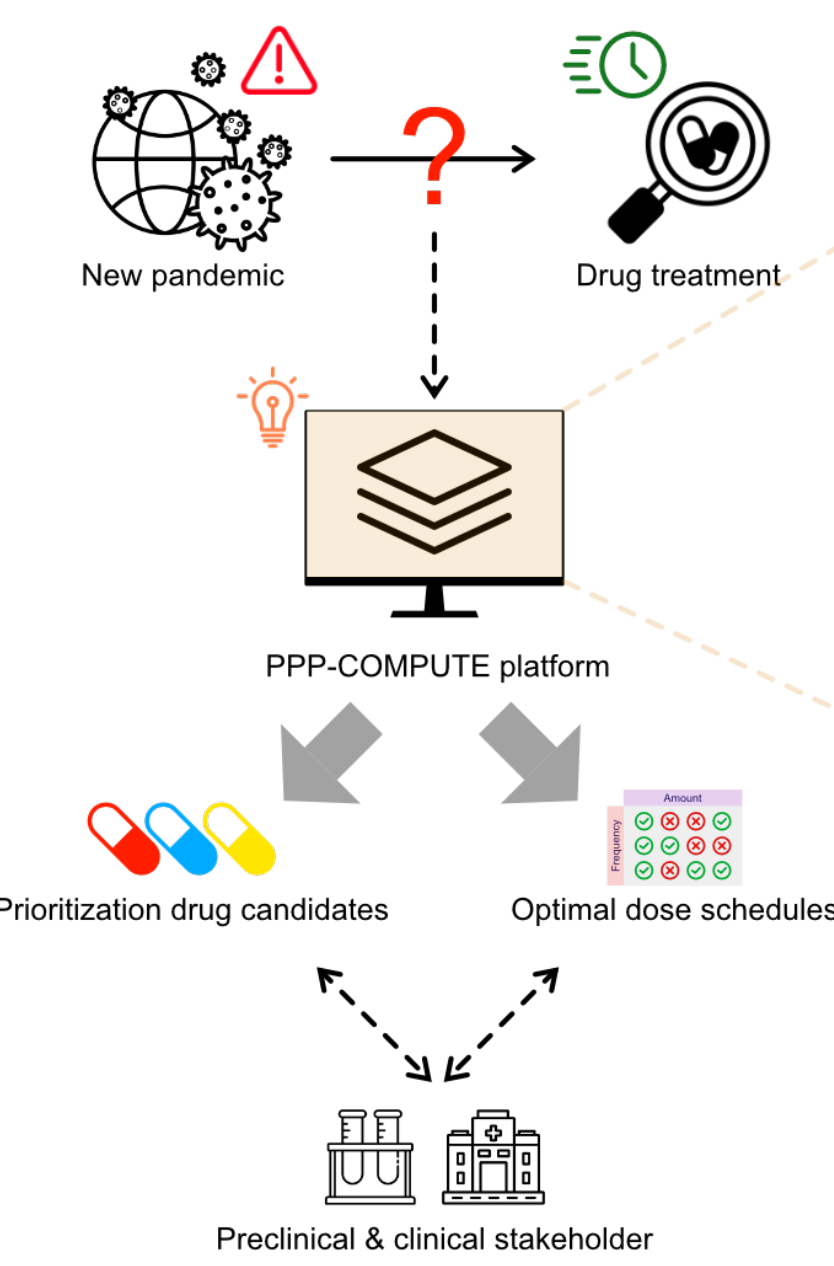




Coen van Hasselt, Linda Aulin, Qinhao Wu, Wisse van Os, Xuanlin Liu, Jiahang Su, Chenyu Wang, Anne-Grete Mårtson, Tingjie Guo
Leiden Academic Centre for Drug Research, Leiden University, Leiden, The Netherlands

Motivation

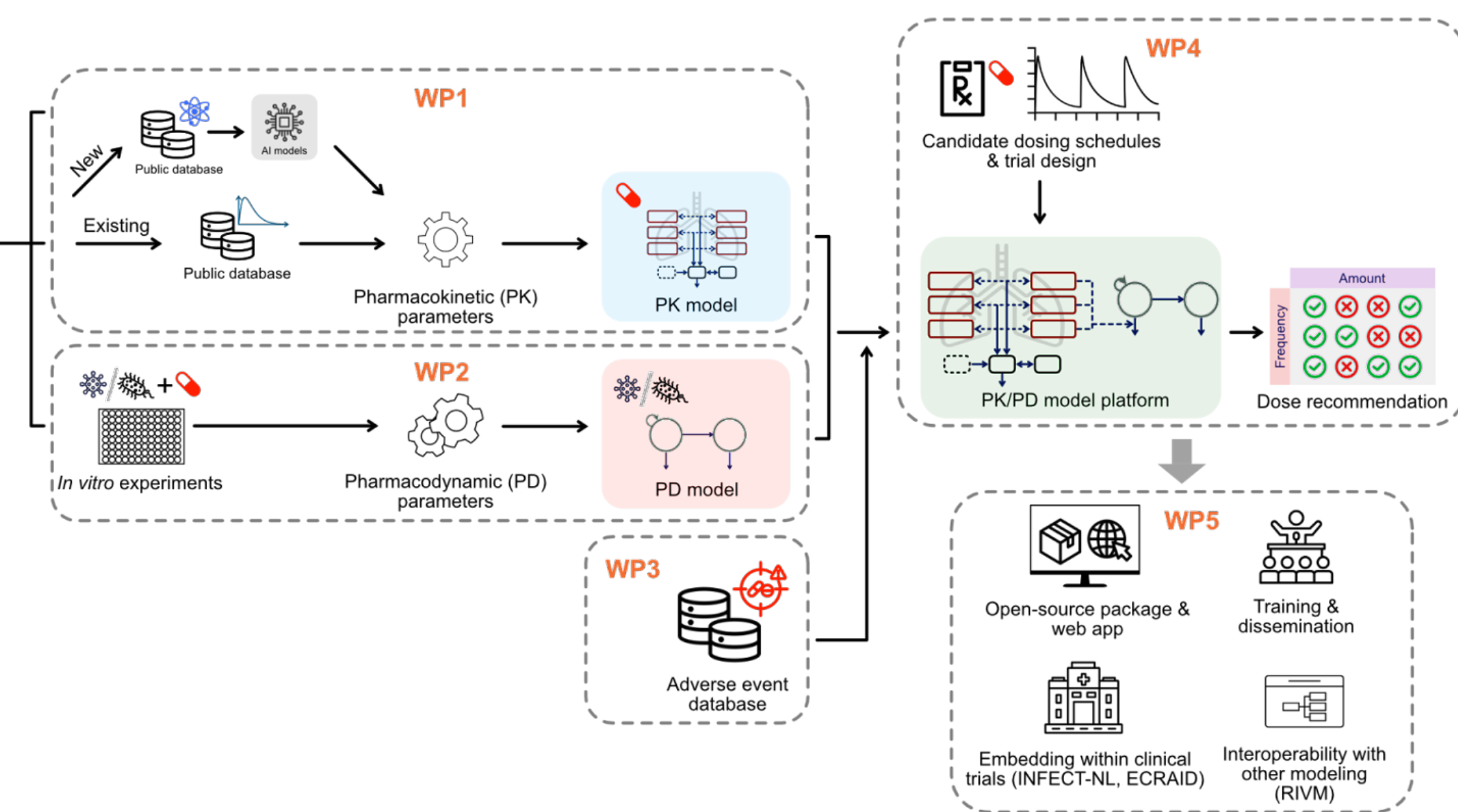
- During the COVID-19 pandemic, many investigational drug treatments were tested sub-optimally.
- A pandemic requires efficient prioritization and evaluation of (candidate) drug treatments.
- Effective translation of experimental data into treatment schedules during a pandemic requires pharmacokinetic-pharmacodynamic (PK-PD) modeling.**



Project design

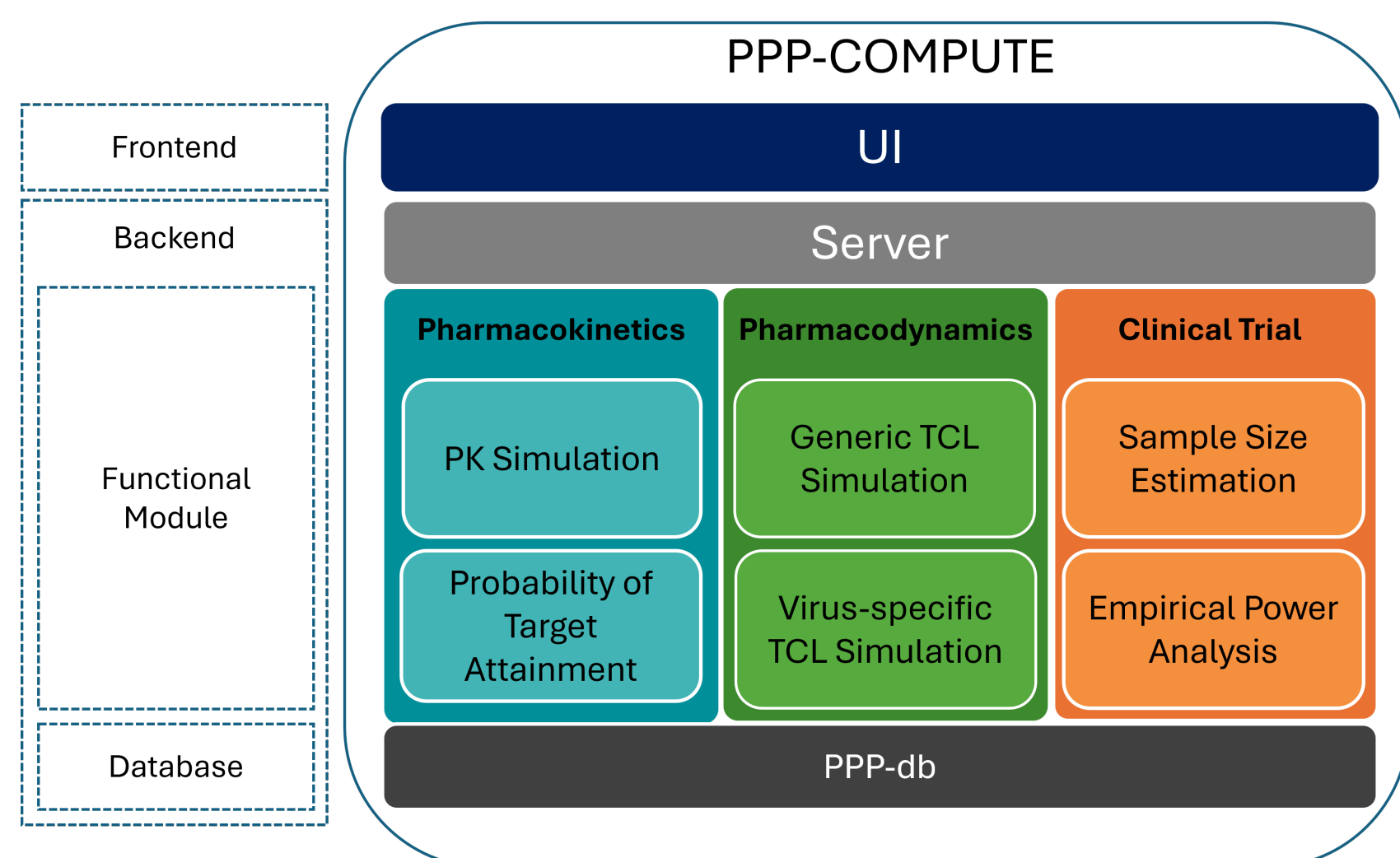
Aim: To develop a generic computational platform to guide selection and treatment/trial optimization for drug candidates during a pandemic.

Approach: Integrate existing PK/PD models with public drug and pathogen data into a flexible computational simulation framework to guide treatment & trial design.

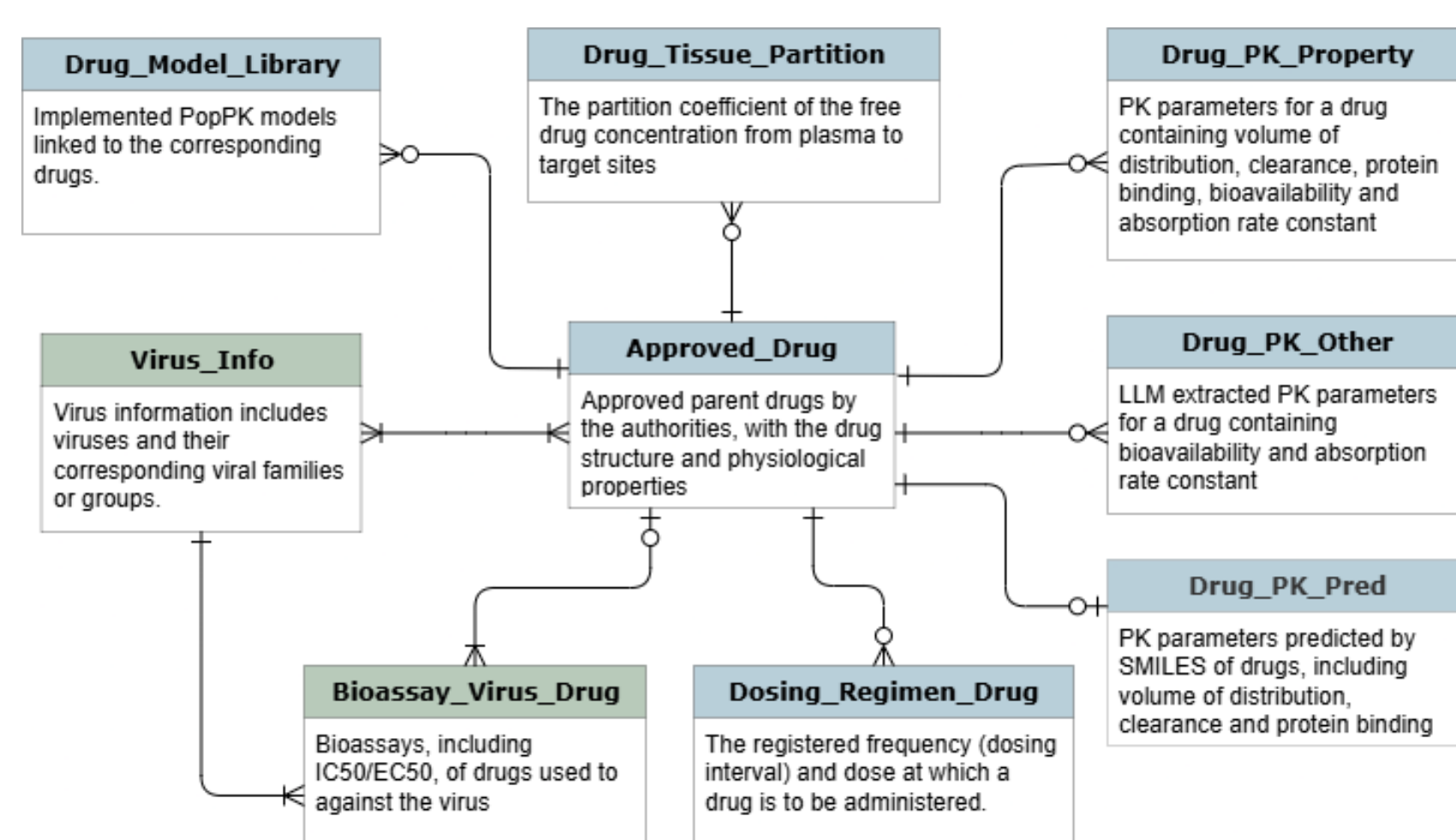


Platform & Database

- PPP-COMPUTE is a **web-based platform** with PK-PD simulation models for PK, PD, and trial designs.



- An **integrated database** of drug PK, pathogen PD, drug dosing, and model structures was developed.



Case study: Ribavirin

- Dosing advice requested (RadboudUMC) for use of ribavirin for **post-exposure prophylaxis to andesvirus**.
- Tailored dosing schedule proposed to rapidly achieve therapeutic exposure.

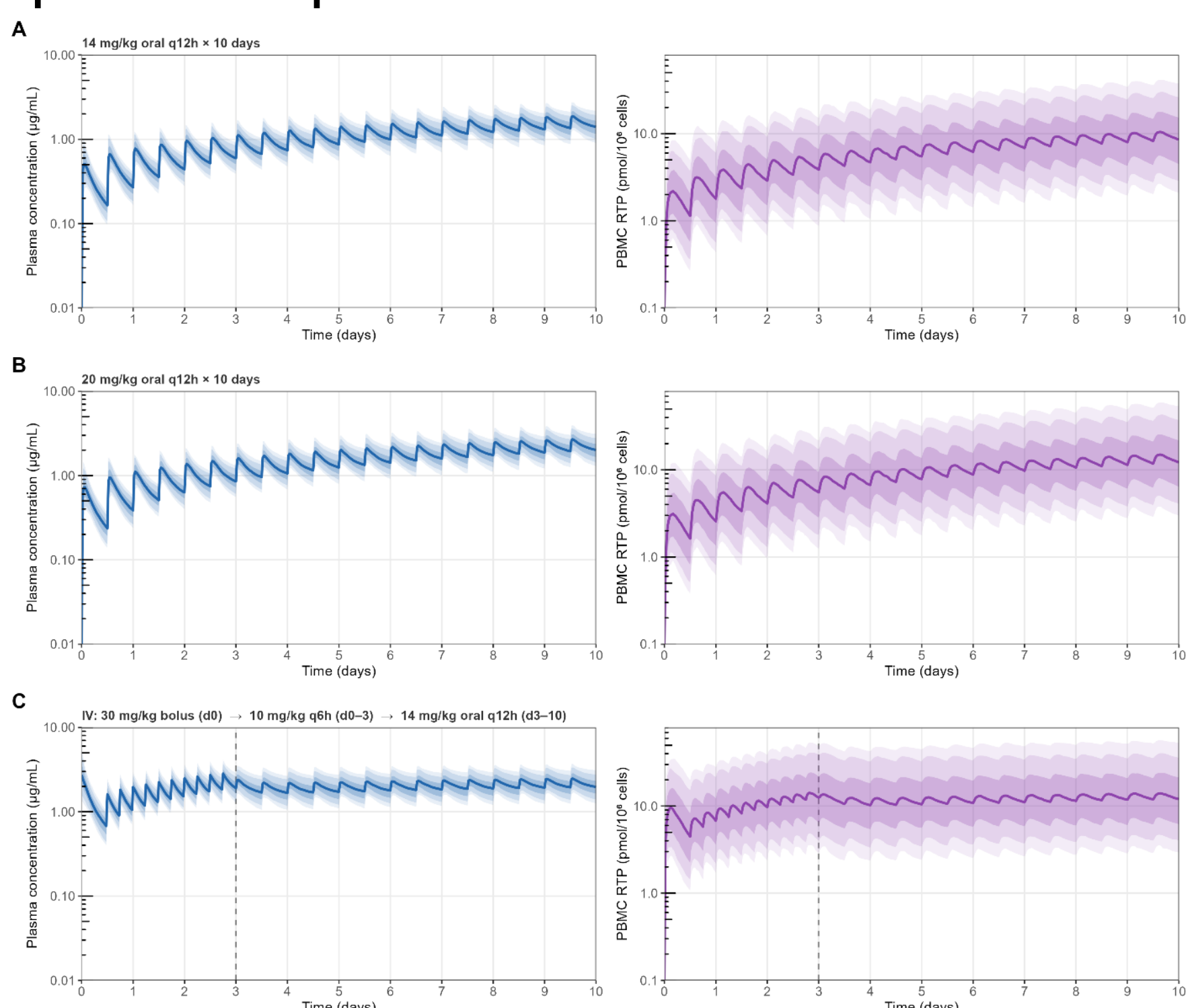
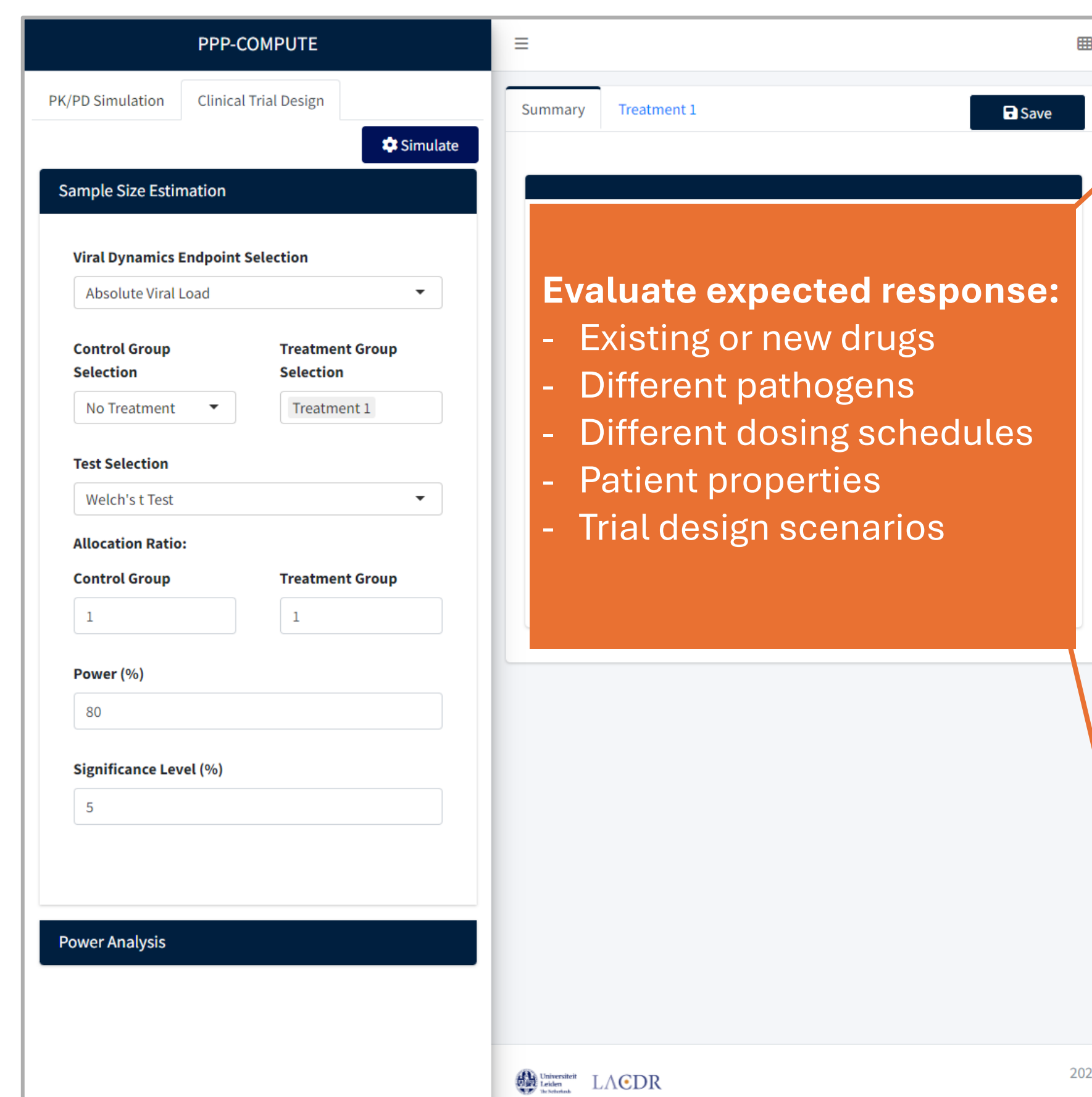


Figure 1. Population pharmacokinetic simulation of ribavirin plasma concentrations and intracellular triphosphate accumulation in PBMCs under three dosing regimens. Simulated ribavirin concentration-time profiles are shown for (A) 14 mg/kg oral twice daily, (B) 20 mg/kg oral twice daily, and (C) an IV-based loading regimen consisting of a 30 mg/kg IV bolus at day 0, followed by 10 mg/kg IV every 6 hours from hour 12 through day 3, then switching to 14 mg/kg oral twice daily from day 3 to day 10. All regimens were simulated over a 10-day treatment course in a reference subject of 70 kg. Left panels show ribavirin plasma concentrations; right panels show intracellular ribavirin triphosphate (RTP) concentrations in peripheral blood mononuclear cells (PBMCs). The dashed vertical line in panel C indicates the transition from intravenous to oral administration. Simulations were performed using the population pharmacokinetic model reported by Wu et al. (2025), comprising a two-compartment plasma model with first-order oral absorption (assuming bioavailability $F = 0.52$ for oral dosing) which incorporated conversion of ribavirin to its phosphorylated forms in PBMCs. Lines represent the median and shaded regions the 10th–90th (dark) and 5th–95th (light) percentile intervals derived from $N = 500$ Monte Carlo simulated subjects.

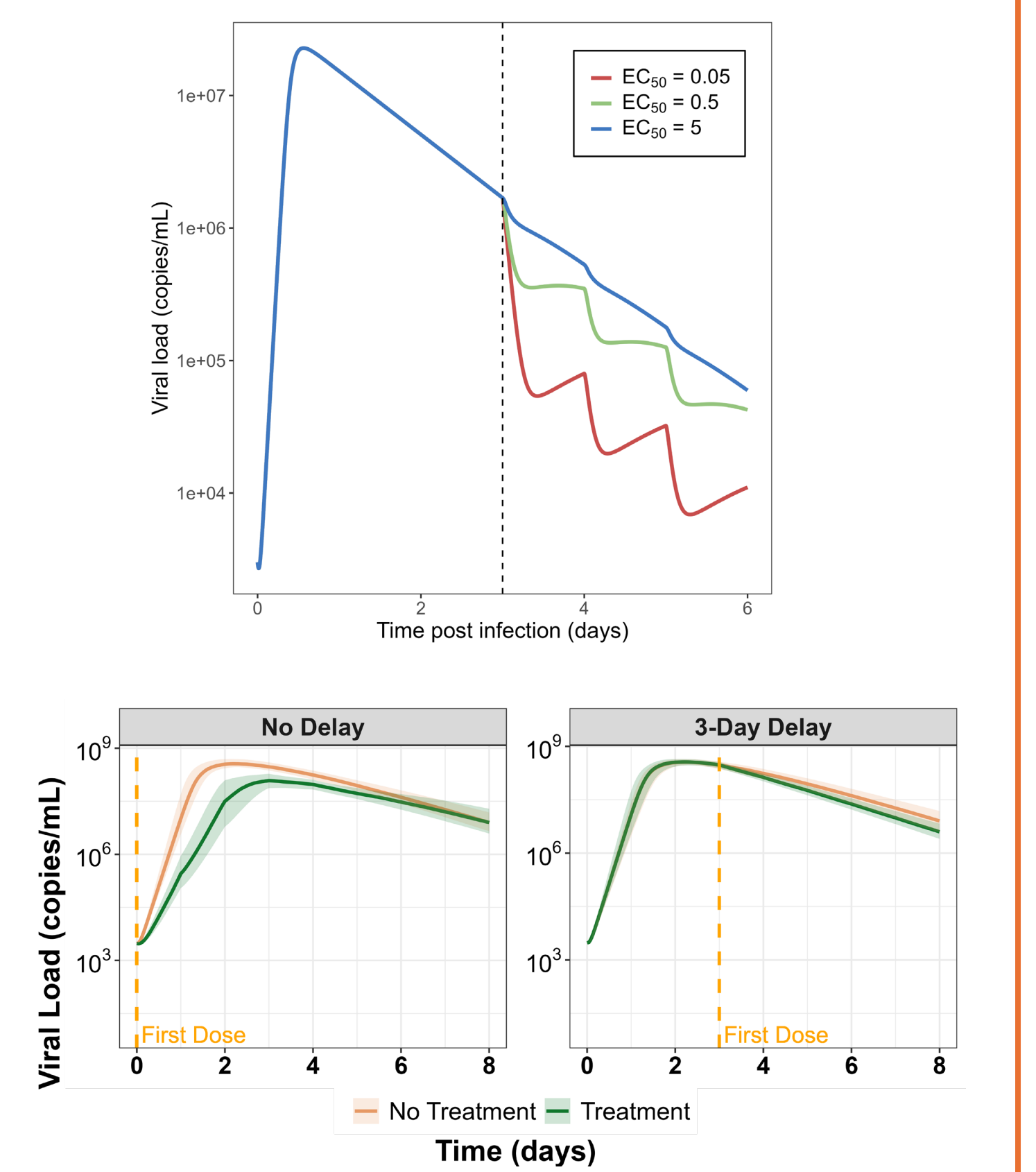
PPP-COMPUTE interface

- Users can interact with the platform through stepwise-selection of pathogen, drug, dosing schedules, to evaluate optimal dose schedules or trial designs.
- The platform is available on pppcompute.lacdr.leidenuniv.nl
- All source code is publicly available on Github.



Evaluate expected response:

- Existing or new drugs
- Different pathogens
- Different dosing schedules
- Patient properties
- Trial design scenarios



Challenges & Lessons learned

- Heterogeneous pharmacological data** in public domain resources.
- Specific drug or pathogen scenarios may require **tailored PK-PD models** (i.e., intracellular activity, complex PK, viral dynamics).
- Translational knowledge gaps** in bridging commonly available early experimental bioactivity data with implementation in PK-PD models
- Early alignment with stakeholders** in translational & clinical drug development is essential.

Outlook & Future Opportunities

- Partnering** with pandemic preparedness initiatives & stakeholders.
- Implementation of model-informed **vaccine development** capability.
- Expansion and curation** of the drug & pathogen database.
- Further developing **training materials** for end-users.

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Funding received from the ZonMW program "Modelleren voor Pandemische Paraatheid: een oproep tot innovatie en kennisontwikkeling". Project number 10710062310003

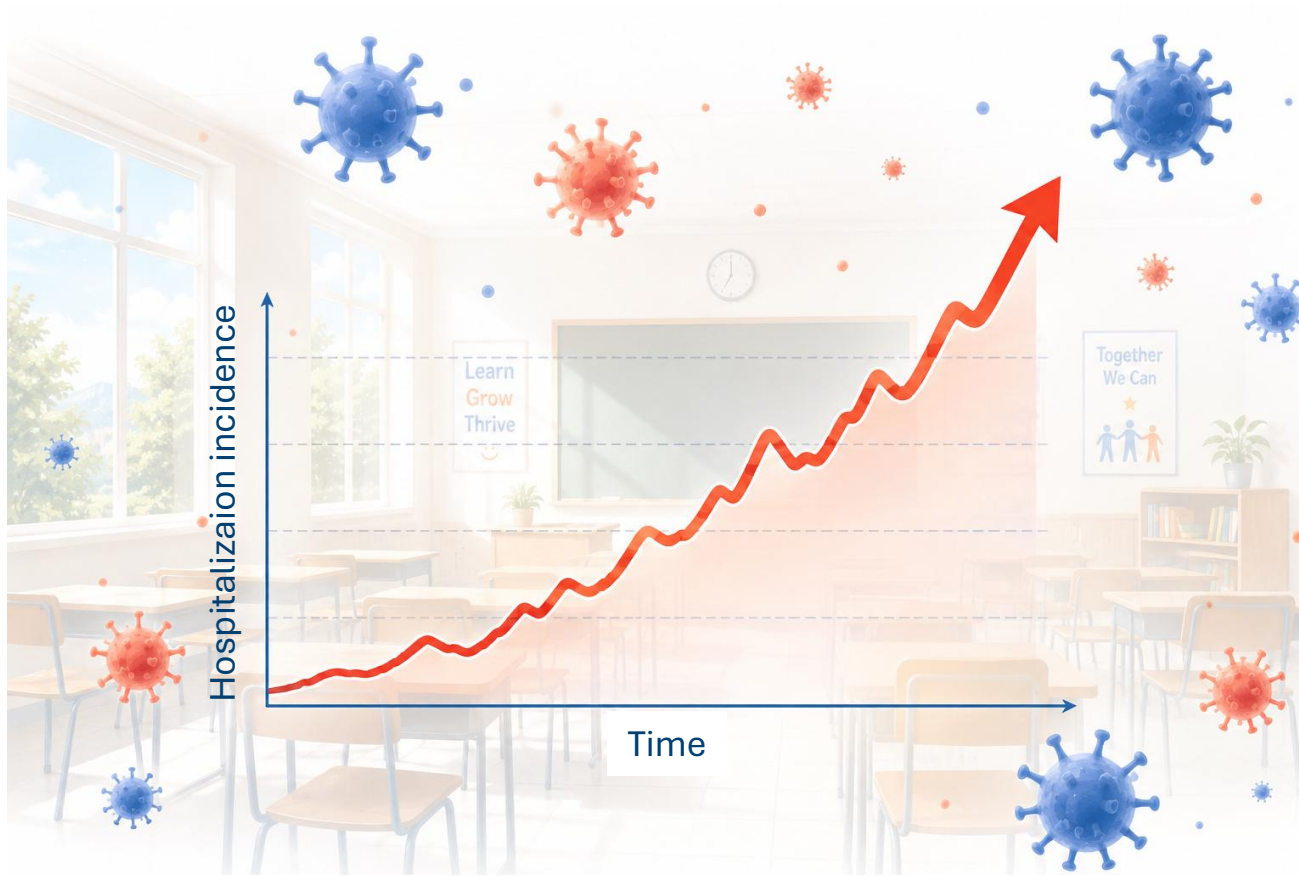


Image credit: ChatGPT 5.5

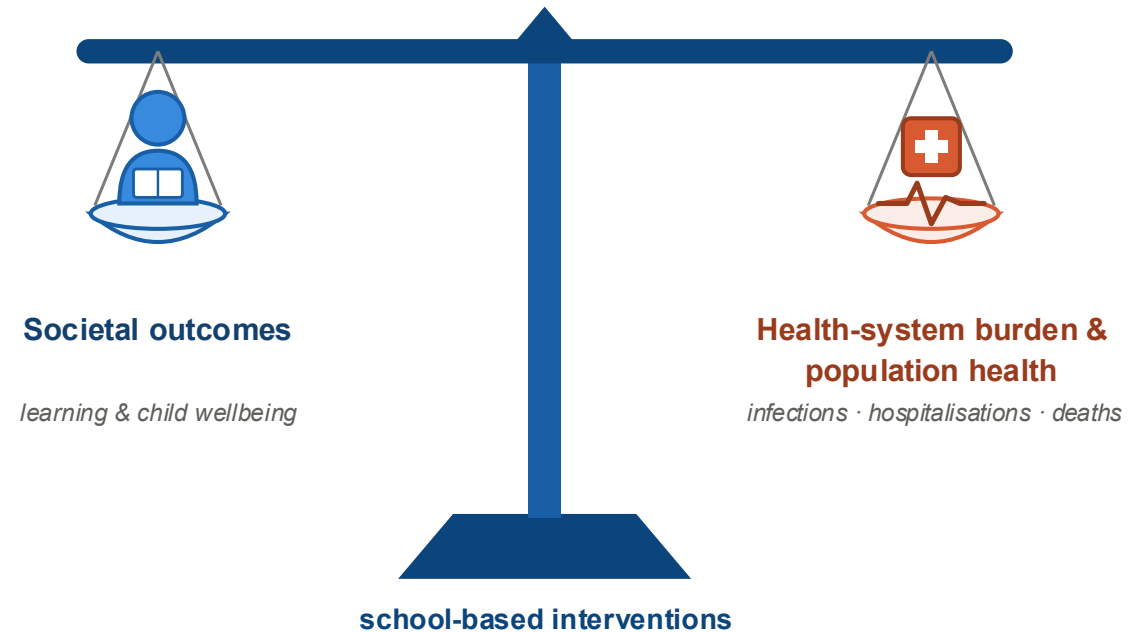
RE-PASS: REfining PAndemic Strategies for Schools: Multiscale modeling of their societal & public health impact

PI Ganna Rozhnova

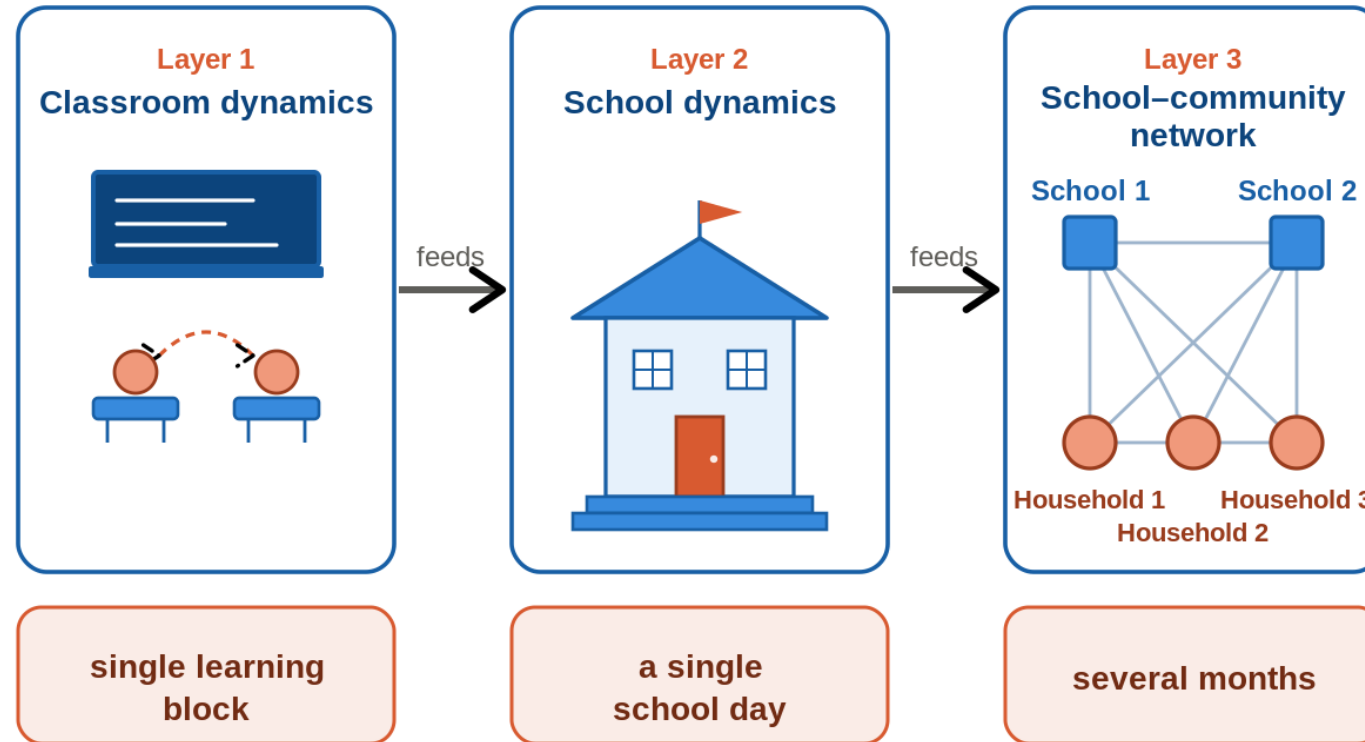


Schools in respiratory pandemics: amplify transmission, yet essential for learning and wellbeing

- **Aim:** To evaluate school-based interventions that balance epidemiological outcomes and societal outcomes
- **RE-PASS:** A novel multi-scale outbreak dynamics modelling framework
- **Pathogen scenarios:** Range of infectivity profiles and epidemiological progression
- **Interventions:** Ventilation, reduced activity, staggered attendance, screening of students and staff, school closures

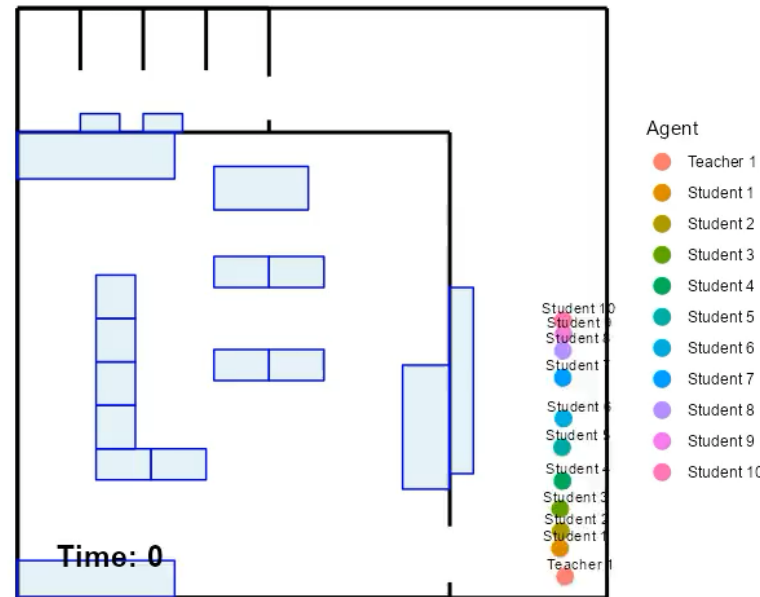
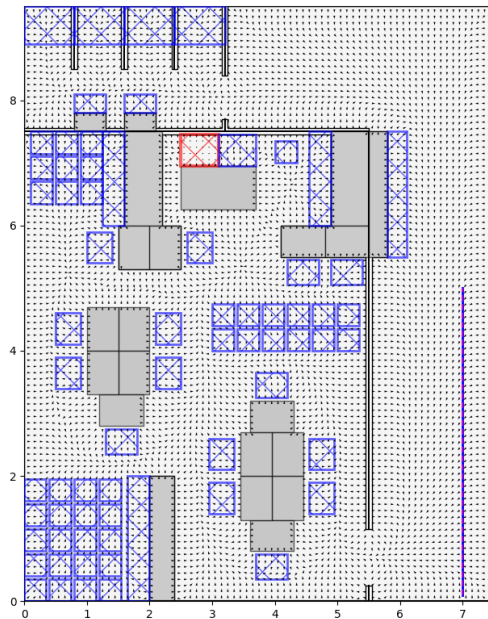


Model structure



Layer 1: classroom level dynamics

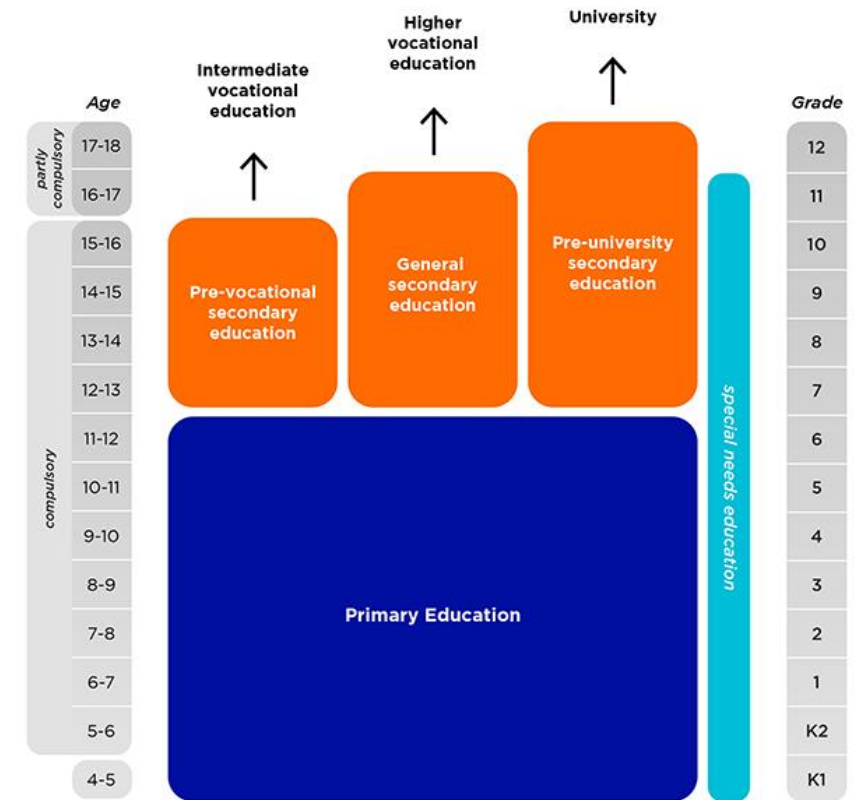
- Single learning block microsimulation
- One infectious individual, remaining are fully susceptible
- NOMAD pedestrian model simulation overlayed with aerosol simulation model
- **Output:** distribution of normalized inhaled doses in exposed individuals



Scenario variation: number of students, number of teachers, layouts, activity levels, ventilation setting, learning block duration

Layer 2: school level dynamics

- Single-day simulation of in-school dynamics
- One infectious individual, remaining susceptible
- Individual attends a number of learning blocks and exposes susceptible individuals to the infection
 - Distribution of normalized inhaled doses in exposed individuals
- **Scenarios variation** across school types and streams, age of the infectious individual, ventilation rate, activity levels and layouts



Layer 3: Simulation overview

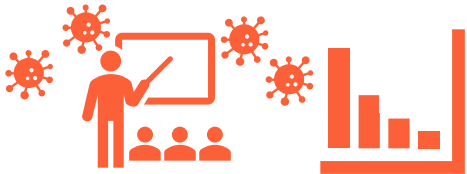
Initialization



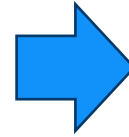
0.1 - Agent generation
as a school-household
network



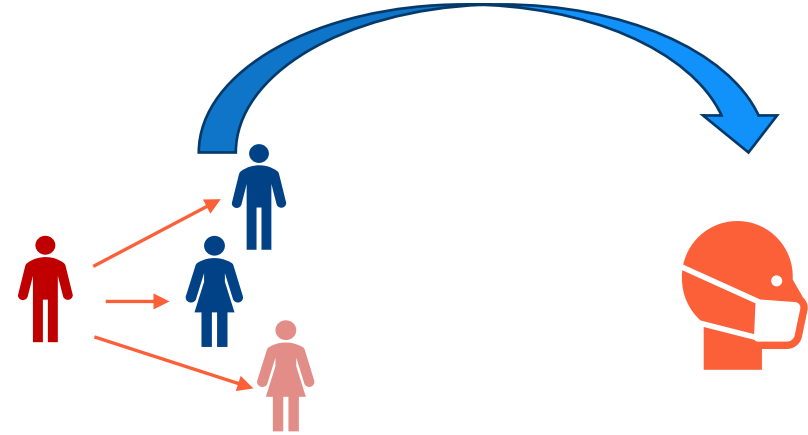
0.2 – Spaces/settings
that agents visit
during a day: **schools**,
homes, community



0.3 – Transmission risk
per space/setting: per
school, household,
community



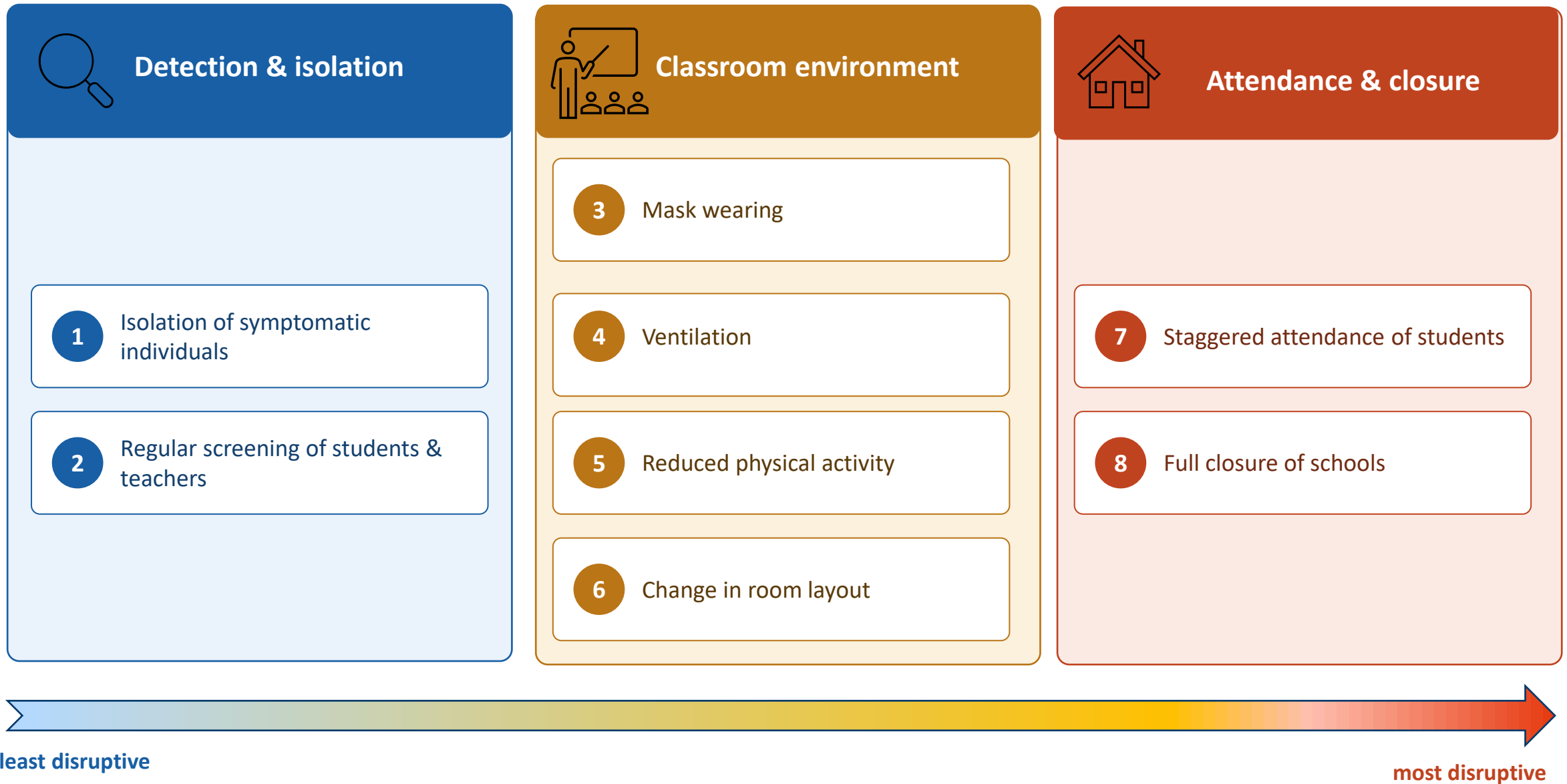
Main simulation



1 – Agent interaction
and disease
transmission

2 – Disease
progression

School-based interventions, by disruption to in-person learning



Stakeholder tabletop exercises: May 29 2026



Case study: Outbreak of an emergent respiratory pathogen in the Netherlands



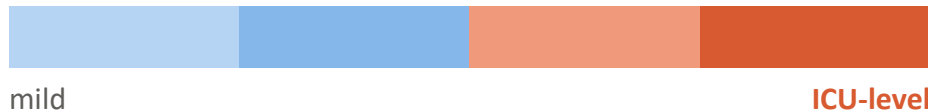
Asymptomatic transmission

Infectious people can spread it while showing no symptoms.



Wide severity range

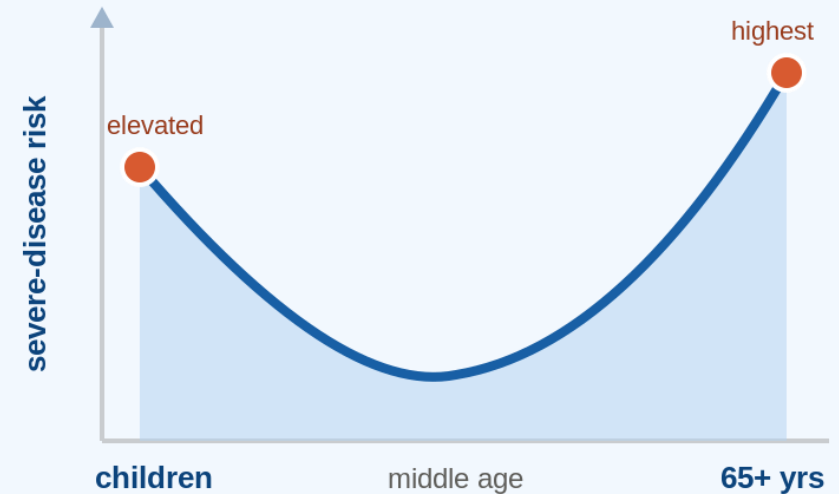
From mild symptoms to ICU-level illness.



Rapid health system saturation

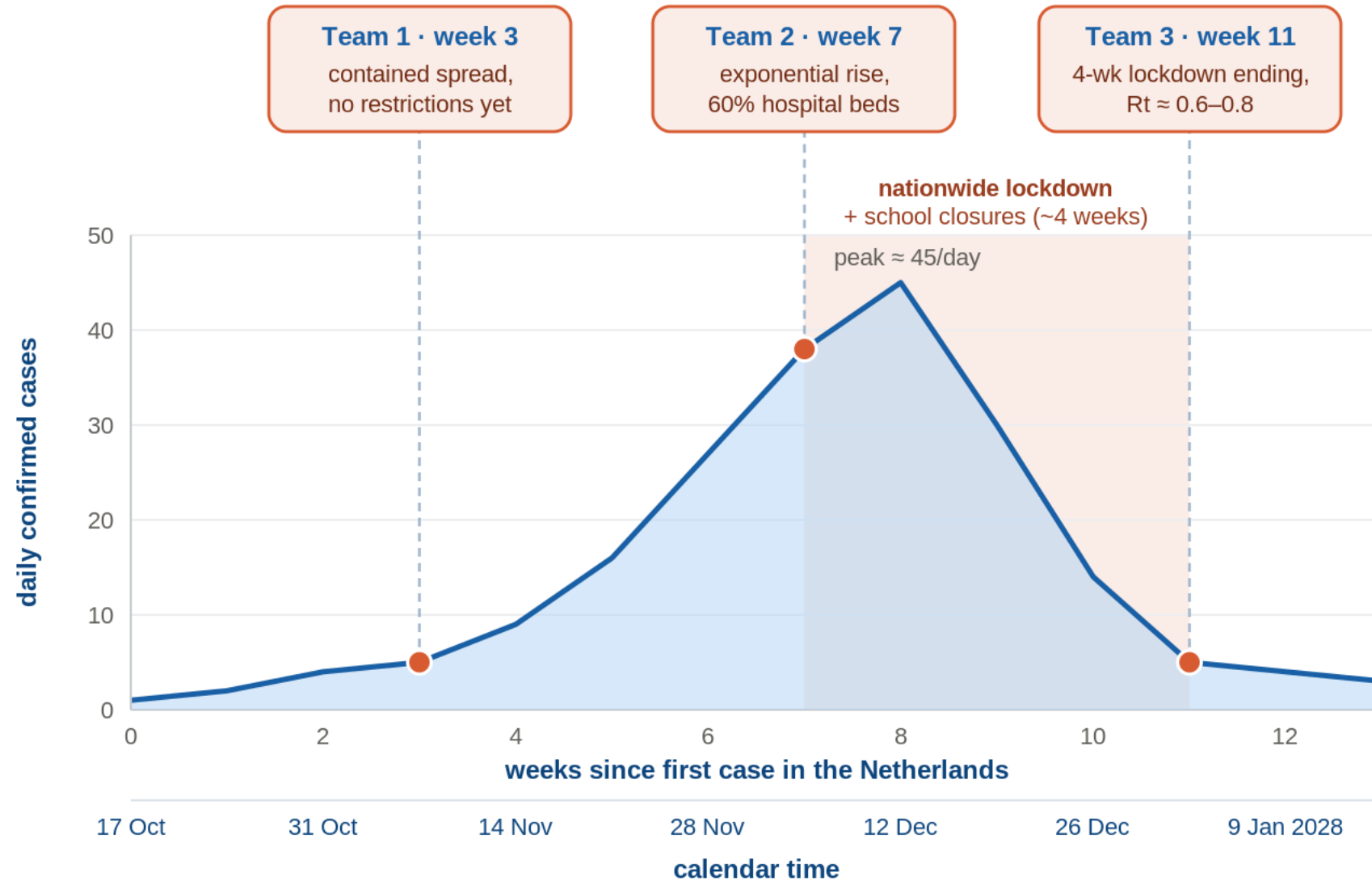
Experience abroad suggests hospital capacity can be reached quickly.

U-shaped risk by age



Children and adults 65+ face the highest risk of severe disease.

Tasks



Example of intervention packages: Team 2

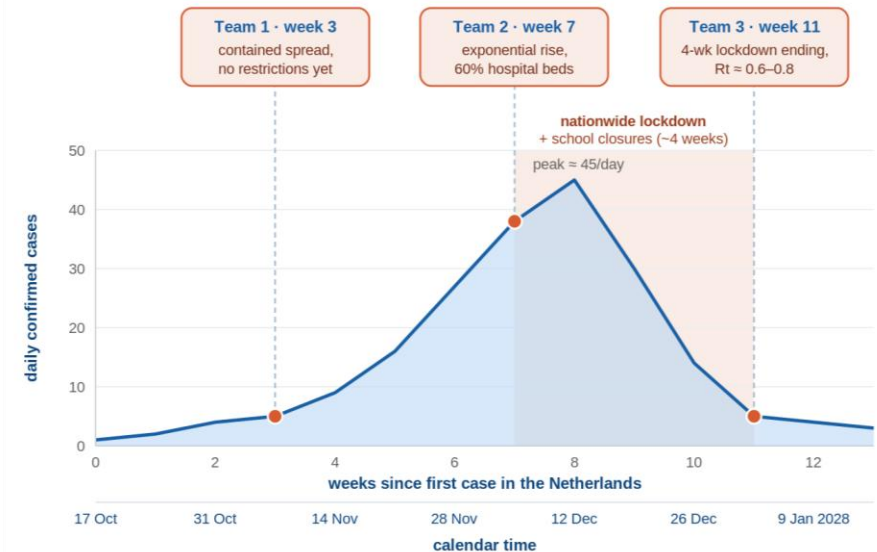
Package 1: Screening of a proportion of students before coming to school

Package 2: Classroom environment modification: the entire routine of the school day is mostly preserved, but the room environment and activity level allowed are modified: Ventilation + Increased physical distancing: reduced activity level + single-row layout of desks

Package 3: Reduced-contact school attendance: the contact rate patterns affected both in frequency and in intensity + Ventilation + Increased physical distancing + Staggered attendance across all schools

Package 4: Full school closure: complete disruption of in-person learning

Package 5: No change



Emergent themes: common ground



1 Underlying goal

Control transmission while limiting the harm done to children.

2 Package & stringency

All three teams favor in-school mitigation over doing nothing; reduced-contact attendance (ventilation, distancing, staggered) looked workable to T2 and T3.

3 Pathogen uncertainty

The age gradient in susceptibility and children's role in spread are two critical pieces that are not known

4 Information priorities

All three teams want to use the window 'bought' by the selected packages to gather information that guides the next decision.

5 Costs to children

Learning loss, mental health and equity for low-SES / vulnerable children is the central cost.

6 Timing & the 4-week limit

School closures only work to a degree since contacts persist outside and may even rebalance. Stress that time-limited measures must be clearly communicated.

Future work

- Using SARS-CoV-2 as a case study, explore how interventions implemented at different scales shape the trade-off between:
 - **Epidemic outcomes** (infections, hospitalizations, deaths)
 - **Learning outcomes** (missed in-person learning, missed digital learning)
- Assess how the trade-offs change under different pathogen properties:
 - Different roles of aerosol vs. droplet transmission
 - Higher overall infectivity
 - Intervention-induced changes in epidemiological flow

Project team

Alexandra Teslya, UMC Utrecht

Ana Maria de Roda Husman, Utrecht
University

Büşra Atamer-Balkan, WUR

Carla Haelermans, Maastricht University

Carlijn Bogaardt, RIVM

Cristiaan Delmaar, RIVM

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Danielle Timmermans, Amsterdam UMC

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Lucie Vermeulen, RIVM

Maartijn Sparnaaij, TU Delft

Matthijs de Winter, RIVM

Mirjam Kretzschmar, UMC Utrecht

Nico Pestel, Maastricht University

Patricia Bruijning-Verhagen, UMC Utrecht

Zicheng Fang, *WUR*

Quirine ten Bosch, *WUR*

Ganna Rozhnova, UMC Utrecht

Additional slides



L3 – Spaces/settings visits

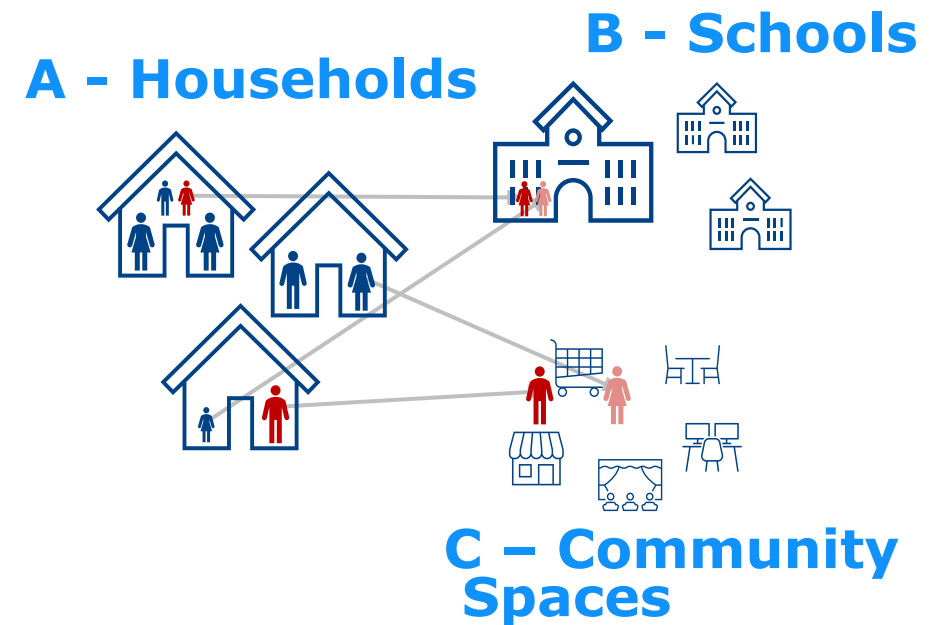
Schools: Each school is a distinct entity

Students and teachers go to the assigned schools according to schedule

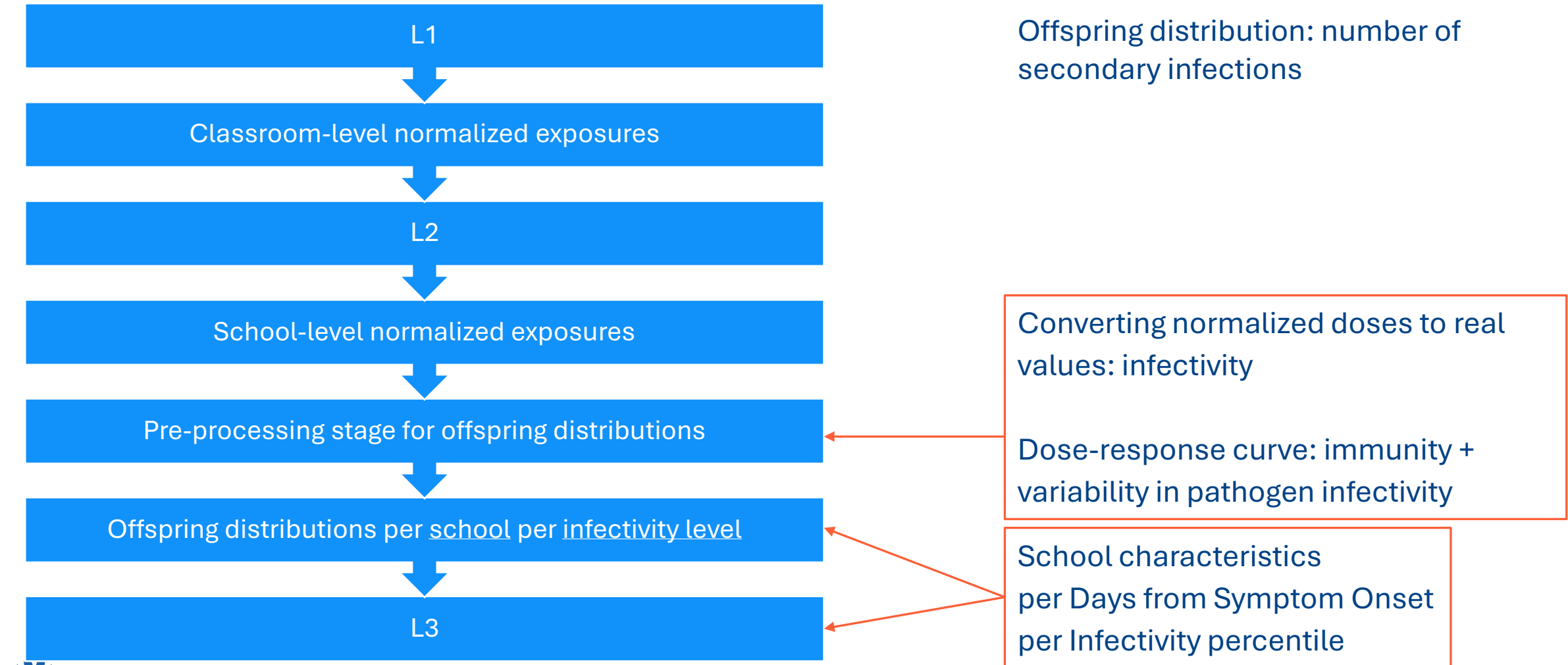
Homes: Each home is a distinct entity

Community: single pool. Individuals have **probability of visiting community spaces** each day. The probability depends on the demographic group (age, gender, socio-economic status)

School-community network



Model Overview



Workshop general discussion: the scenario



Decisions within the exercise's constraints

- Clear, structured starting points for each group worked well
- Exercise centred on trade-offs — closer to real policy debate (Team 1)
- Worst-case (sick children) pushed Team 2 to closure, leaving little trade-off room
- Hard to agree on a package; Team 1 nearly chosen to 'doing nothing'
- Screening's effect was surprising — worth emphasising
- Stochastic results sometimes defied expectations (Team 3)

Real-life considerations

- Balancing learning vs epidemiology is genuinely hard (e.g. staggered attendance)
- Socioeconomic costs matter but frequently sit outside the models (VWS)
- Mental-health harm is real but hard to quantify as compared to epi outcomes such as deaths
- Real-life deliberations run to fine detail (e.g. 17:00 vs 18:00 closing)
- Communication: be explicit on knowns vs unknowns; best/worst-case ranges facilitate transparency
- Unified message to public is ideal but unrealistic

Workshop general discussion: organisation & limitations



- 
- Valued: a narrative + deciding under uncertainty, balancing outcomes
 - Desirable: more intervention options to explore and combine
 - Desirable: Involve more people, with focus on ethics
 - Stakeholders could help set the model's assumptions
 - Limitation: within the scenario all schools modelled as a single bloc (vs primary and secondary)
- 

Emergent themes



1 Underlying goal

Agreement

Control transmission while limiting the harm done to children.

Difference

Team 1 — act fast with “low-cost” measures while numbers are low; buy time and protect children.

Team 2 — buy time and cut severe child outcomes amid rapidly rising pressure.

Team 3 — increase in-person learning while protecting hard-won control.

2 Package & stringency

All three teams favour in-school mitigation over doing nothing; reduced-contact attendance (ventilation, distancing, staggered) looked workable to T2 and T3.

Team 1 — chose the lightest real measure — classroom modification (ventilation + distancing); full closure “out of the question” at these low numbers. Staggered attendance did not look desirable to implement.

Team 2 — primary choice is full school closure; reduced-contact attendance as the backup.

Team 3 — primary choice is reduced-contact attendance; full closure seen as unnecessary. Augmentation with screening is strongly suggested.*

3 Pathogen uncertainty

The age gradient in susceptibility and children's role in spread are two critical pieces that are not known

Team 1 — unsure how effective measures are and of the transmission route (if aerosol, ventilation works); flags up to 40% asymptomatic.

Team 2 — names it THE key uncertainty; warns closure will prevent collection of relevant data

Team 3 — wants the infection pattern investigated before committing to the chosen package (to support the strength of screening component).

Emergent themes



Agreement

Difference

4

Information priorities

All three teams want to use the window 'bought' by the selected packages to gather information that guides the next decision.

Team 1 — wants the transmission route and clusters-vs-community spread clarified — “we can only act on actual numbers.”

Team 2 — identify the vulnerable groups hit hardest and design support for them during the lockdown.

Team 3 — collect epi data on infection patterns to predict how well screening would actually work..

5

Costs to children

Learning loss, mental health and equity for low-SES / vulnerable children is the central cost.

Team 1 — equity is the key consideration — only 50% of schools can ventilate, so deprived regions and single-parent homes are hit hardest.

Team 2 — adds exceptions for vulnerable students and essential workers' children.

Team 3 — flags teacher burden; 50% still home, learning aims slipping.

6

Timing & the 4-week limit

All three teams agree that school closures only work to a degree since contacts persist outside and may even rebalance and stress that time-limited measures must be clearly communicated.

Team 1 — **cautions that public** acceptance falls if measures outrun the communicated ~4 weeks

Team 2 — pushes to revisit / lengthen it — duration “will need renegotiating”; 4 wks maybe too short to work, too long for parents.

Team 3 — the opposite caution — reopen carefully, screen before easing; winter may weaken ventilation.



UMC Utrecht
Julius Center

Predicting immunity to emerging viruses

Michiel van Boven

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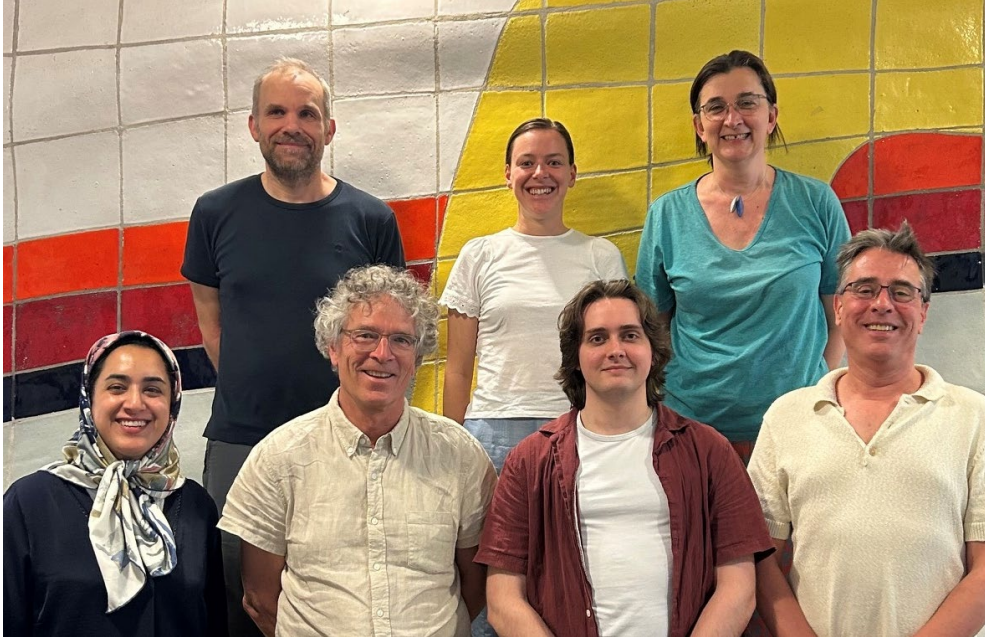


ZonMw



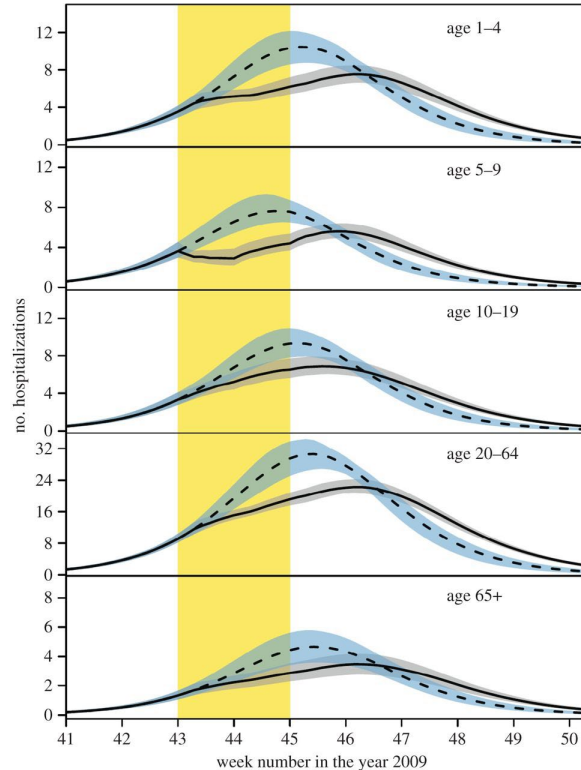
University Medical Center Utrecht

The consortium



- Dr Farzaneh Meimandi Parisi,
Dr Johannes Textor (Radboud)
- Oscar Jordan, Madelon Zwerink,
Dr Can Kesmir, Prof Rob de Boer (UU)
- Dr Michiel van Boven (UMCU)

Why study pre-existing immunity?



- Population level mortality and cross-sectional serological data to study the transmission and disease dynamics of the influenza A/H1N1 pandemic of 2009
- Fitted transmission model to the joint data
- The one-week autumn school holiday is estimated to have reduced transmission
- Substantial immunity in older adults profoundly reduced the impact of the 2009 influenza pandemic
- This has been confirmed in multiple studies

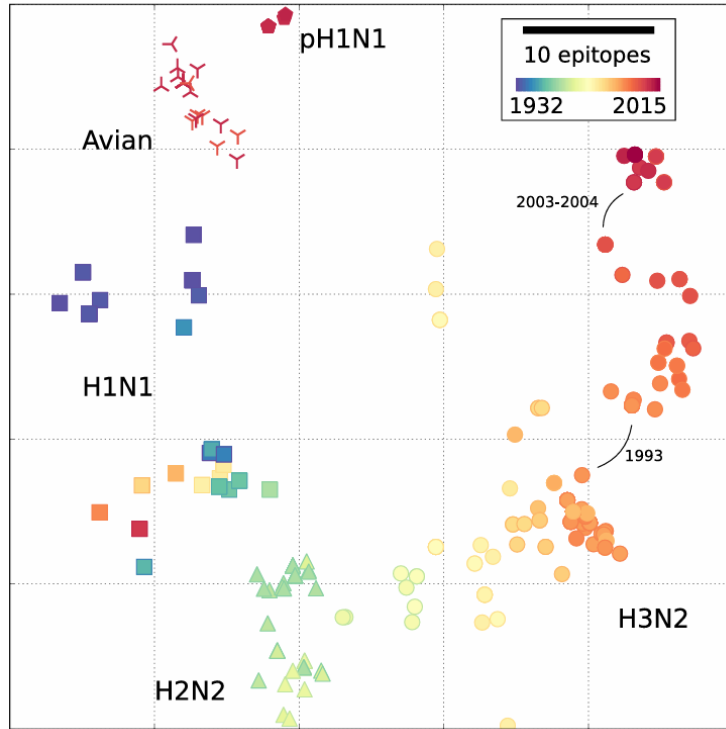


Why study pre-existing immunity?

parameter	age group (years)	estimate	(95% CrI)
fraction immune before the pandemic	1–4	0 ^a	
	5–9	0.08	(0.00–0.24)
	10–19	0.29	(0.20–0.41)
	20–64	0.72	(0.63–0.78)
	65+	0.91	(0.75–0.95)
infection attack rate	1–4	0.28	(0.24–0.33)
	5–9	0.53	(0.43–0.58)
	10–19	0.34	(0.27–0.40)
	20–64	0.05	(0.04–0.09)
	65+	0.01	(0.00–0.02)
reduction of transmission during school holiday	5–9	0.54	(0.29–0.82)
	10–19	0.10	(0.00–0.29)
basic reproduction number		2.2	(2.0–2.6)
reproduction number at the start of the pandemic		1.42	(1.37–1.48)
probability of hospitalization	1–4	0.00096	(0.00078–0.0012)
	5–19	0.00036	(0.00031–0.00044)
	20–64	0.0015	(0.00091–0.0020)
	65+	0.0084	(0.0028–0.016)



Why study pre-existing immunity?



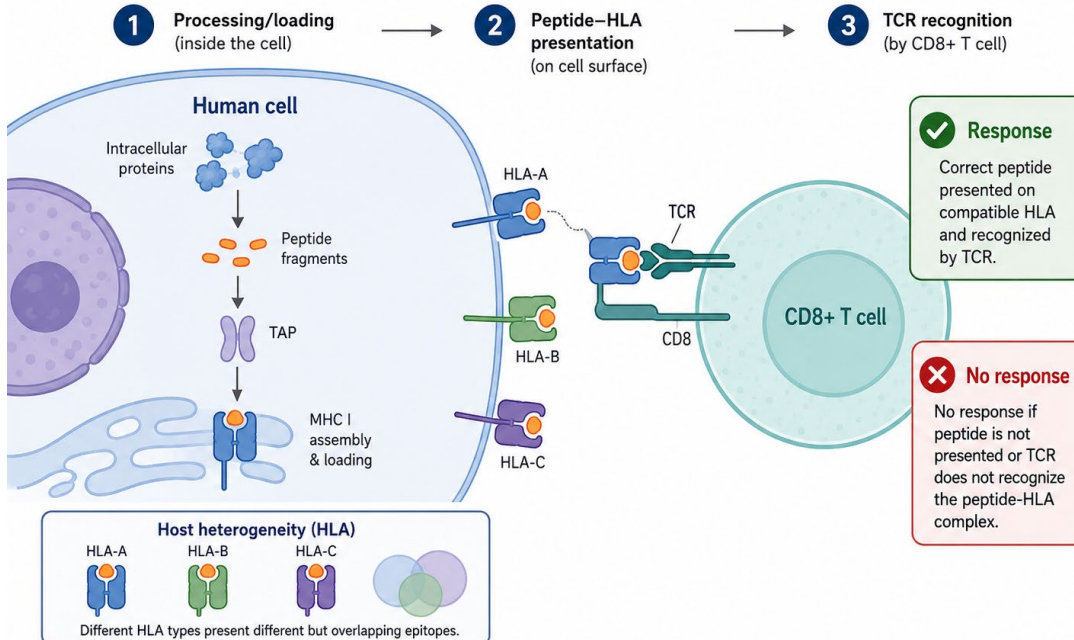
- Pre-existing immunity to novel viruses is likely mediated by cytotoxic T cell responses
- Antigenic mapping of 134 T cell epitopes in 295 representative influenza A viruses
- T cell Immunity extends across subtypes!
- Avian influenza A viruses (H5N1, H7N9, H9N2) are close to human H1N1 viruses!
- Based on a small number of empirically confirmed epitopes. **Need comprehensive predictions!**



The basics of CD8 T cell immunity

T-cell response requires peptide presentation and TCR recognition

Epitope availability, HLA type, and TCR specificity all shape CD8+ T-cell immunity.



- CD8 T cell immunity is essential modulating disease severity
- It is often more conserved than antibody mediated immunity
- It is highly host-specific (HLA)

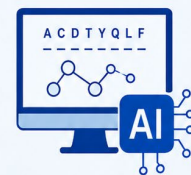


T-cell immunity is complex:
presentation and recognition are both required.



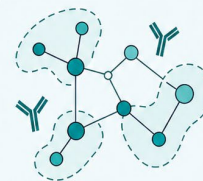
Our project

- **Workpackage 1.** Develop a novel protein language model (large antigen language model or LALM) trained to existing data to construct a representation of peptide-HLA space
- **Workpackage 2.** Use the LALM to estimate distances between coronaviruses and influenza A viruses ("antigenic cartography")
- **Workpackage 3.** Develop transmission models that can incorporate age and highly heterogeneous host populations



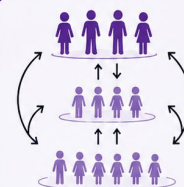
WP1. Improved antigenic cartography using antigen language models

- Build a large antigen language model (peptide-HLA)
- Characterize T-cell antigenic space
- Predict cross-reactivity and immune similarity



WP2. Antigenic maps and empirical validation

- Construct antigenic maps for influenza A and coronaviruses
- Use epitope predictions and empirical epitopes for validation
- Develop HLA-specific antigenic maps

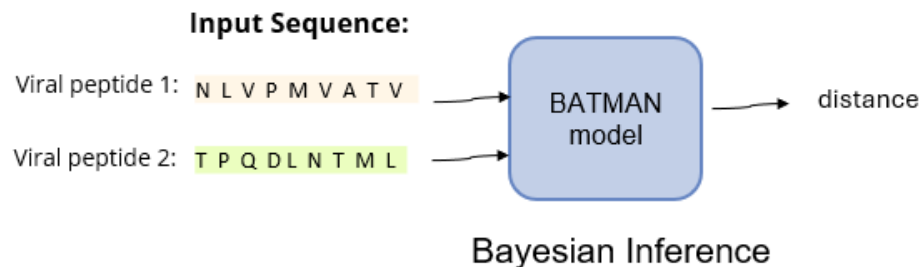


WP3. Transmission modelling with semi-realistic cross-immunity

- Build age- and HLA-structured transmission models
- Incorporate infection history and host heterogeneity
- Explore scenario analyses for emerging threats

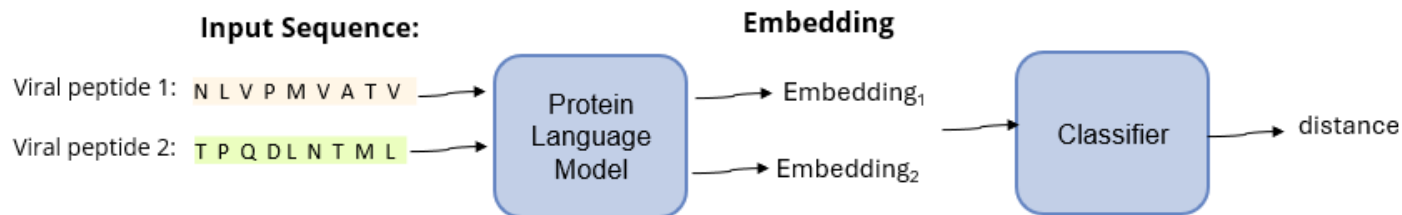
Peptide distances (>22k TCR-pMHCs)

A- BATMAN



Banerjee, A. *et al.* (2025). *Cell Systems*.

B- Protein Language Model



Lin, Z., *et al.* (2023). *Science*

Retrospective SARS-CoV-2 predictions

- Goal: predict pre-existing immunity to SARS-CoV-2
- We correctly predict NQKLIANQF as a protective epitope in *HLA-B*15* (B*62 supertype) carrying individuals (10-15% carrier frequency, lower in people of African descent)
- Note: preliminary analyses!

A common allele of *HLA* is associated with asymptomatic SARS-CoV-2 infection

<https://doi.org/10.1038/s41586-023-06331-x>

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Open access

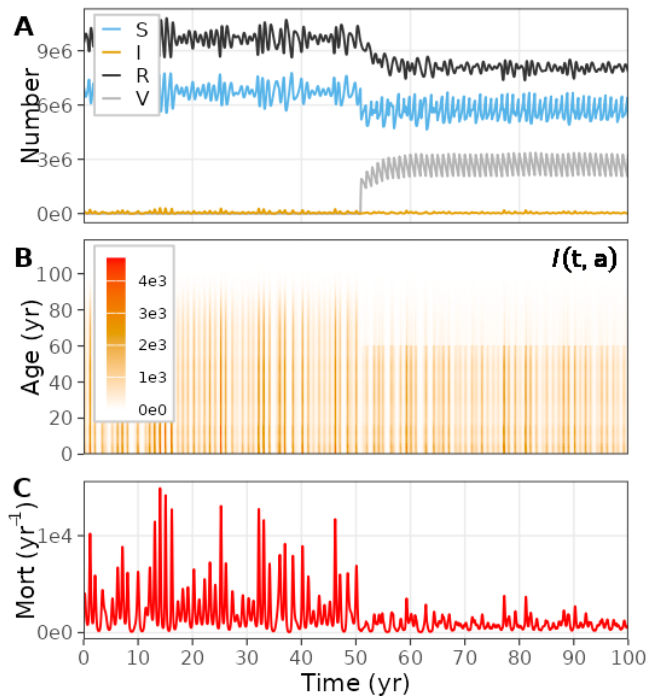
 Check for updates

Danillo G. Augusto^{1,2,3,18}, Lawton D. Mordolo^{4,18}, Demetra S. M. Chatzileontiadou^{4,5,18}, Joseph J. Sabatino Jr¹, Tasneem Yusufali¹, Noah D. Peyser⁶, Xochitl Butcher⁶, Kerry Kizer¹, Karoline Guthrie¹, Victoria W. Murray⁷, Vivian Pae⁷, Sannidhi Sarvadhavabhatla⁷, Fiona Beltran⁷, Gurjot S. Gill⁷, Kara L. Lynch⁸, Cassandra Yun⁸, Colin T. Maguire⁹, Michael J. Peluso⁷, Rebecca Hoh⁷, Timothy J. Henrich¹⁰, Steven G. Deeks⁷, Michelle Davidson¹¹, Scott Lu¹², Sarah A. Goldberg¹², J. Daniel Kelly^{12,13}, Jeffrey N. Martin¹², Cynthia A. Vierra-Green¹⁴, Stephen R. Spellman¹⁴, David J. Langton¹⁵, Michael J. Dewar-Oldis⁴, Corey Smith¹⁶, Peter J. Barnard⁴, Sulggi Lee⁷, Gregory M. Marcus⁹, Jeffrey E. Olgin⁹, Mark J. Pletcher^{12,17}, Martin Maier¹⁴, Stephanie Gras^{4,5,19} & Jill A. Hollenbach^{11,20,21}

Novel epitope (SARS-CoV-2)	Reference epitope	HLA supertype	Reference virus
IFVDGVPFV	IFVDGVPFV	B62	HCoV-HKU1 HCoV-OC43
LITGRLQSL	LITGRALAAL	A02	HCoV-229E HCoV-NL63
LIVAAIVFI	IICAALSF	A02	HHV-6B
	VIIAALVLV	A02	HHV-1
LLLSVCLGS	NMLSTVLGV	A02 / A03	IAV-H1N1 IAV-H2N2 IAV-H3N2
LPYPDPSRI	LPYPDPSRI	B07	IAV-H1N1 IAV-H2N2 IAV-H3N2
NQKLIANQF	NQKLIANAF	B62	HCoV-HKU1 HCoV-OC43
QYIKWPWYI	MYVKWPWYI	A24	HCoV-HKU1
	MYVKWPWYV	A24	HCoV-HKU1
	NYIKWPWV	A24	HCoV-NL63
	TYIKWPWV	A24	HCoV-229E
	YVVKWPWYV	A24	HCoV-OC43
RQLLFVVEV	KQLLFVLEV	A02	HCoV-HKU1 HCoV-OC43
SPRWYFYLL	LPRWYFYLL	A02 / B07	HCoV-HKU1 HCoV-OC43
TMADLVYAL	TMDLFCYAL	A02	HCoV-HKU1 HCoV-OC43
	TMDLFCFAL	A02	HCoV-229E
VLAWLYAAV	FLAWLYAAI	A02	HCoV-OC43
	VIAWLYAAI	A02	HCoV-HKU1

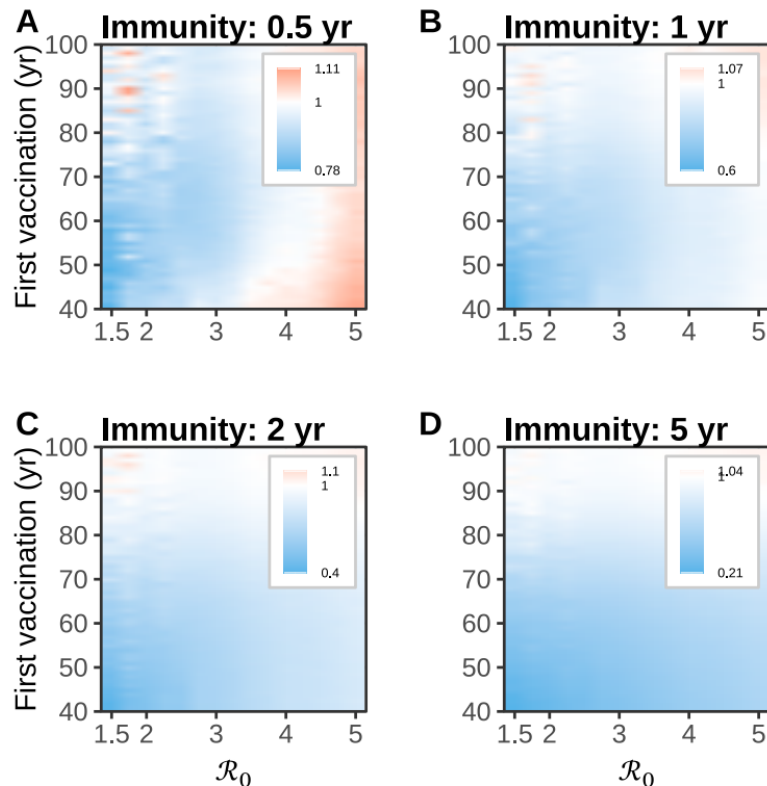
Immunity and vaccination against influenza A

- Time-age partial differential equations model inspired by influenza A, based on SEIRS-type epidemic model
- Repeated vaccination every year in October-November from a certain age onwards; realistic coverage and vaccine effectiveness; weak seasonal forcing (5%); semi-realistic contact rates
- Variable immunity after infection: 2-7 years
- Immunity after vaccination: ≤ 5 years



Immunity and vaccination against influenza A

- When $\mathcal{R}_0$ is low, young ages of first vaccination reduce mortality by herd immunity effects
- When $\mathcal{R}_0$ is high, young ages of first vaccination are beneficial IF immunity by vaccination is long-lived
- When $\mathcal{R}_0$ is high AND immunity by vaccination is short-lived, vaccination shifts the infection ages upwards, resulting in increased mortality
- First vaccination at old age is ineffective; benefits of vaccination are offset by shifting age at infection upwards



Projected scientific outputs

- Schröder G et al (2026) What does the shape space of T cell epitopes look like? *Manuscript*
- Jordan O et al (2026) Predicting pre-existing CD8 T cell immunity to emerging viruses.
In preparation
- van Boven M et al (2026) Optimal vaccination in aging populations under age-dependent infection fatality risks. *Under review*
- De Boer RJ et al (2026) Influenza A dynamics shaped by heterogeneous immune histories and B- and T-cell immunity. *In progress*



Save the date!

We will host a **multi-project workshop** on **October 6 in Utrecht**, aiming to integrate scientific findings in the morning and discuss implications for public health policy in the afternoon.

Participating projects are

- Voorspellen van immuniteit tegen nieuwe pandemische virussen (van Boven)
- Real-time ruimtelijke data-gedreven modellering van uitbraken van infectieziekten (Litvak)
- Controle van infectieziekten: modellering van gedrag in sociale netwerken (Kretzschmar)
- De effectiviteit van toegangsbewijzen voor bijeenkomsten als infectiepreventie maatregel (Bootsma)
- De invloed van clustering op de effectiviteit van contact tracing (Bootsma)



Readying Regional Mobility data for Modeling Pandemic Preparedness

F. Scott Dahlgren^{1, *}, Marloes Verhoeven², Tom Emery³, Peter Lugtig⁴, Debabrata Panja⁴, Frank P. Pijpers⁵,
Matthijs Romeijnders⁴, Ganna Rozhnova⁶, Sake J. de Vlas¹, and Luc E. Coffeng^{1, †}

¹Erasmus MC, ²Nationaal Dataportaal Wegverkeer, ³Open Data Infrastructure for Social Science and Economic Innovations, ⁴Universiteit Utrecht,

⁵Centraal Bureau voor de Statistiek, and ⁶Universitair Medisch Centrum Utrecht.

*f.dahlgren@erasmusmc.nl

†l.coffeng@erasmusmc.nl

Introduction

Mobility of people between municipalities and regions plays a significant role in the spread and control of infectious diseases. Existing computational models for the spread of infectious diseases fail to adequately capture the role of regional mobility, or such models focus only on a limited set of types of mobility. Although there is a wealth of Dutch mobility data, much of its potential for pandemic preparedness remains untapped due to limited accessibility, which is often related to privacy considerations and the intrinsic complexity and sheer scale of such data.

Mobility Data Sources

Onderweg in Nederland (ODiN) is an annual survey of Dutch residents who detail all their travel for a single day. ODiN also collects information about respondents such as age, linking trips to people.

Translink manages mobility data for Dutch public transport companies. Before censoring small numbers to protect privacy, the Translink data contain nearly all trips by public transportation in the Netherlands.

TomTom centrally records all the journeys from their navigation devices. After truncating the start and end of each journey for privacy, trips are tabulated by origin and destination of the trip as well as date and time.

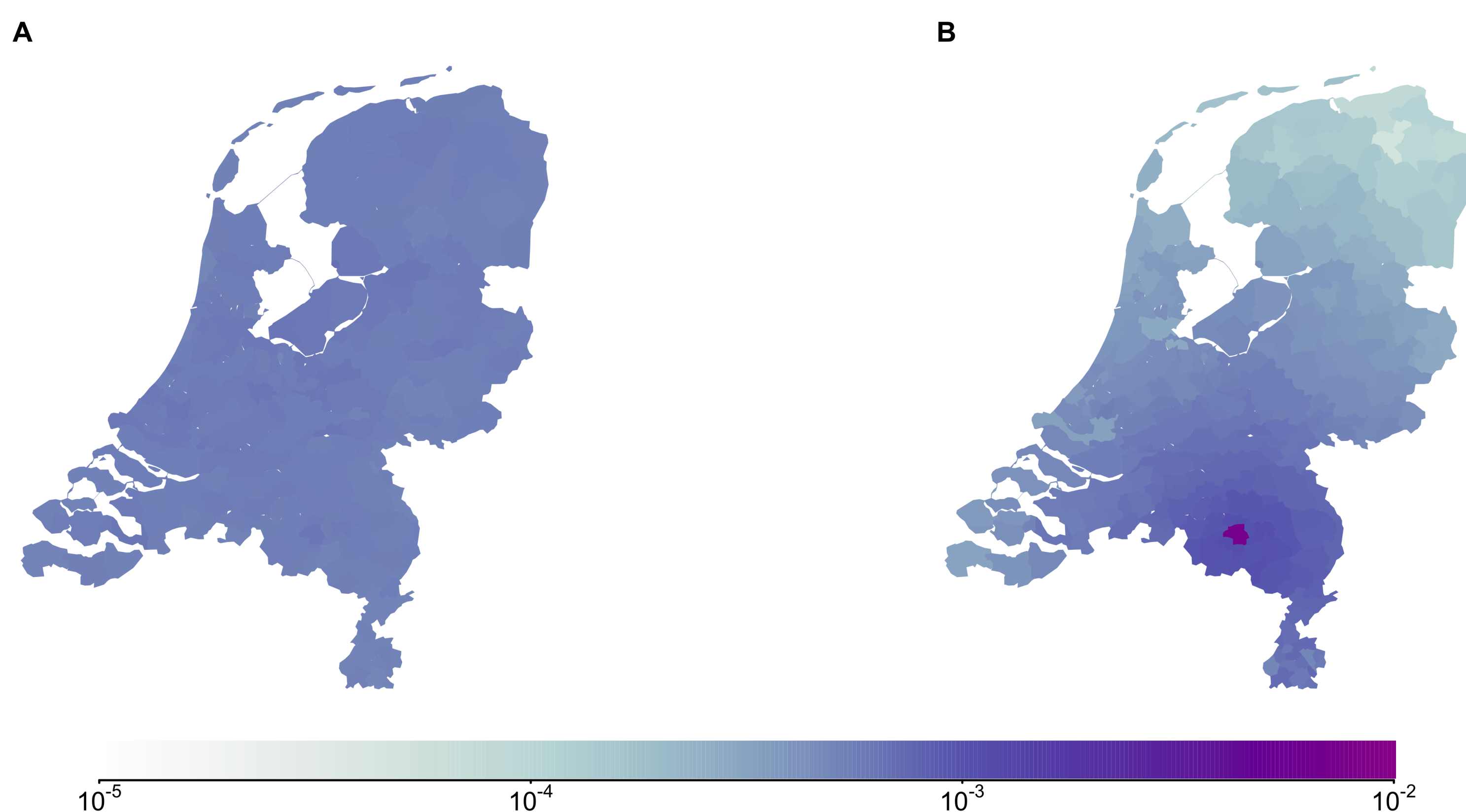


Figure 1: Model estimates of the cumulative proportion of infected people during an outbreak which starts in Eindhoven, (A) ignoring spatial movement and (B) including spatial movement informed by mobility data. Both maps represent the first 10,000 cases of an outbreak of a person-to-person respiratory infection similar to COVID-19 or influenza. Each map is the average of 1,000 simulations using the Erasmus MC **virsim** model^a, which we extended to include mixing between age groups and mixing between municipalities for this project.

^a Achieving herd immunity against COVID-19 at the country level by the exit strategy of a phased lift of control (2021).

S. de Vlas and L.E. Coffeng. *Scientific Reports* 11: 4445.

Added Value of Mobility Data

The mobility data allows us to construct empirical estimates of the mixing between municipalities. When used as inputs in the model, these data inform where outbreaks are likely to spread when they begin in a limited geographic area. To better inform policy decisions, the model can estimate the epidemiological effects of interventions which limit human mobility, such as lockdowns, work from home policy, or school closures.

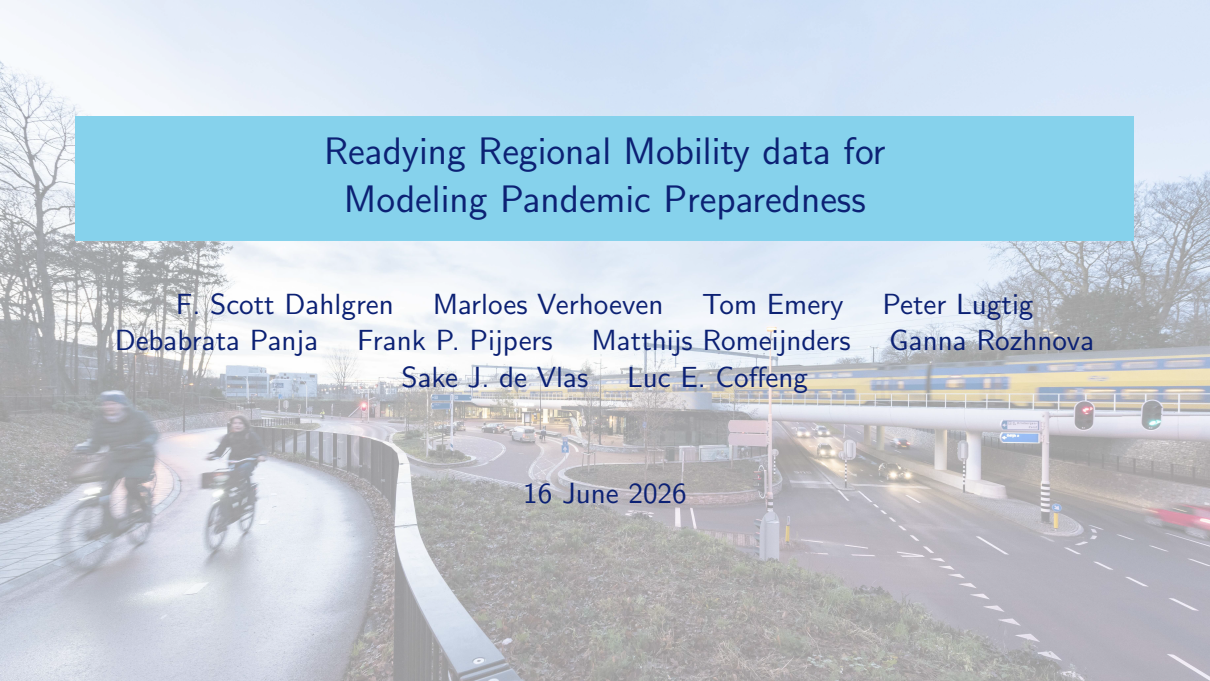
Conclusions

Translating human mobility data into accurate inputs for infectious disease models is key to better inform decision makers. To operationalize the maintenance of these data for future crises requires the establishment of appropriate mandates and a legal framework with data owners.

Reading Regional Mobility data for Modeling Pandemic Preparedness

F. Scott Dahlgren Marloes Verhoeven Tom Emery Peter Lugtig
Debabrata Panja Frank P. Pijpers Matthijs Romeijnders Ganna Rozhnova
Sake J. de Vlas Luc E. Coffeng

16 June 2026



- Mobility drives the spread of person-to-person infectious diseases such as COVID-19 and influenza.
- Many high quality data sets exist about Dutch mobility.
- In the Netherlands, infectious disease models rarely include data-driven estimates of mobility.
- Access to data is limited by privacy protections and commercial interests.

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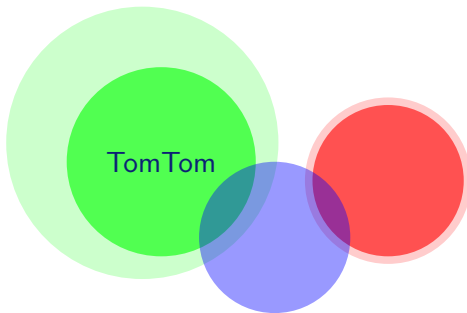
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Mobility Data

Data Sources

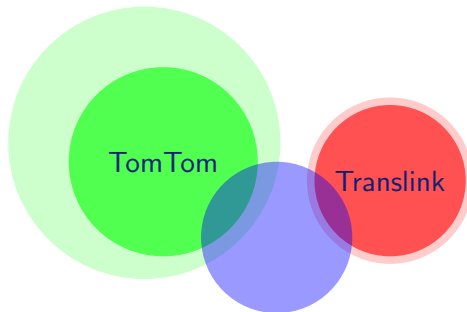
- TomTom
 - Sensor data in cars
 - Marketshare depends on place and time
- Translink
 - Travel on public transportation
 - Complete data except for paper tickets
- ODIN
 - Survey of Dutch residents about travel for a single day.
 - Information about the people who travel.



Mobility Data

Data Sources

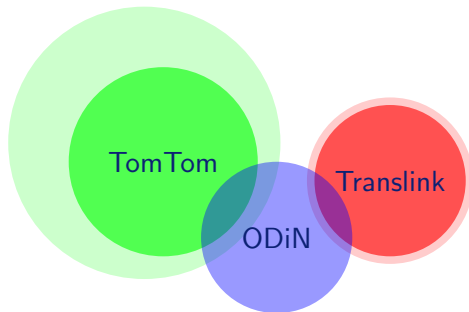
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Data acquisition

- Infectious disease modelers are not 'the usual customer' for mobility data.
- Poor fit between the approval pipeline and our project.
 - First data request submitted in December 2024
 - Data shared with Erasmus MC in December 2025

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Mobility Data

Infectious Diseases Models

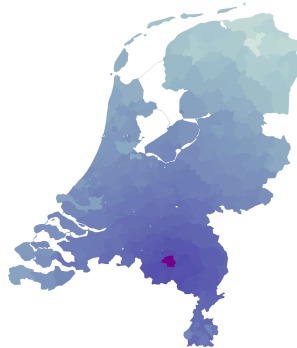
No mobility data

A



Including mobility data

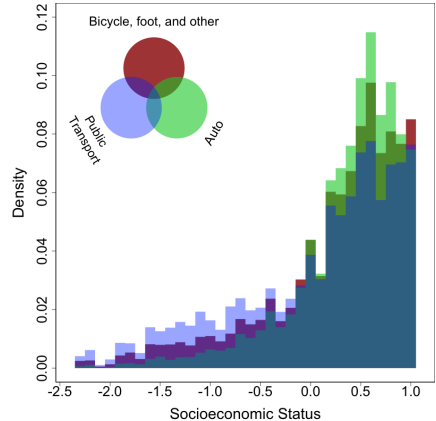
B



Mobility

Vulnerable People

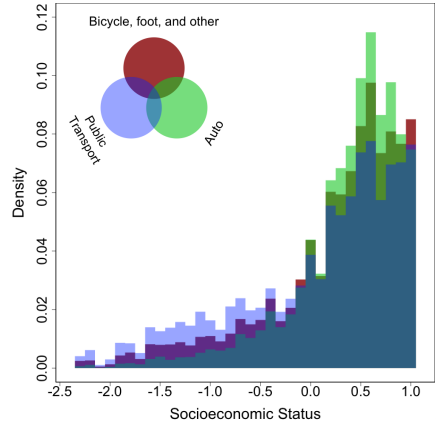
- People with lower socioeconomic status (SES) use public transportation more than people with higher SES.
- People who cannot always seek medical care because of access to transportation have lower SES than people who can always seek care.
- Interventions aimed at reducing mobility, such as limiting public transportation, can disproportionately impact people with lower SES.



Mobility

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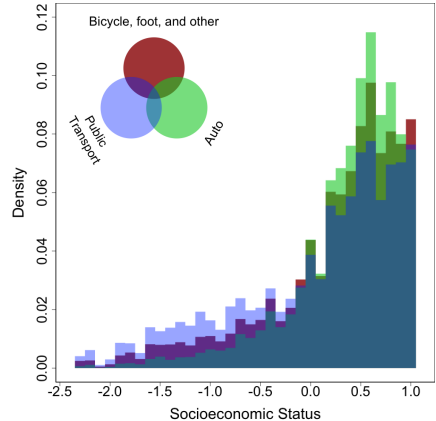
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Mobility

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- Mobility data are important for modeling person-to-person respiratory infectious diseases, **especially** during the start of an outbreak.
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Phaeton: Crowdsourced, Privacy Respecting Data Analysis and Modeling for Pandemic Preparedness

Özsezen, S. (Serdar)

[Start presentation](#)

Origin of the project idea

- [Report Audit RIVM COVID-19 data analytics and modelling for scientific advice to policy makers \(2023\) | RIVM](#)
- Some important points:
 - **Human resources:** *The societal and time pressure on the staff was immense, so additional staff is also needed to prevent burnouts in the long term. Many teams across the world experienced difficulties in hiring and training DAM (data analysis and modeling) experts; this was nearly impossible during the acute phase of the pandemic. In addition, there are structural obstacles that hinder the recruitment of high-quality external senior DAM experts at RIVM. These difficulties must be urgently addressed.*
 - **Access to data streams:** *DAM teams had to spend a disproportionate amount of time on collecting and linking some types of data and were unable to obtain others. This was due to a variety of reasons, including very strict interpretations of the GDPR in the Netherlands, scattering of data sets over different sources, delays in the availability of some types of data, and non-structural funding for some data collection efforts. These issues should be evaluated and resolved before a new pandemic occurs.*
 - **Research quality:** *While there was much international scientific cooperation, there was relatively limited cooperation with Dutch academic modelling groups during the audit period. While this was understandable given the time pressure, intensifying such cooperation and use of expertise could have contributed to the replicability of and the public trust in the modelling work.*

Origin of the project idea

 code ocean

Product Solutions



Compute Capsules

A shareable, traceable, reproducible encapsulation of the code, data, and environments used in computational research, version controlled and linked to the results they produce.

kaggle

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Phaeton: Crowdsourced, Privacy-Respecting Data Analysis and Modeling for Pandemic Preparedness

Serdar Özsezen¹, Eugene van Someren¹, Marieke Vinkenoog²

¹ Health & Work, TNO, Leiden, the Netherlands

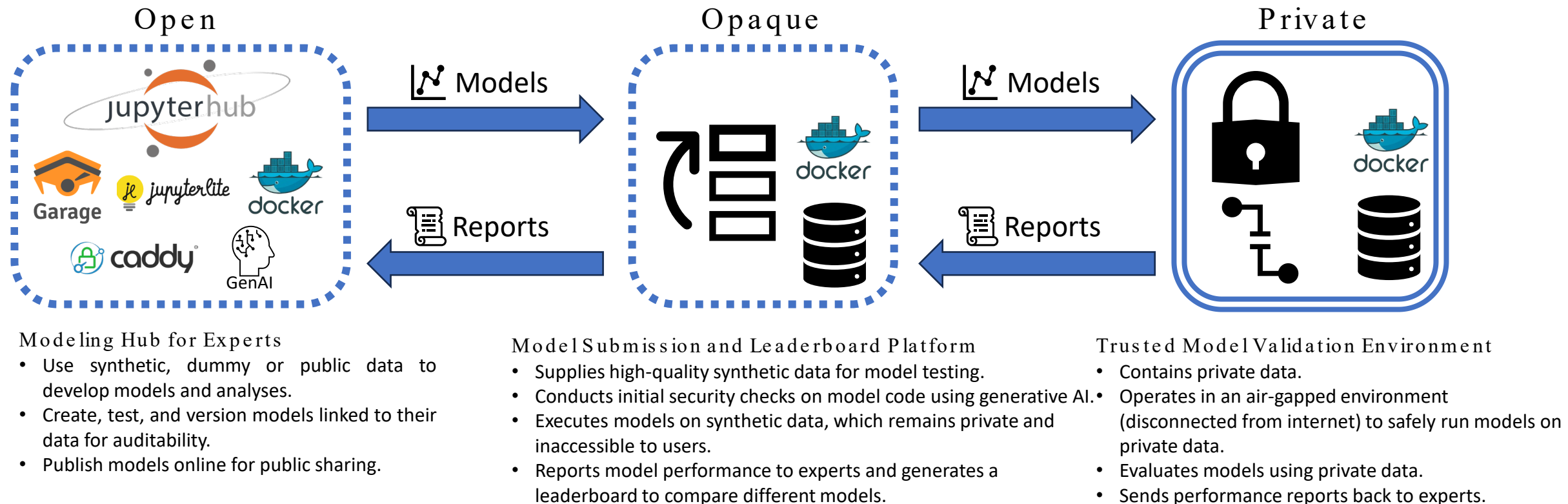
² Public Health en Eerstelijns geneeskunde, Leiden University Medical Center, Leiden, the Netherlands



For more information and access to repositories:

<https://phaeton.codeberg.page>

- Project Phaeton aims to create a collaborative, privacy-respecting data analysis and modeling infrastructure for pandemic response. It enables experts to develop high-quality models and predictions without compromising privacy or auditability.
- The project addresses data access challenges with a layered privacy-by-design approach, combining synthetic data access and federated model testing on real data, ensuring privacy compliance.
- Phaeton is a free and open-source software project, all of the code and documentation is freely accessible in our public repositories.



What did we learn?

- Although we can create the technical tooling to minimize the risks for data sharing and processing, legal and governance issues still need to be resolved.
- There should be data sharing agreements established (at least) between the public institutions for speeding up response in a possible pandemic. These agreements are also relevant for use of synthetic data.
- Either structural or on-demand funds should be made available to support deployment of modeling and data infrastructures at the time of a possible pandemic.
- Structural funding could be made possible by multiple uses of the same infrastructure.

Outlook

- Phaeton has become a DigiLab Toegepaste Kennis use-case project.
- Deploy and test our model development/exchange infrastructure using TNO and RIVM resources.
- Explore governance structures for this solution.
- Seek opportunities for multidisciplinary applications besides pandemic preparedness for long-term funding.



Rijksinstituut voor Volksgezondheid
en Milieu
*Ministerie van Volksgezondheid,
Welzijn en Sport*





TNO innovation
for life

Thank you!

Hoe epidemiologische modellen gedrags- en communicatiewetenschappen nodig hebben

Pieter Trapman



university of
 groningen

faculty of science
and engineering

ZonMW Pandemic Preparedness Slotbijeenkomst
16 juni 2026

Het team

Twente: Marielle Stel, Shenja van der Graaf, Annemarie Nanne, Johanna de Silva, Sina Frerichs, Iris van Sintemaartensdijk
Groningen: Victor Bernal, Maddalena Doná, Slavik Koval

Modellen voor infectieziekten

- SIR epidemie en varianten
- Sociale netwerken
- Globale invloed van verspreiding van ziekte op gedrag

Modellen voor opinieformatie en polarisatie

- Voter-model
- Schelling-model en dynamische (random) netwerken

Wat de gedragswetenschappen inbrengen

Resultaten survey:

- Hoe ernstiger de ziekte voor besmette persoon is, hoe meer men overheidsaanbevelingen/-maatregelen wil volgen
- Meeste invloed hebben directe familie en wetenschappers
- Sociale media minder belangrijk
- Veranderende aanbevelingen verlagen vertrouwen in aanbevelingen en maatregelen worden als minder effectief gezien

Wat de gedragswetenschappen inbrengen

Literatuurstudie:

- Familie, vrienden, collegas belangrijkst voor opinievorming
- Sociale media dragen bij aan misinformatie, maar ook “goed gedrag”
- Niet-volgen aanbevelingen door anderen, verlaagt vertrouwen in aanbevelingen

De wiskunde van opinies

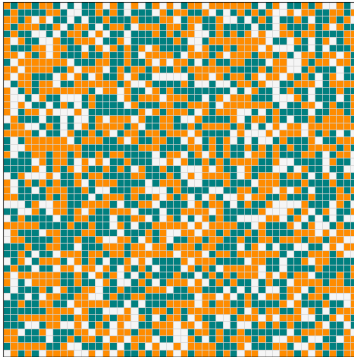
- Wat is misinformatie?
- Hoe beïnvloeden mensen elkaar?
- We bestuderen Schelling-model en Voter-model

Schelling model: het origineel

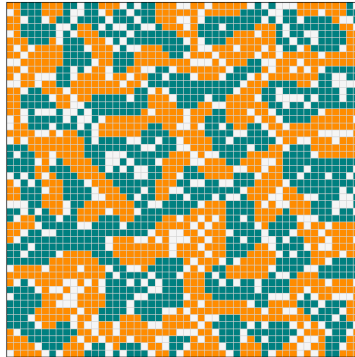
- Thomas Schelling bestudeerde model om segregatie te verklaren in ruimtelijke setting
- Twee mogelijke opinies
- Mensen verhuizen, met voorkeur naar plekken waar het percentage burens met zelfde opinie boven bepaalde drempelwaarde is
- Drempelwaarde relatief dichtbij 50% geeft al segregatie

Schelling model: het origineel

Initial configuration



Final configuration



Schelling model op dynamische random intersection graph

- Mensen hebben twee mogelijke opinies
- Iedereen is deel van verschillende mogelijke “invloedsgroepen”
- Aantal groepen verandert niet
- Mensen worden deel van groep met rate die afhangt van fractie mensen met zelfde mening in groep
- Mensen verlaten groep met rate die afhangt van fractie mensen met andere mening in groep

Schelling model op dynamische random intersection graph

- Directe equivalent van “vierkantsrooster” Schelling model is moeilijk te analyseren
- Identificeer modellen waarbij Markov model, “reversible” is
- Groepen krijgen dominante opinie

Het Voter-model: Het origineel

- Mensen leven op een netwerk
- Mensen hebben twee mogelijke opinies
- Mensen heroverwegen hun mening allemaal met zelfde rate
- Heroverwegen betekent de mening van een random buur aannemen
- Model terug in tijd zijn random wandelingen die bij botsing samen verder gaan

Het Voter-model

- Dynamiek redelijk goed begrepen op vierkantsroosters en regelmatige “bomen”
- Vooral interesse in: Wordt iedereen het uiteindelijk eens met elkaar? En, zo ja, hoe lang duurt dat?
- Andere netwerken verrassend slecht begrepen

Het Voter-model: Nieuw theoretisch werk

- Op regelmatig netwerk met overlappende groepen duurt het langer tot consensus is bereikt dan op regelmatige netwerk zonder groepen.
- Beter begrip van Voter-model op minder regelmatige netwerken

Het Voter-model: Simulaties en uitbreidingen

- Radicalisering
- Op dynamisch Schelling model netwerk
- Asymmetrische overtuigingskracht
- Combinatie met SIR epidemie
- Toekomstig werk: Deterministisch model

IMPROVING REGIONAL PATIENT ADMISSIONS AND INTER-REGIONAL PATIENT TRANSFERS DURING A PANDEMIC

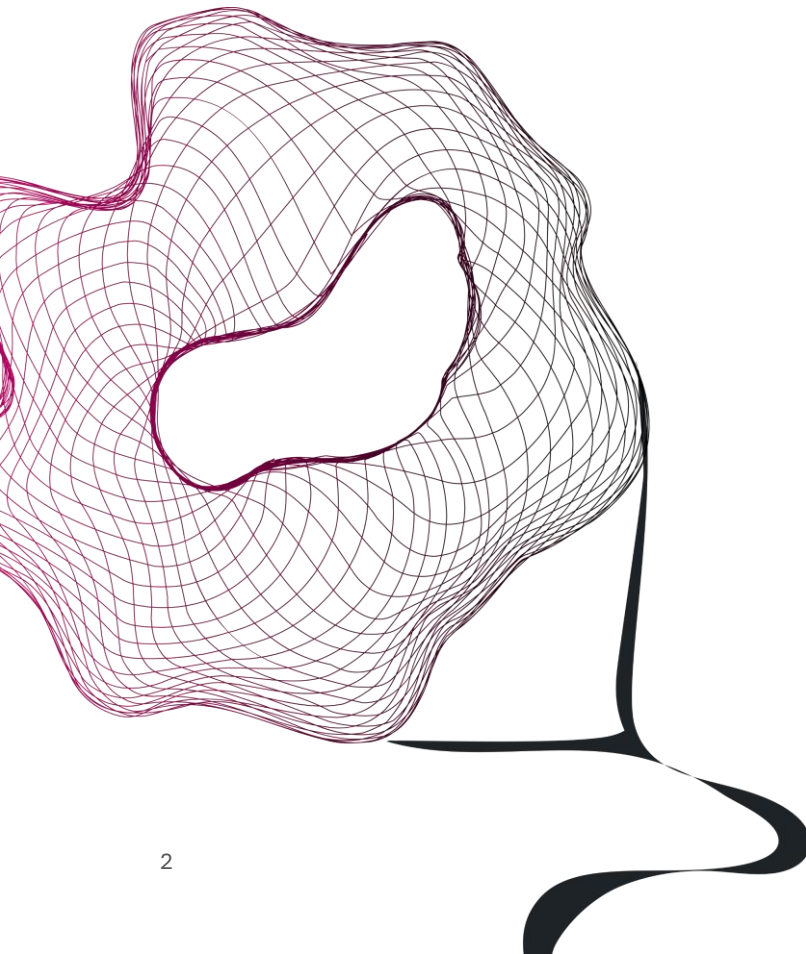
**PRESENTER:
ANNE ZANDER (UNIVERSITY OF TWENTE)**

**PROJECT LEADER:
RICHARD BOUCHERIE (UNIVERSITY OF
TWENTE)**



AGENDA

- 01 Project overview**
- 02 New patient allocation rule
- 03 Proof of concept
- 04 Conclusion



PROJECT OVERVIEW

Project goal: Develop and test a data-driven decision-support concept for pandemic patient allocation

Project consortium:

- **University of Twente (project lead):** mathematical modeling (forecasting, optimization), and project coordination
- **Radboud UMC:** medical and data-analytic expertise
- **ORTEC/Rhythm bv:** implementation of healthcare software solutions
- **University of Groningen:** operations management and stakeholder perspective
- **LNAZ/LCPS:** national implementation and patient-spreading coordination
- **Other involved hospitals and acute-care networks:** MST, ZGT, AZE, AZB, AZO

MOTIVATION

- During COVID-19, hospital pressure varied across regions
- Patient transfers were necessary, but difficult to coordinate fairly
- “Available capacity” was not always clear or comparable across hospitals
- Decisions were often urgent, local, and reactive
- Both pandemic and non-pandemic patients were affected

Our goal:

Develop a **data-driven decision-support system** that helps **hospitals, (ROAZ) regions, and the national coordination center** to make **timely, efficient, and fair patient allocation decisions** during a pandemic.

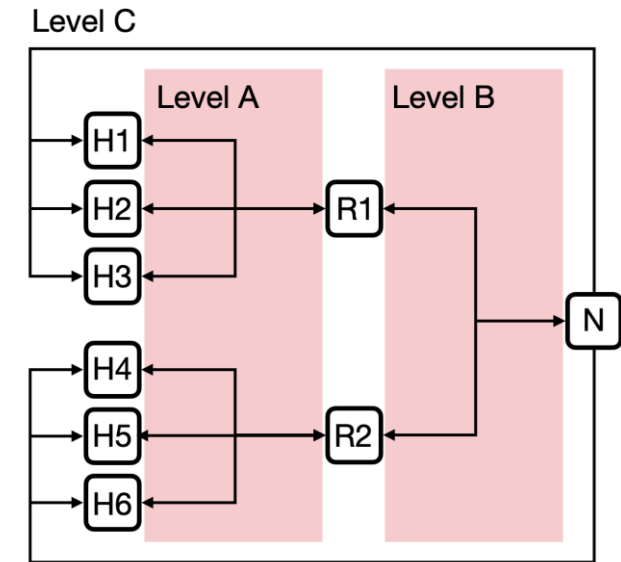
NOS, nieuwsuur, 15-06-2026

Artsen over corona: 'Code zwart was er feitelijk wél, honderden overlijdens door beddentekort'



OVERALL STRUCTURE

- **Hospitals:** use patient-flow data to forecast bed census
- **(ROAZ) regions:** combine hospital outputs to support regional allocation decisions
- **National coordination:** combine regional outputs to support national allocation decisions
- **Information sharing:**
 - aggregated outputs move upward
 - allocation advice moves back to regions and hospitals



Level A: Hospital/region sharing
Level B: Regional/national sharing
Level C: National/hospital sharing

SHORT-TERM FORECASTING

Goal: forecast hospital bed census over the upcoming days

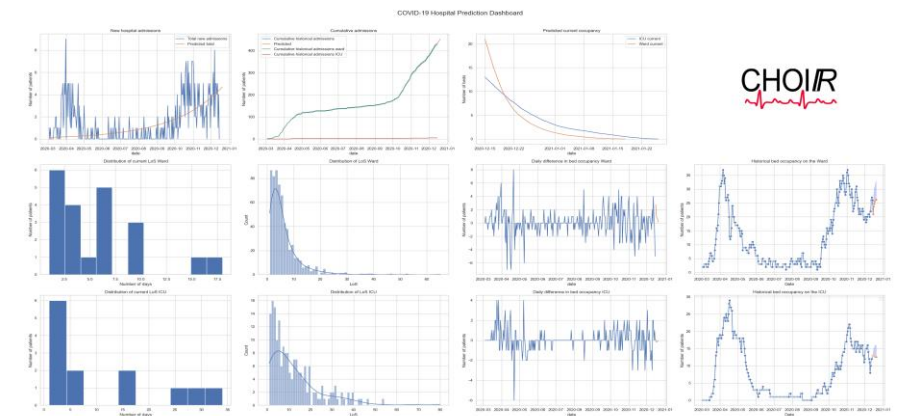
Modeling (queueing theory and simulation):

- Predict arrivals of pandemic patients (autonomous and non-autonomous)
- Estimate length-of-stay distributions (ward and ICU)

Output per hospital: resulting bed occupancy distribution (ward and ICU) over the next days

Use: input for regional and national allocation models

opname	Herkomst	Bestemming	startdatumtijd	einddatumtijd	IC opname
1	Eigen woonomgeving	Covid-19 afdeling Ziekenhuis 1	26-3-2020 17:05	31-3-2020 15:11	Ja
2	Kliniek	Covid-19 afdeling Ziekenhuis 2	27-3-2020 12:28	27-3-2020 22:59	Ja
2	Eigen woonomgeving	IC	26-3-2020 16:58	27-3-2020 12:28	Nee
3	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 19:54	30-3-2020 16:15	Nee
4	Uit eigen ziekenhuis	Eigen woonomgeving	26-3-2020 17:59	1-4-2020 14:23	Nee
5	Eigen woonomgeving	niet-Covid afdeling Ziekenhuis 2	26-3-2020 19:38	31-3-2020 15:55	Ja
6	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 18:41	4-4-2020 11:35	Nee
7	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 19:39	29-3-2020 18:58	Nee
8	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 19:59	29-3-2020 12:10	Nee
9	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 21:50	27-3-2020 20:34	Nee
10	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 20:37	29-3-2020 13:18	Nee
11	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 22:40	28-3-2020 19:57	Nee
12	Eigen woonomgeving	Eigen woonomgeving	26-3-2020 23:54	6-4-2020 17:35	Nee
13	Eigen woonomgeving	Eigen woonomgeving	27-3-2020 12:48	31-3-2020 12:33	Nee
14	Eigen woonomgeving	Covid-19 afdeling Ziekenhuis 1	27-3-2020 12:59	31-3-2020 15:11	Ja
15	Eigen woonomgeving	Overleden (zonder obductie)	27-3-2020 12:59	1-4-2020 18:31	Ja
16	Eigen woonomgeving	Eigen woonomgeving	27-3-2020 14:36	3-4-2020 14:59	Nee
17	Eigen woonomgeving	niet-Covid afdeling Ziekenhuis 2	27-3-2020 15:19	28-3-2020 22:00	Nee
18	Eigen woonomgeving	Eigen woonomgeving	27-3-2020 15:23	7-4-2020 15:18	Nee
19	Eigen woonomgeving	niet-Covid afdeling Ziekenhuis 1	27-3-2020 15:46	28-3-2020 19:47	Nee



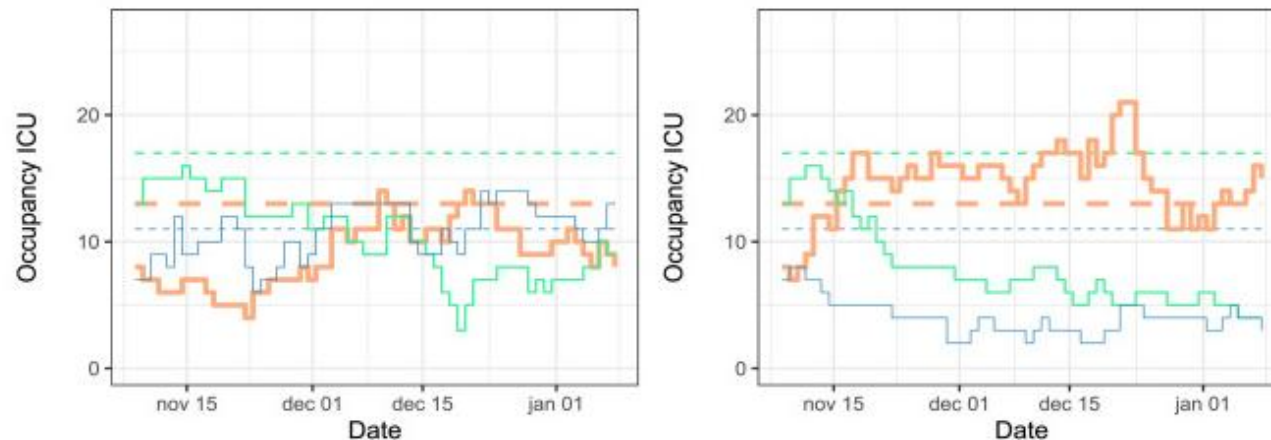
ORIGINAL ALLOCATION MODEL

Goal: allocate pandemic patients while anticipating uncertain future demand

Model:

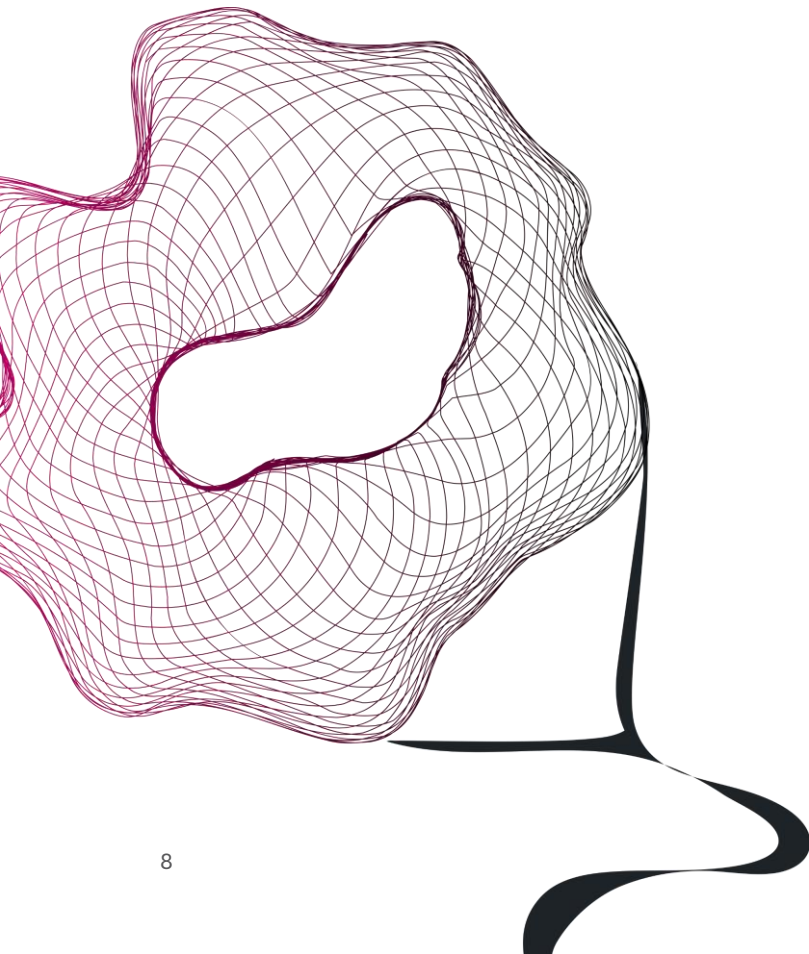
- Decide the number and type of reallocations today
- Minimize total travel distances of patient reallocations over the upcoming days
- Generate scenarios for future hospital bed occupancy (based on the forecast) -> shortages and surplus of beds
- Resolve all shortages and fairly distribute surplus

Use: allocate patients on the regional and national levels



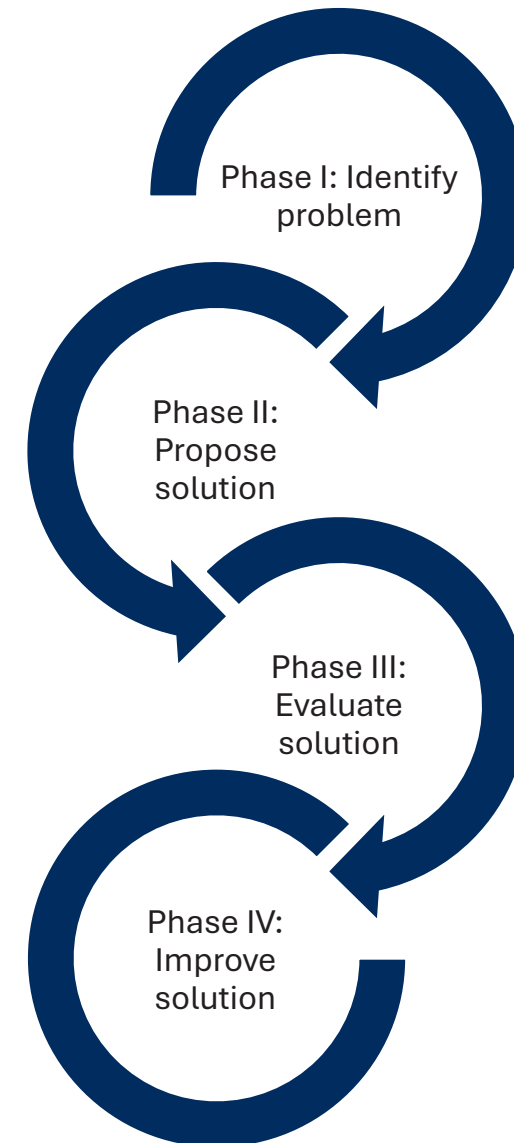
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NEW PATIENT ALLOCATION RULE

- Original allocation model gives a first allocation framework
- However, stakeholder input showed that implementation requires:
 - explicit consideration of regular care
 - limited data requirements (incl. avoidance of having to report “available beds”)
 - easy to interpret advice
- This led to the development of a new allocation rule



PHASES I AND III: INPUT FROM STAKEHOLDERS

2021:

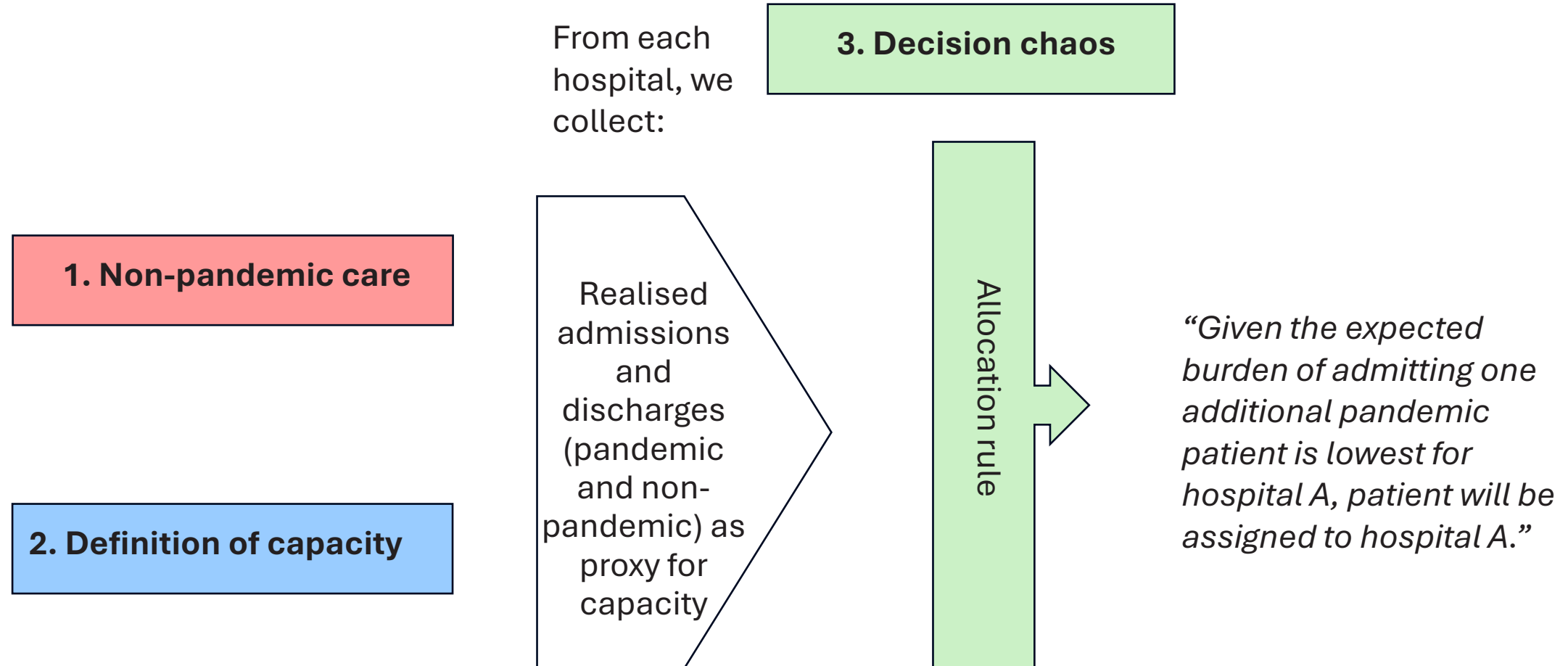
- Interviews with 7 heads of ICU, 4 ICU staff members, 8 capacity managers, 9 hospital chief executive officers, 14 staff from regional coordination centres, 7 staff from the national coordination centre
- Topics: ICU capacity, managing scarcity, organizing patient transfers and information exchange (hospitals)

2024/25:

- Interviews with 3 hospitals: 2 general hospitals and 1 tertiary care center (UMC)
- Topics: Feedback on the initial new allocation rule

- 1. Perceived unfairness in balancing pandemic and non-pandemic care**
- 2. Capacity: an unclear concept**
- 3. Decision chaos**
- 4. Admittance and discharge data are reliable, while regular care waiting list data is not**

PHASES II AND IV: SOLUTION



PHASES II AND IV: SOLUTION

a_0 : average daily workload inflow in regular times

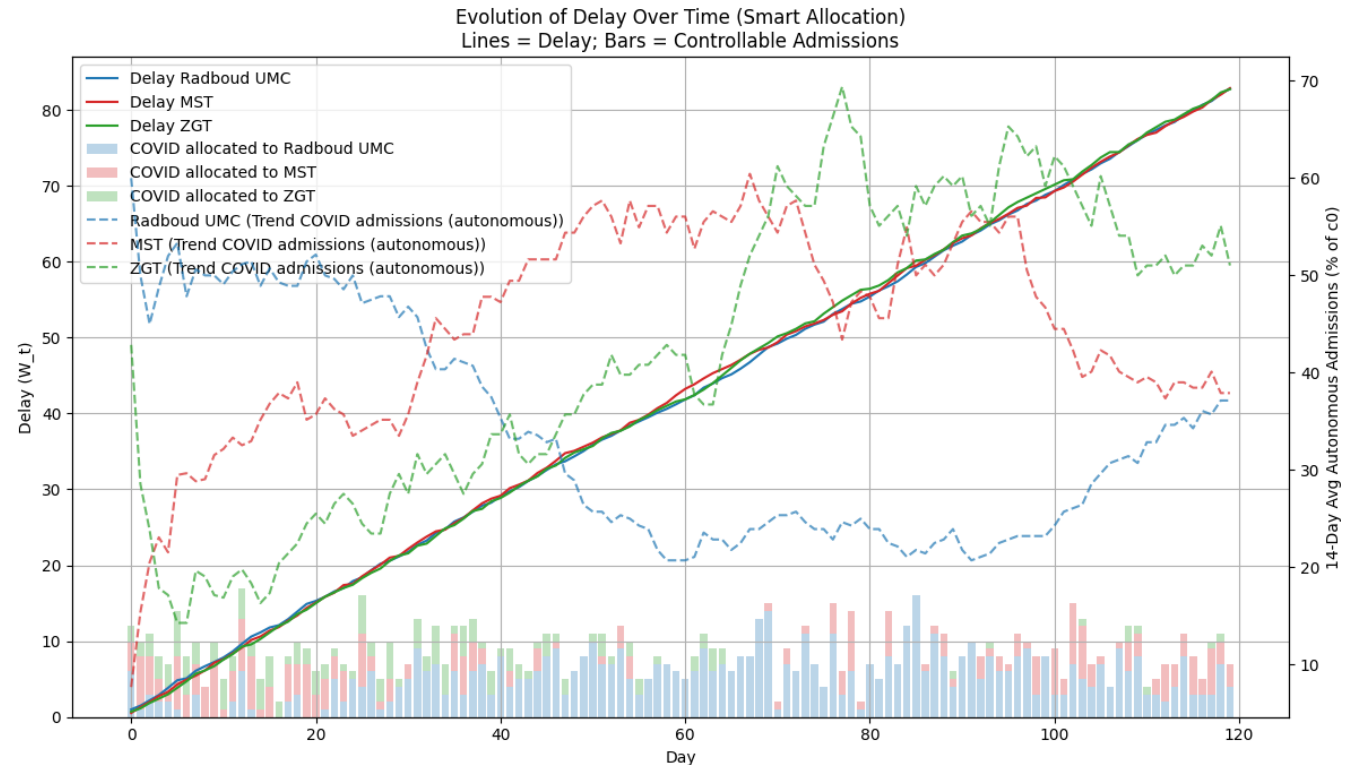
a_t^r : workload inflow from regular non-pandemic patients at day t

$b_t = a_0 - a_t^r$: additional workload that accumulates on day t

w^p : average workload of a pandemic patient

c : daily capacity, e.g., total workload inflow

Allocation rule: direct controllable pandemic patient to the hospital where the expression $\frac{1}{c} (w^p + \sum_{k=t-L}^t b_i)$ is the lowest

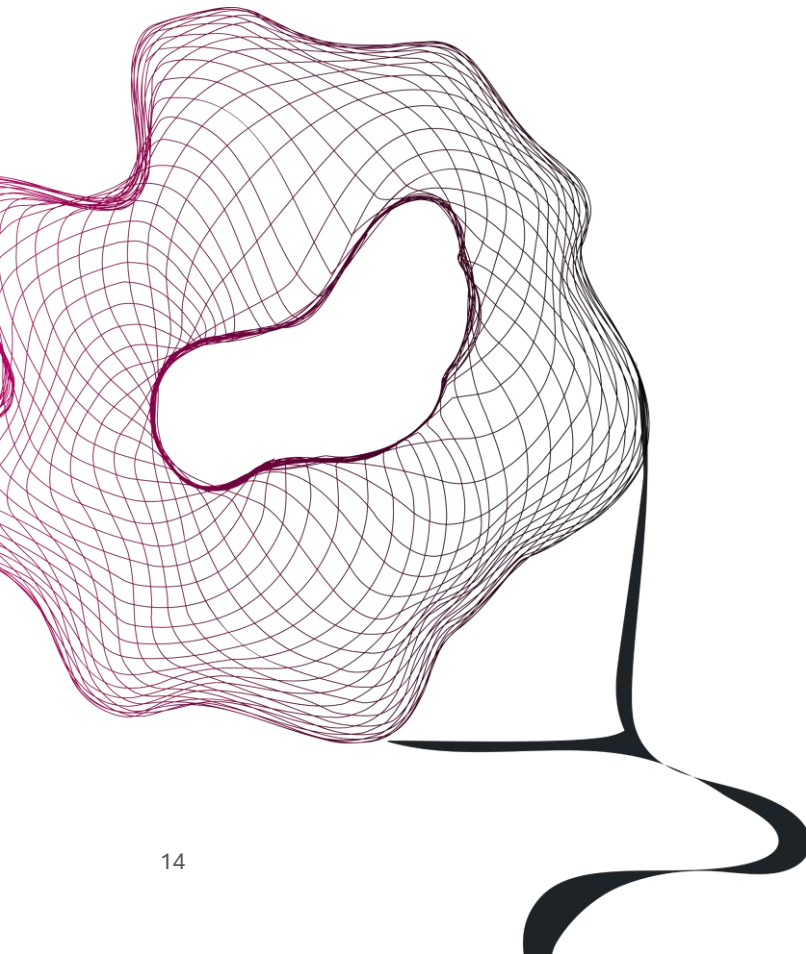


UPCOMING PAPERS

- Designing an allocation rule for pandemic patients: a feasibility study with stakeholders in hospital bed capacity coordination in the Netherlands
- *Authors: A. Dankers, V. Ploeg, P. Buijs, A. Zander, S. Dijkstra, A. van Gils, T. van der Vaart, R. Boucherie*
- Dynamic behavior of regular care waiting list: stability and fairness for allocation of pandemic patients
- *Authors: V. Ploeg, E. Castiel, R. Boucherie*

AGENDA

- 01 Project overview
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- 03 Proof of concept**
- 04 Conclusion



PROOF OF CONCEPT

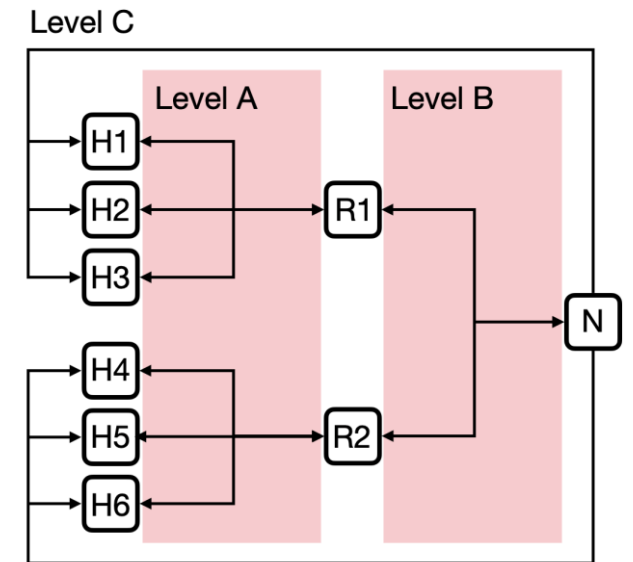
Aim: Test whether the proposed information flow works in practice

POC setup (all code in Python packages):

- Hospitals run local forecasting model
- Aggregated output is exported as .json and send to regional level
- Regional level combines hospital-level outputs and runs allocation model
- Aggregated output is exported as .json and send to national level
- National level combines regional-level outputs and runs allocation model
- PECC checks suggested transfers and gives okay via an API
- National level reports results to regional level via .csv

Demonstrated:

- Data pipeline works and can support regional and national decision-making
- Concept is technically feasible and scalable

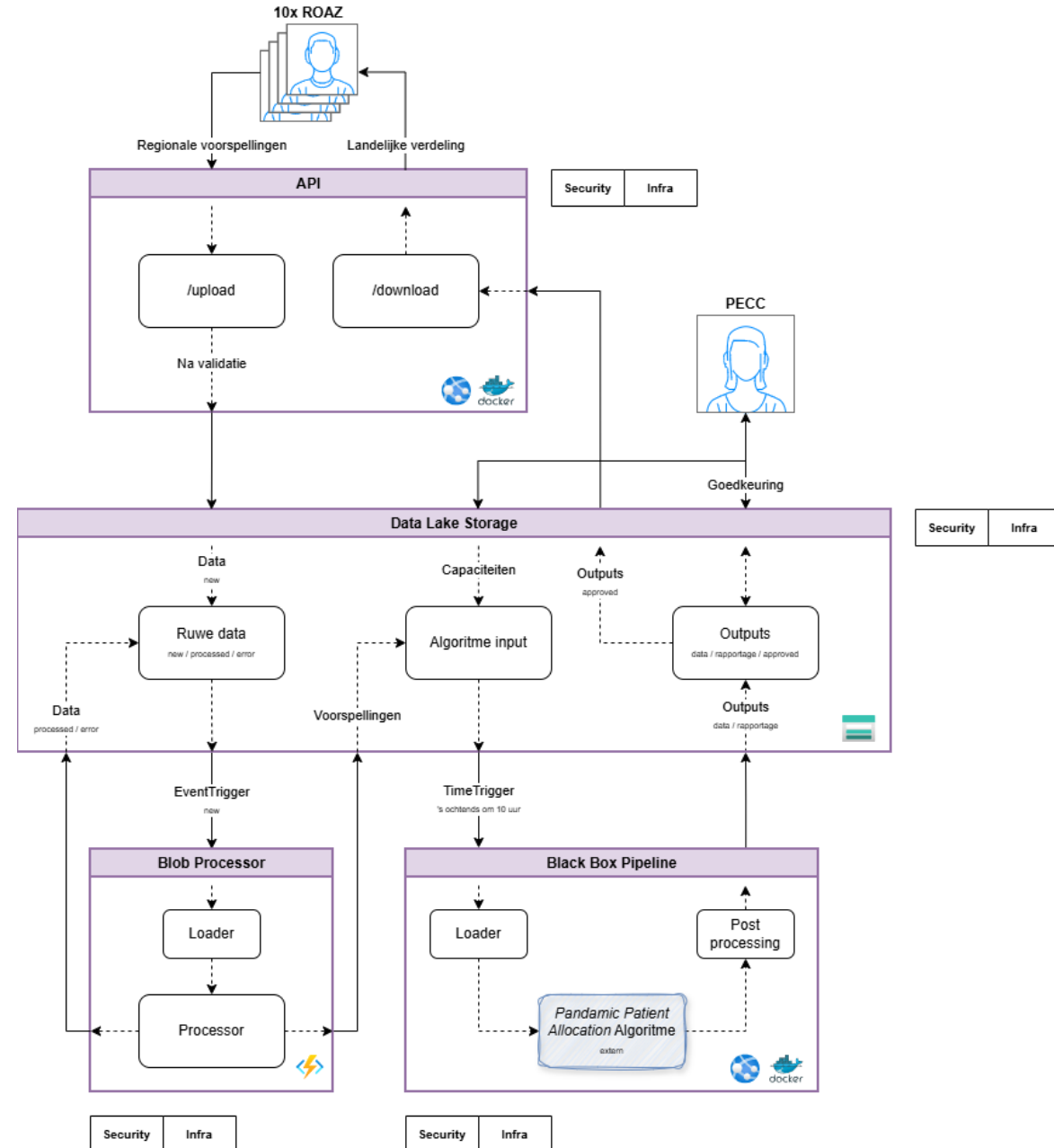


Level A: Hospital/region sharing

Level B: Regional/national sharing

Level C: National/hospital sharing

PROOF OF CONCEPT: FLOWCHART FOR THE INTERFACE AT THE REGIONAL AND NATIONAL LEVELS



EXAMPLARY RESULTS OF THE PROOF OF CONCEPT

Demo Rapportage PECC

Gegenereerd op 2026-06-10 15:04:32

Inleiding

Deze rapportage wordt dagelijks gegenereerd voor het PECC. Aan de basis van dit rapport staan:

- Het (nationale) allocatie algoritme, dat een optimale spreiding van patiënten over de regio's schetst.
- De (regionale) allocatie algoritmes, die een optimale spreiding van patiënten binnen de regio's schetsen.

Landelijke spreiding van patiënten

Nationaal is de volgende spreiding van patiënten geadviseerd:

Regio	IC capaciteit	IC overplaatsingen	Kliniek capaciteit	Kliniek overplaatsingen
AZE	6 plekken over	0 overnames	2 plekken tekort	2 uitplaatsingen
AZO	34 plekken over	0 overnames	38 plekken over	2 overnames
Buitenland	-	0 overnames	-	0 overnames

Regionale spreiding van patiënten

AZE

AZO

Binnen de regio AZE is de volgende spreiding van patiënten geadviseerd:

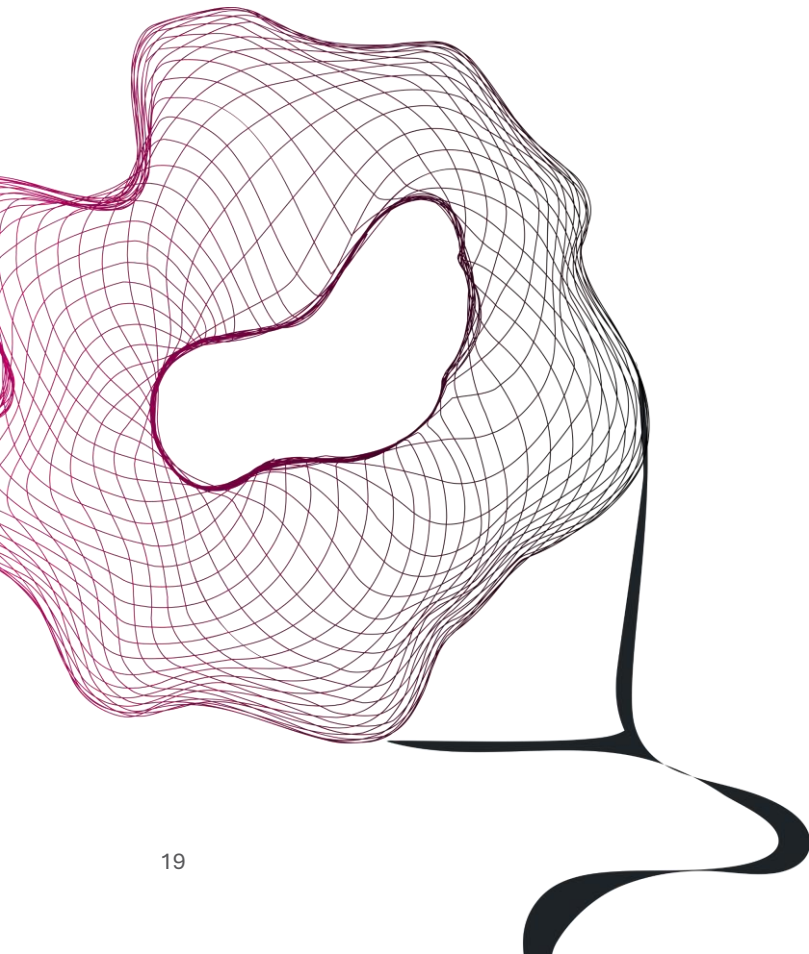
Ziekenhuis	IC capaciteit	IC overplaatsingen	Kliniek capaciteit	Kliniek overplaatsingen
mc1	4 plekken over	1 uitplaatsingen	1 plekken tekort	2 uitplaatsingen
mc2	0 plekken over	0 overnames	2 plekken over	3 overnames
mc3	2 plekken over	1 overnames	3 plekken tekort	3 uitplaatsingen
Bovenregionaal	-	0 overnames	-	2 overnames

UPCOMING PAPERS

- Bringing OR models for pandemic preparedness to healthcare practice
- *Authors: V. Ploeg, M. uit het Broek, L. Deis, M. Hattingh, D. de Jong, K. Mann, A. Zander, R. Boucherie*
- Implementation of a model for bed occupancy forecasting: a Python package
- *Authors: V. Ploeg*

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CONCLUSIONS

We developed and tested a data-driven decision-support concept for pandemic patient allocation across hospitals, regions, and the national level.

Scientific contributions:

- Short-term forecasting of hospital bed occupancy
- Allocation model under pandemic demand uncertainty
- New allocation rule based on least impact on regular care delivery

Practical contributions:

- New allocation rule uses routinely available patient-flow data
- Requires limited data sharing through aggregated outputs
- Supports transparent regional and national allocation decisions
- Proof of concept showed technical feasibility

NEXT STEPS/POLICY ADVICE

- **Further develop the allocation rule** by refining it and testing it under different pandemic and capacity scenarios
- **Broaden stakeholder involvement** by involving more hospitals and ROAZ regions and using their feedback to improve the allocation rule
- **Implement the new allocation rule** into the current workflow
- **Standardize hospital data extraction** by developing a general process for obtaining the required patient-flow data from different EHR systems
- **Move toward scalable deployment** by making the workflow robust across hospitals and regions