

Background

Understanding the mechanisms of **within-host kinetics** of the humoral (and cellular) immune response to a viral, parasite, or bacterial infection is crucial to foresee better surveillance and intervention strategies in the context of infectious diseases.

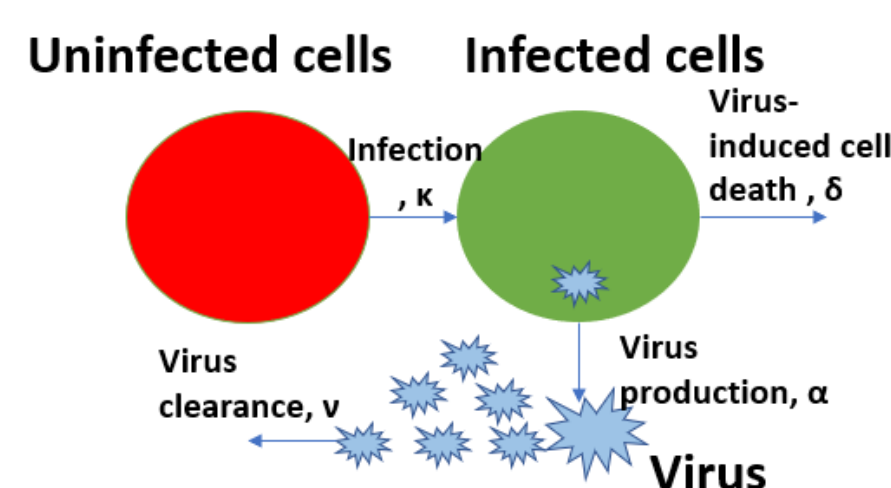


Figure 1: Flow describing the dynamics of uninfected cells, infected cells, and infectious virus [3]

Objectives

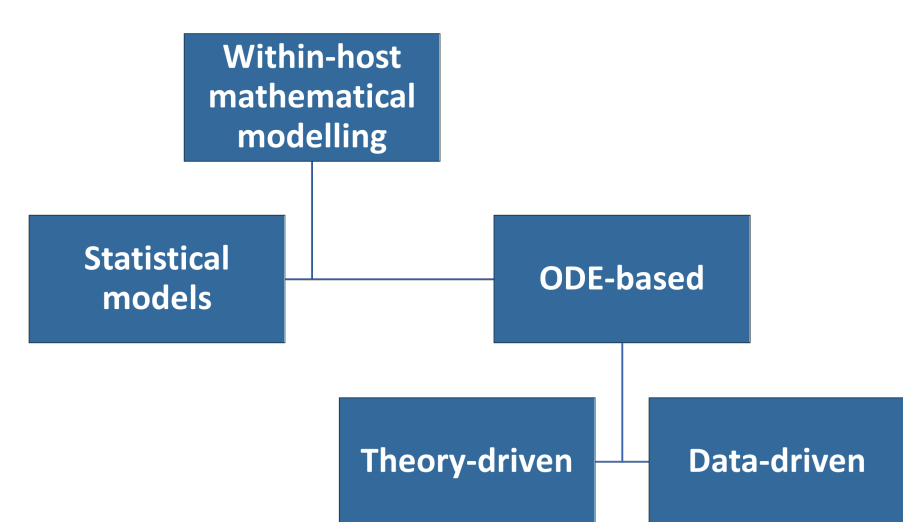
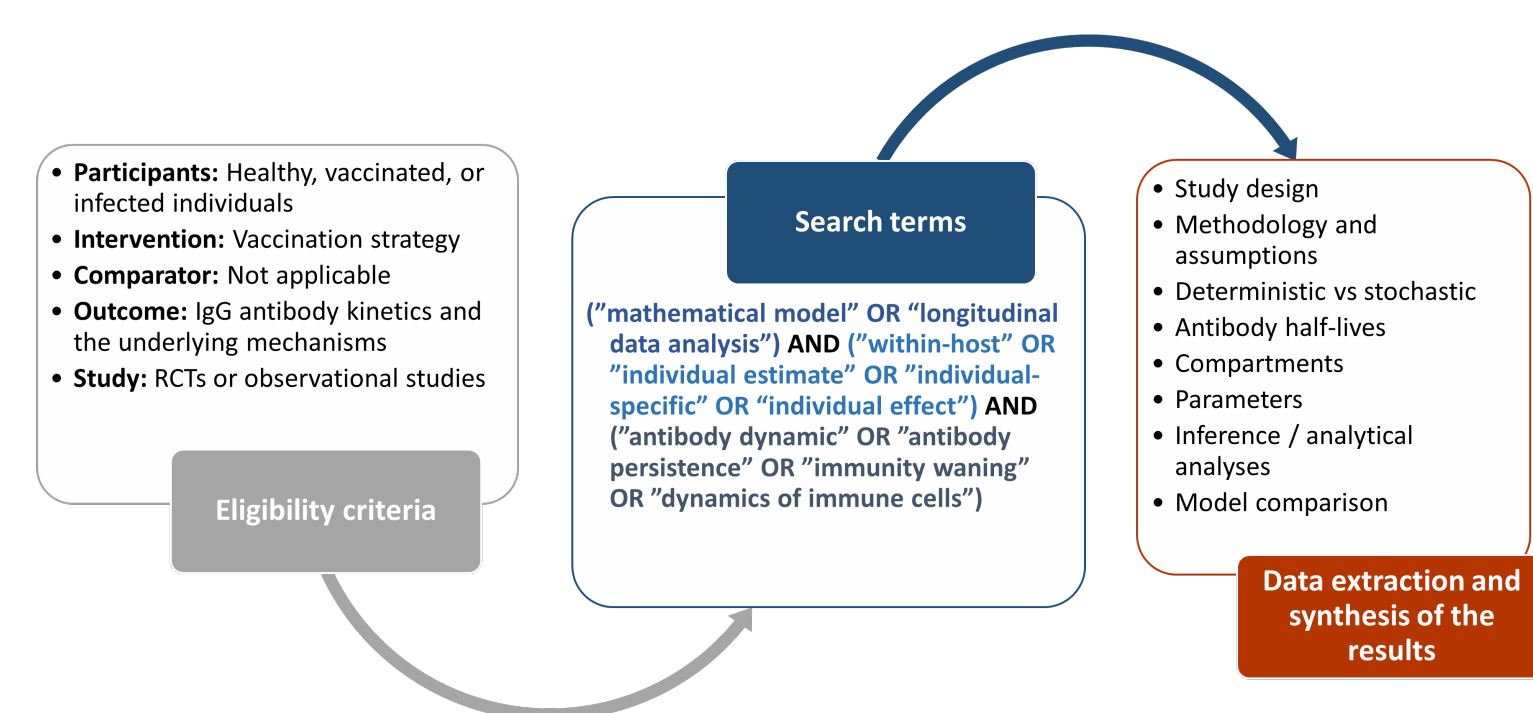


Fig. 2: Classification of the within-host mathematical models

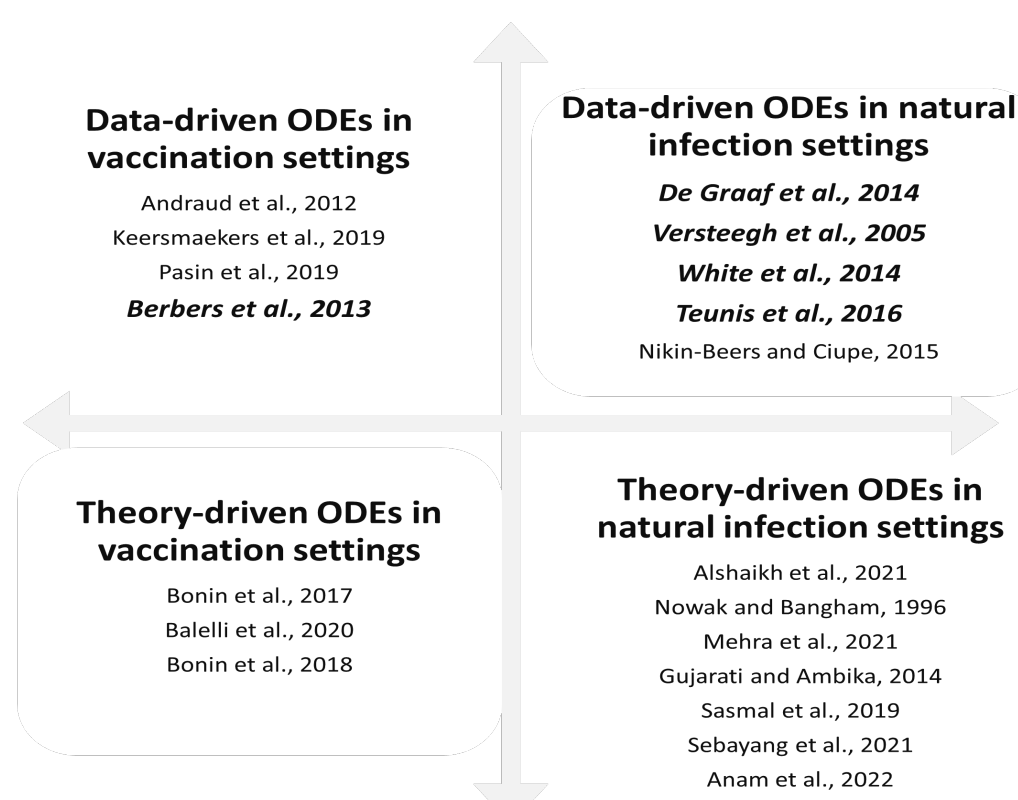
- To find within-host **mechanistic modeling** to **study humoral immunity processes** after vaccination or natural infection. This is crucial to unravel the specific components of the immune system and their dynamics.
- Describe the underlying dynamics of immune cells when encountering a pathogen, and how these processes can lead to an **individual-specific response**.

Methodology



Results

To date, only 20 publications out of 77 have relied on mechanistic models to study the dynamics of humoral immunity.



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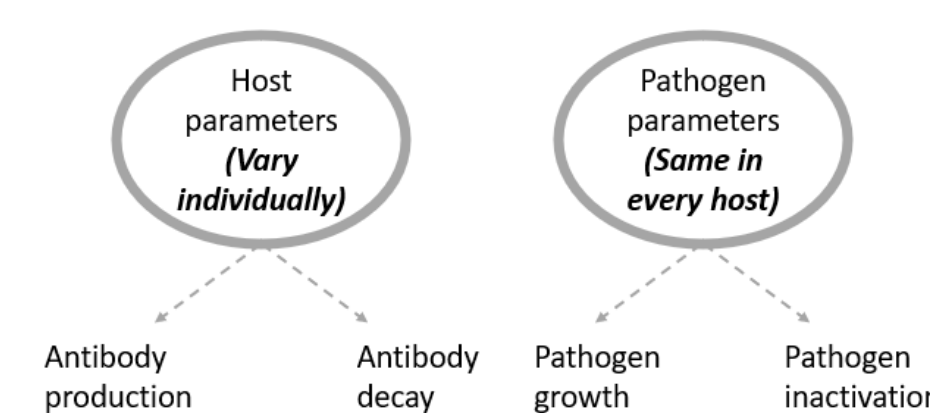


How can Bayesian methods be applied in the parameter estimation of such models?

Vaccine-induced setting: Berbers et al., [4]

Estimation of the model parameters and prediction of the **peak antibody concentrations together with half-time antibody values** were performed using Hierarchical Bayesian methods and Monte Carlo Markov Chain (MCMC).

- Simple exponential decay**
- Parametric distributions** for the antibody growth and decay (e.g., Gamma, Inverse gamma).



Natural infection setting: White et al., [1]

White et al., [1] studied the impact of maternal immunity on Malaria infections in children. MCMC iteration using a random walk Metropolis-Hastings algorithm (Model 1):

- Local parameter (n)
 - $\vec{\theta}^{n'} = [d_m^{n'}, d_a^{n'}, A_m^n, \theta_1^n \dots \theta_N^n]$
 - $L_{mix}^n(\theta_n' | D_n)$
 - Accept probability $min = \left\{ 1, \frac{L_{mix}^n(\theta_n' | D_n)}{L_{mix}^n(\theta_n | D_n)} \right\}$
- Nuisance parameter (n)
 - $\vec{\theta}^{n'} = [d_m^n, d_a^n, A_m^{n'}, \theta_1^{n'} \dots \theta_N^{n'}]$
 - $L_{mix}^n(\theta_n' | D_n)$
 - Accept probability $min = \left\{ 1, \frac{L_{mix}^n(\theta_n' | D_n)}{L_{mix}^n(\theta_n | D_n)} \right\}$
- Global parameter
 - $\vec{\theta} = [d_m', d_a', \sigma_m', \sigma_a', \sigma_{obs}', \theta^1 \dots \theta^N]$
 - Calculate the total likelihood $L_{TOTAL}(\theta' | D_n)$ and update the prior $P(\theta')$
 - Accept probability $min = \left\{ 1, \frac{L_{TOTAL}(\theta' | D_n) * P(\theta')}{L_{TOTAL}(\theta | D) * P(\theta)} \right\}$

Truncated normally distributed measurement error
200 million MCMC iterations computed with acceptance rates using Robins-Munro algorithm.

Natural infection setting: Teunis et al., [5]

Teunis et al., [5] extended the work by de Graaf et al., [6] defining multiple antibody production sites defined as c_k below.

Infection and waning immunity process respectively

$$\begin{aligned} b'(t) &= \mu_0 * b(t) - \sum c_k * y_k(t) & b(t) &= 0 \\ y_k'(t) &= \mu_k * y_k(t) & y_k'(t) &= -w_k^* * y_k(t) \end{aligned}$$

What functions are studied?

- Non-exponential decay
- Bi-exponential decay
- Power functions

All models used 3 chains and 10^6 iterations. A multivariate normal prior was chosen for the different model parameters, and a Wishart distribution for the random effects.

Findings

1. COMPARTMENTS

- Data-driven approaches:** Typically study the interaction between pathogen growth with antibody production, or the dynamics between short- and long-living cells with antibodies.
- Theory-driven approaches:** Typically study more complicated processes, starting from susceptible cells population to neutralizing antibody production.

2. PARAMETERS

- Data-driven approaches:** Linear, non-linear mixed approaches. **Exponential decay**, bi-exponential, power functions. Smoothing functions and binary functions represent normally the time of vaccination.
- Theory-driven approaches:** Simulation approaches to generate the parameters (e.g., Poisson or Binomial distributions).

3. INFERENCE/ANALYTICAL ANALYSES

- Data-driven approaches:** Use of Maximum likelihood estimation (MLE) and Bayesian hierarchical approaches with Monte Carlo Markov Chain (MCMC).
- Theory-driven approaches:** Model's equilibria and stability.

4. COVARIATES

Study groups are widely studied. However, there is a **lack of information on geographical background**, surveillance systems, and age.

5. MODEL COMPARISON

- Data-driven approaches:** Difficulties in Bayesian approaches due to the number of parameters and complexity issues. WAIC (Watanabe-Akaike information criteria) for future modelling work AIC (Akaike information criteria) within MLE [2].
- Theory-driven approaches:** Comparison to simulated data.

Conclusion

- More research is needed on the **methods of inference** in data-driven mechanistic models, such as semi-parametric to full parametric tools.
- Biological mechanisms must be distinguished in vaccination or natural infection settings.

Acknowledgments

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