountering the competing event (death without ICU-acquired infection) before being able to develop an ICU-acquired infection²⁴; additionally, the discharge hazard for patients with an ICU-acquired infection is smaller than the discharge hazard for patients without an ICU-acquired infection, resulting in a higher chance of dying (longer ICU stay) and a delay in deaths in the former group, leading to a negative attributable mortality fraction in the earlier days.

eFigure 3. SOFA scores up to 2 days before event (ICU-acquired infection or discharge/mortality) in patients admitted with sepsis stratified by development (or not) of an ICU-acquired infection



Multi-state model: progressive disability model



Progressive disability model

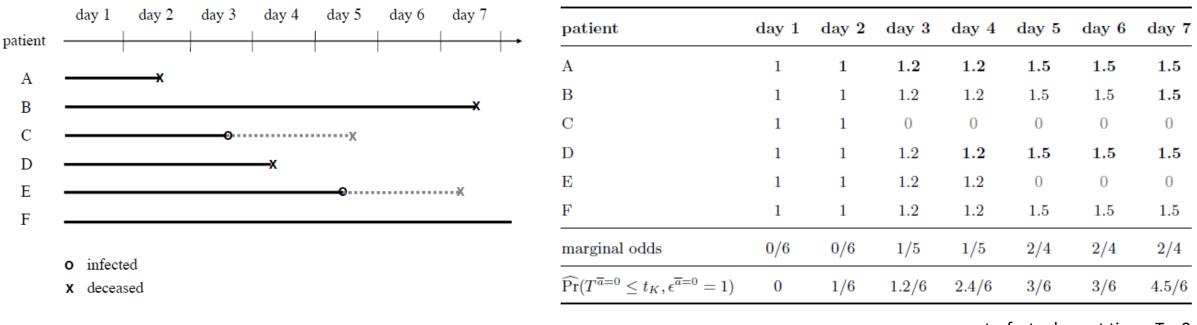
Exposure treated as a time-dependent variable

Discharge competing event for Death

Transition probabilities are estimated with the Aalen-Johansen estimator

As soon as patients acquire infection, they are excluded from the risk set and transfer their weight to patients who have until that time remained uninfected.

Why multi-state-survival cannot give a causal interpretation (1)



counterfactual event times Ta=0 tK = interval time Ea=0 = event type indicator

This implies that an event that has already occurred gets reweighed based on information (on future infections) that is not available at the time of that event.

Johan Steen PM, Wim Van Biesen, Johan Decruyenaere, Stijn Vansteelandt. (2023) Handling time-dependent exposures and confounders when estimating attributable fractions — bridging the gap between multistate and counterfactual modeling. *arXiv preprint arXiv*; **:04833**.

Ideal causal model ICU-acquired complications

In a hypothetical RCT: Relative mortality reduction that would be found in eligible patients that are randomly assigned to receive either a fully effective bundle of preventive measures or standard of care

Control arm: correspond to the observed cumulative incidence in an observational study where all patients received standard of care

Treatment arm: corresponds to the 'counterfactual' ICU-complication-free cumulative incidence

- Weight of newly ICU-A-complication should only be distributed among ICU-complication-free that are still hospitalized at the ICU at that time
- Weight of newly ICU-A-complication should only be distributed among ICU-complication-free with the same patient profile in terms of admission characteristics and evolution of disease severity up to that time wave.
- Treating ICU-A-complication as an informative censoring event

3 steps in Marginal Structural Models

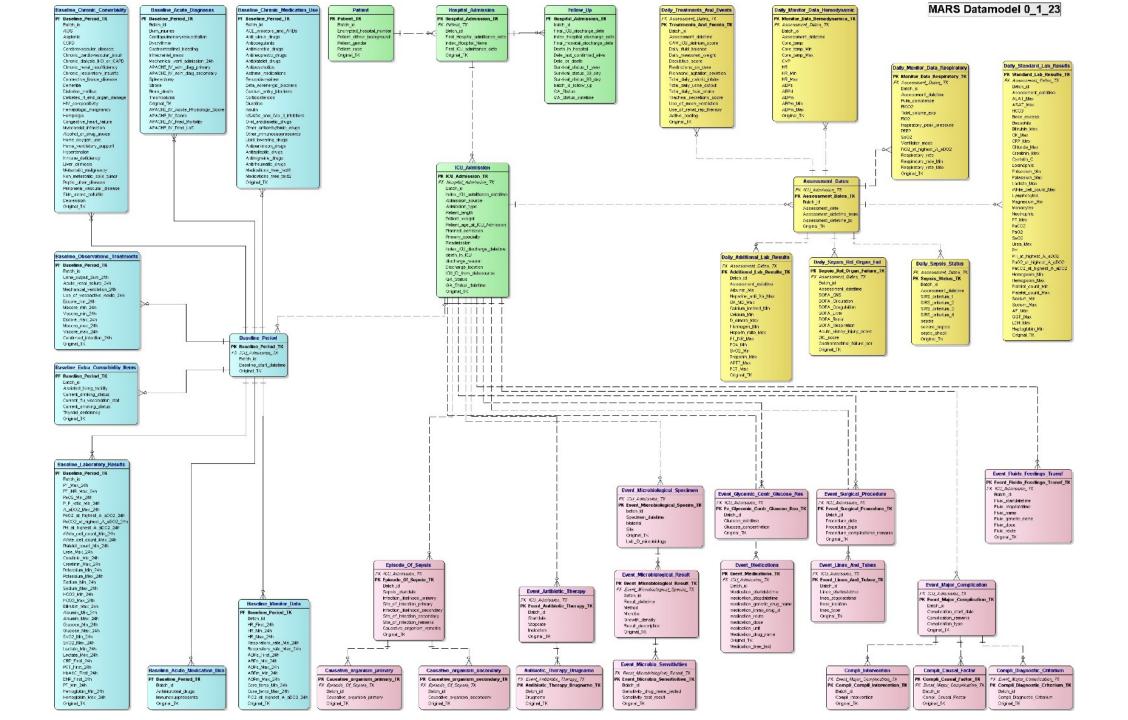
1: Make a time-dependent Survival model with ICU-acquired infections (yes) vs No ICU-acquired infections, given all covariates:

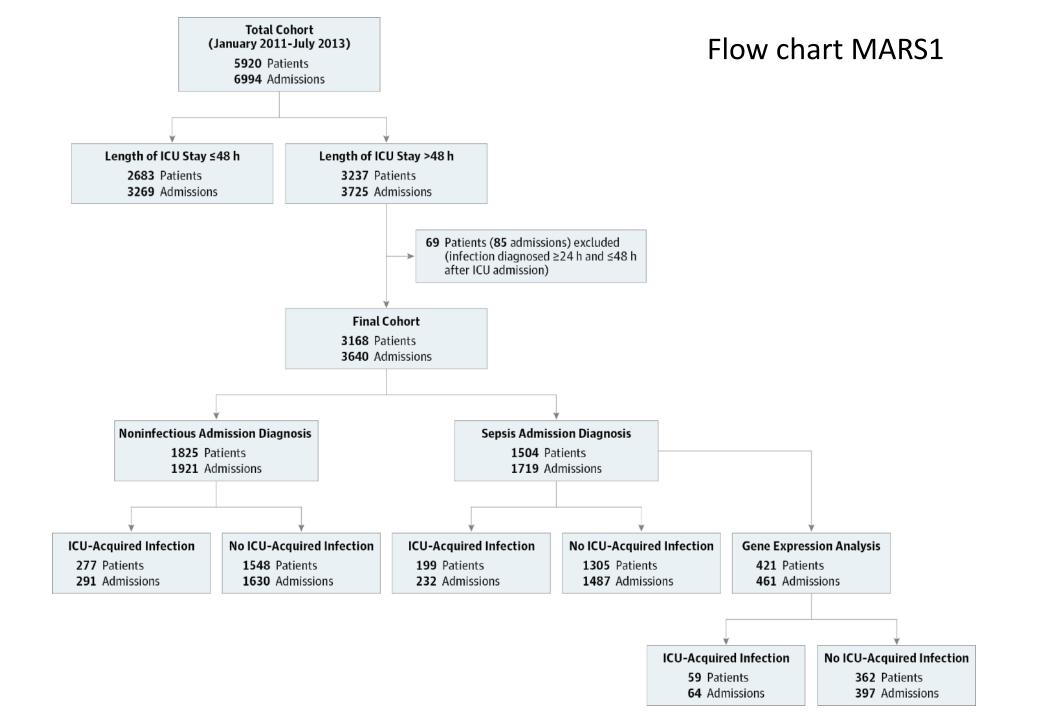
- Baseline covariates
- Time-varying covariates
- Cumulative number of treatment history

2: Extract stabilized IPWs

3: Include everyday IPW weights based in final time-dependent Survival model for ICU-death (vs ICU discharge)

$$\text{Binary stabilized IPW}_{it} = \prod_{t=1}^{t} \frac{P[X_{it} | \bar{X}_{i,t-1}, V_i]}{P[X_{it} | \bar{X}_{i,t-1}, Y_{i,t-1}, C_{it}, V_i]}$$





Step 1: MARS dataframe

- Make within a patient for every day a row, based on ICU length of stay
- Merge daily MARS data (SOFA score, lab values, RRT, MV)
- Merge Lines/tubes
- Merge surgery events
- Merge other complications (ARDS, AKI, etc)
- Count cumulative events (MV, RRT, Lines etc)
- Include one-day LAG of all variables (SOFA score, cumulative events)

Step 1: impute some missing data

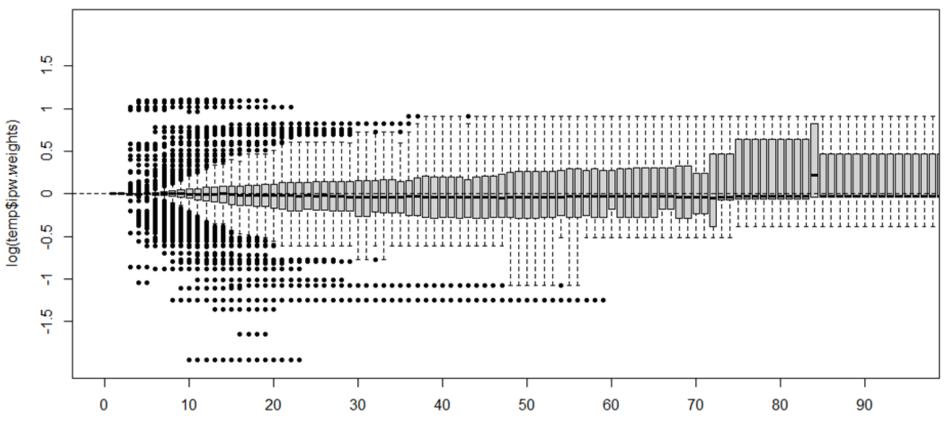
- Impute missing daily values with Mixed models
 - Applied for SOFA score (~1.5% missing)

> anova(sofa.lme)				
	numDF	denDF	F-value	p-value
(Intercept)	1	18227	14642.701	<.0001
ns(fuptime, 3)	3	18227	633.226	<.0001
Charlson_without_age	1	1884	42.903	<.0001
Patient_age_at_ICU_Admission	1	1884	12.513	4e-04
icu_sepsis2	1	18227	103.985	<.0001
Acute_kidney_injury_score_imputed	3	18227	1008.673	<.0001
ALI_ARDS2	1	18227	171.716	<.0001
Use_of_mech_ventilation_imputed	1	18227	506.275	<.0001
vasopressor	1	18227	3539.187	<.0001

^ 10	CU_ID_from_datasource ‡	Patient_TK [‡]	Patient_race [‡]	Patient_gender ‡	urinary_catheter	central_venous_catheter +	arterial_catheter	peripheral_catheter +	surgical_drain	diff_daily	; tstart	† fuptime	¢ icu_sepsis	¢ event2 ¢
1	157	18339	non-caucasian	male	0	0	o	0		0 ()	-1	0) No-death
2	157	18339	non-caucasian	male	1	1	1	1		0 1		0	1 () No-death
3	157	18339	non-caucasian	male	1	1	1	1		0 1		1	2) No-death
4	157	18339	non-caucasian	male	1	1	1	1		0 1		2	3) No-death
5	157	18339	non-caucasian	male	1	1	1	1		0 1		3	4) No-death
6	157	18339	non-caucasian	male	1	1	1	1		0 1		4	5) No-death
7	157	18339	non-caucasian	male	1	1	1	1		0 1		5	6) No-death
8	157	18339	non-caucasian	male	1	1	1	1		0 1		6	7) No-death
9	157	18339	non-caucasian	male	1	1	1	1		0 1		7	8) No-death
10	157	18339	non-caucasian	male	1	1	1	1		0 1		8	9) No-death
11	157	18339	non-caucasian	male	1	1	1	1		0 1		9	0) ICU-discharge
12	160	18472	caucasian	female	1	0	0							No-death
13	160	18472	caucasian	female	1	1		1		0 1				No-death
14	160	18472	caucasian	female	1	0	1	1		0 1				No-death
15	160	18472	caucasian	female	1	0	1	1		0 1		2	3	No-death
16	160	18472	caucasian	female	1	0		1		0 1				No-death
17	160	18472	caucasian	female	1	0	1	1		0 1				No-death
18	160	18472	caucasian	female	1	0	1	1		0 1		5		No-death
19	160	18472	caucasian	female	1	1		1		0 1) ICU-discharge
20	165	19052	caucasian	female	0	0	0			0 ()	-1	0	No-death
21	165	19052	caucasian	female	1	1	1	1		0 1		0	1	No-death
22	165	19052	caucasian	female	1	1	1	1	(0 1		1	2	No-death

Step 2: extract weights

Stabilized weights



df_ipw3\$fuptime

numerator = ~ Patient_age_at_ICU_Admission + ns(APACHE_IV_Acute_Physiology_Score,3),

denominator = ~ Patient_age_at_ICU_Admission + ns(APACHE_IV_Acute_Physiology_Score,3) + ns(SOFAtot_imputed.lag2,3) + ns(SOFAtot_imputed.evo,3) + Use_of_mech_ventilation_imputed+Acute_kidney_injury_score_imputed,

Step 3: make final model

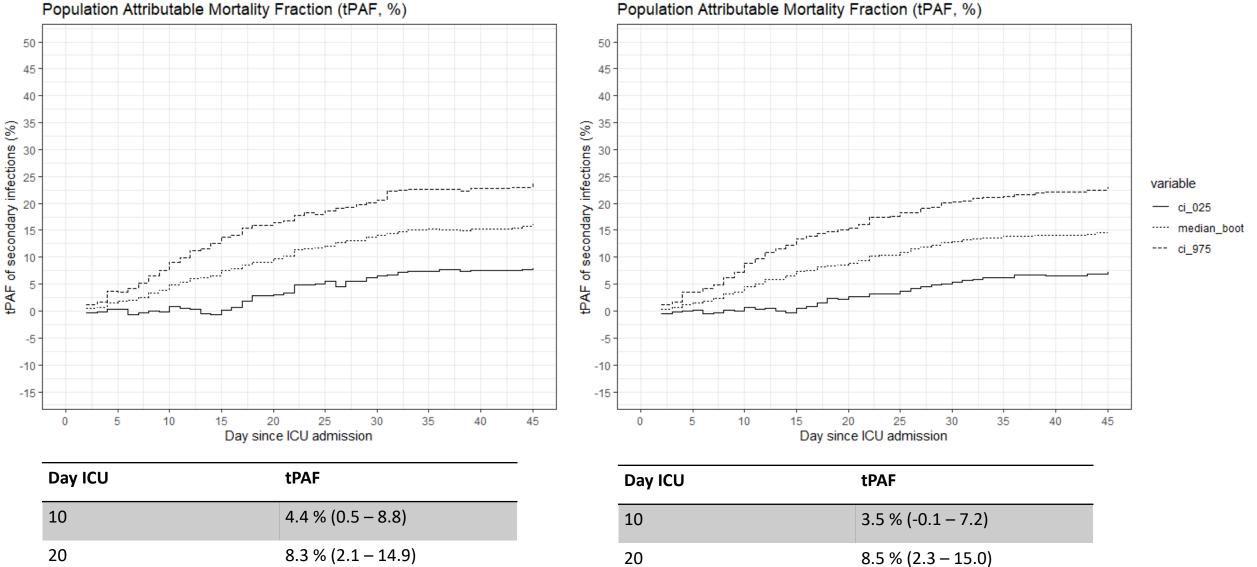
Model	HR (95%CI)	P-value			
Unadjusted					
ICU-acquired infections	1.59 (1.23-2.07)	0.000422			
Adjusted (only baseline)					
ICU-acquired infections	1.52 (1.17-1.98)	0.00181			
Adjusted (baseline + (t-2)SOFA)					
ICU-acquired infections	1.34 (1.02-1.75)	0.0348			
Adjusted (baseline + (t-2)SOFA + evoSOFA + MV + AKI)					
ICU-acquired infections	1.31 (0.99-1.74)	0.0565			

Inverse probability treatment weighting (IPTW)

13.1% (5.3 – 20.2)

Inverse probability treatment censoring weighting (IPTCW)

12.7% (5.1 – 20.0)



30

Population Attributable Mortality Fraction (tPAF, %)

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Conclusions I

IPCW (with MSM) ideal method for estimating causal effects in ICU data

Easy quantifiable interpretation of how much mortality is reduced by theoretically preventing ICU-acquired infection

Assumptions of MSM

- exchangeability
- positivity
- consistency
- no measurement error
- no model misspecification

ICU-acquired Acute Kidney Failure (AKI)

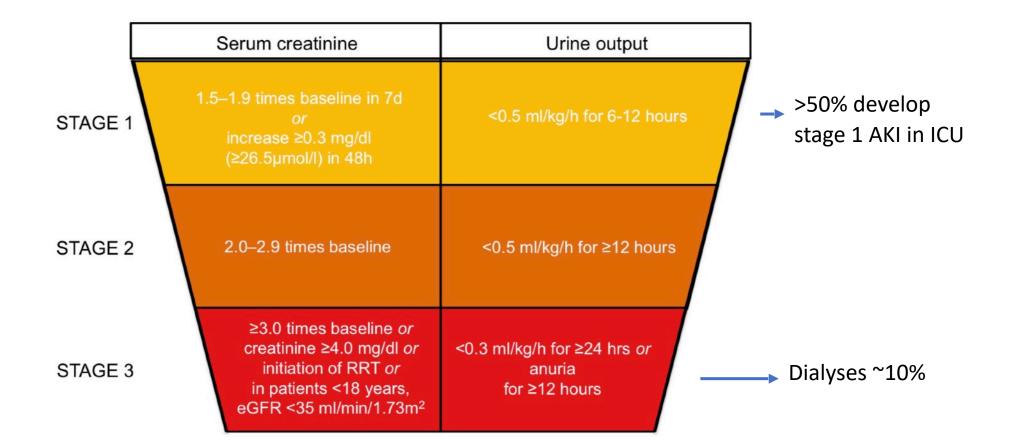
Objectives:

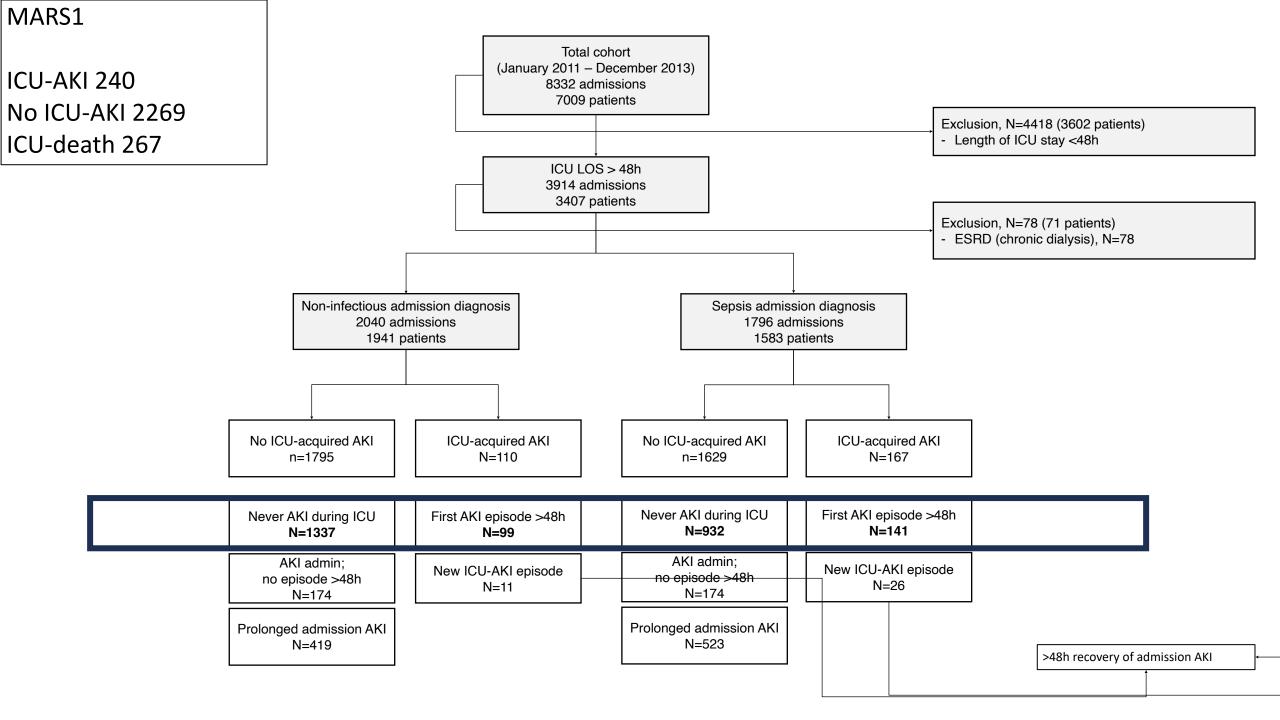
Attributable mortality of an ICU-acquired AKI?

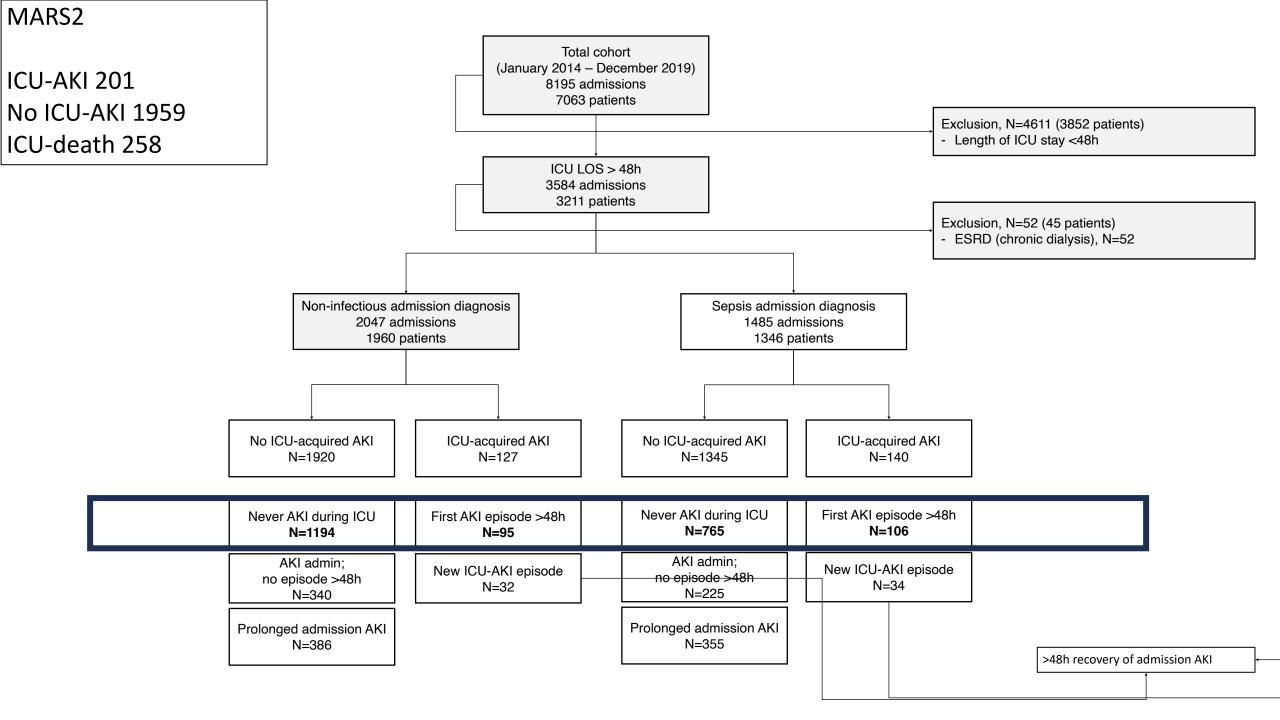
Are there specific (immune system) pathways leading to development of AKI?











KNMP (Dutch library of Pharmacie)

Grouped >400 different ICU meds into KNMP categories, based on mechanistic functions

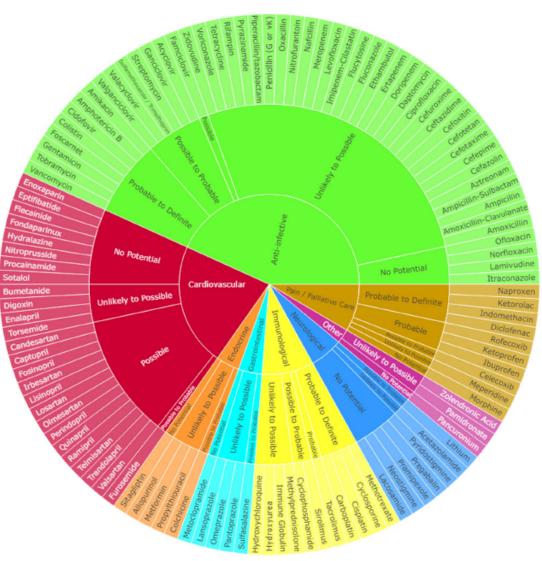
- 1. glycopeptide antibiotics
- 2. sulfanomides
- 3. aminoglycosides
- 4. antimycotic antibiotics
- 5. penicillins
- 6. phosphodiesterase inhibitors
- 7. antiarrhythmics
- 8. loop diuretics
- 9. sympathomimetics alpha/beta
- 10. phenethylamine derivatives
- 11. antihypertensives
- 12. immunosuppressants
- 13. neurological
- 14. opioids
- 15. polypeptides
- 16. calcineurin inhibitors

Drug Safety (2022) 45:389–398 https://doi.org/10.1007/s40264-022-01173-4

ORIGINAL RESEARCH ARTICLE

Consensus Obtained for the Nephrotoxic Potential of 167 Drugs in Adult Critically III Patients Using a Modified Delphi Method

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MARSID 1503 ICU admission: 2011-08-29 07:57:00 ICU discharge: 2011-08-29 07:57:00

Day	
1	
2	
3	
4	
5	
6	

1. Make rows according to Admission and ICUdischarge

Day	RIFLE score
1	0
2	0
3	0
4	1
5	1
6	1

- 2. Merge baseline & daily data
- 15% of patients RIFLE score is missing
- Mostly at last day of ICU, solution:
 - Last AKI carried forward
 - If >40% of daily AKIs is missing pp, exclude (32 pts)

Day	RIFLE score	Event
1	0	No-death
2	0	No-death
3	0	No-death
4	1	No-death
5	1	No-death
6	1	ICU-discharge

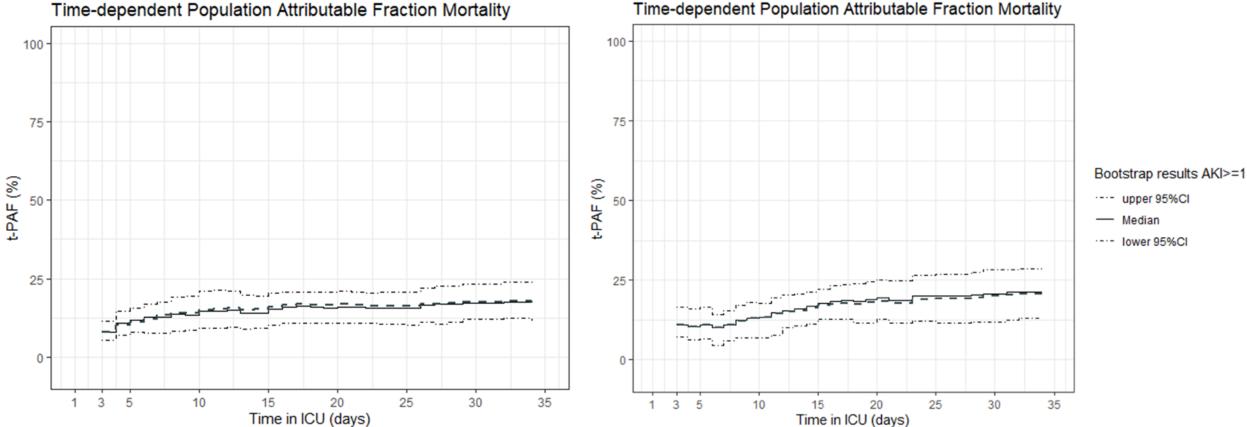
2. Merge other longitudinal data

- Cumulative dosages of nephrotoxic meds
- Shock
- Complications

Note. Contrast media not retrievable

Dataset MARS1 (2011-2013): 17870 days of data

Dataset MARS2 (2014-2019): 25092 days of data



Time-dependent Population Attributable Fraction Mortality

Conclusions II

- ICU-acquired AKI has an incidence of ~10%
- tPAF day 10 was 10.2% (95%CI 6.3-15.2)
- tPAF day 20 was 16.3% (95%CI 12.1-24.9)
- tPAF increased in the MARS2 cohort

Patients with ICU-acquired AKI exhibited increasingly higher levels of biomarkers over time reflecting:

- inflammatory response
- endothelial activation





AKI Team

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