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Keynote presentation at the Academy of Medical Sciences Joint Workshop  
*Advancing research to tackle multimorbidity: the UK perspective*

# Methodological approaches to multimorbidity research

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Thanks to Jessica Barrett, Steven Kiddle, Kirsty Rhodes, Li Su & Brian Tom  
(MRC Biostatistics Unit)

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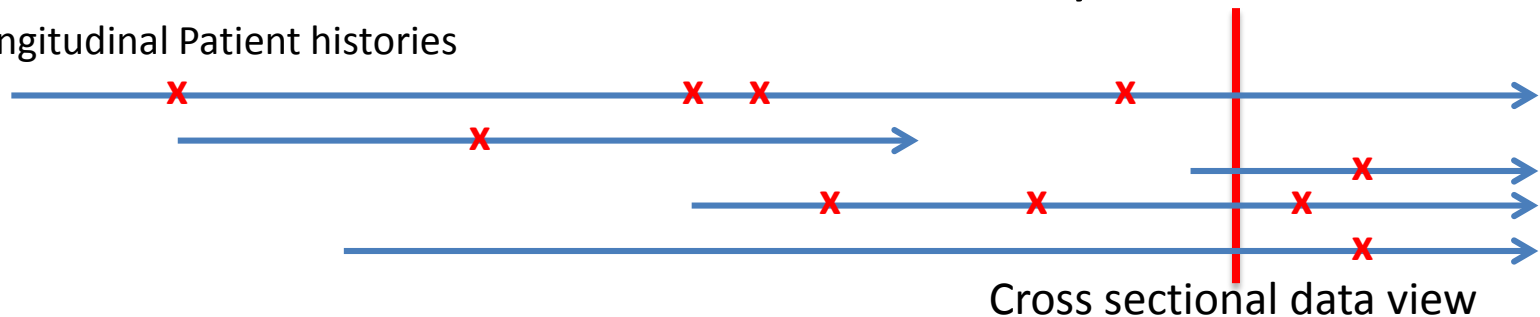
# Research priorities

- The main key words of the outlined six research priorities interface with different methodological approaches and needs:
  - Trends and patterns: descriptive → data quality
  - Clusters of conditions: descriptive → data compression
  - Burden: analytic → estimation of link, prediction of risk
  - Determinants: analytic → event history modelling
  - Benefits and risks of treatment: beyond RCT → trial emulation to account for multimorbidity.

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Longitudinal Patient histories



# 1 Data issues

- Central issue of adopting a coherent definition of comorbidity has been highlighted in the report.
- Much of the descriptive research is cross-sectional and utilises large primary care databases.
- A recent Danish study used their national patient registry of all hospitals.
- UK studies have relied on GPs recording conditions, by giving patients diagnosis codes or by prescribing medications.

Issues that have been discussed

- inconsistent labelling of conditions, choice of granularity,
- Under reporting, differential validity in assessment of conditions,
- How representative are the sample of GP practices that are used (e.g. CPRD)?

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Issues that have been discussed:

- inconsistent labelling of conditions, choice of granularity,
  - Under reporting, differential validity in assessment of conditions,
  - How representative are the sample of GP practices that are used (e.g. CPRD)?
- Careful assessment of data quality, sources of missingness, mismeasurement and biases is of crucial importance alongside any pattern extraction.
    - Some of these issues might be addressed through specially designed calibration studies.

# Recent cross sectional study investigating multimorbidity in CPRD

Patient	Hypertension	Depression	Diabetes	Asthma	...	Cancer
1	0	1	0	0	...	0
2	1	0	0	0	...	1
3	1	1	0	1	...	0
4	1	0	0	0	...	0
5	1	0	1	0	...	0
...	...	...	...	...	...	...
403,985	1	1	0	0	...	0

Binary comorbidity matrix X

## Dataset

- 403,985 adult patients
- 37 long-term conditions coded
- Recorded characteristics:
  - Gender
  - Age
  - Socioeconomic status
- Health service utilisation outcomes:
  - General practice consultations
  - Prescriptions
  - Hospitalisations

Cassell et al. (2018), British Journal of General Practice

# Recent cross sectional study investigating multimorbidity in CPRD

Table 2. Ten most prevalent morbidities and associated comorbidities

Moridity	Prevalence, %	Mean number of comorbidities associated with condition, <i>n</i>	Three most frequently associated comorbidities	
			Condition	Prevalence, <sup>a</sup> %
Hypertension	18.2	3.0	Painful condition	24.3
			Diabetes	19.4
			Hearing loss	16.7
Depression/anxiety	10.3	3.1	Painful condition	32.7
			Hypertension	28.9
			Irritable bowel syndrome	17.2
Chronic pain	10.1	3.7	Hypertension	44.0
			Depression/anxiety	35.5
			Hearing loss	18.4
Hearing loss	9.5	2.8	Hypertension	32.0
			Painful condition	19.4
			Depression/anxiety	14.8
Irritable bowel syndrome	7.9	1.8	Depression/anxiety	22.3
			Hypertension	20.5
			Painful condition	18.4
Diabetes	5.9	3.5	Hypertension	60.1
			Painful condition	26.6
			Depression/anxiety	17.9
Prostate disorders	5.7	3.5	Hypertension	44.1
			Hearing loss	25.3
			Painful condition	20.7
Thyroid disorders	4.7	3.1	Hypertension	37.0
			Painful condition	23.4
			Depression/anxiety	19.7
Coronary heart disease	4.3	4.0	Hypertension	56.5
			Painful condition	30.3
			Diabetes	23.3
Asthma	3.7	3.2	Hypertension	30.3
			Painful condition	26.6
			Depression/anxiety	22.4

<sup>a</sup>Prevalence in male participants only.

## Dataset

- 403,985 adult patients
- 37 long-term conditions coded ([http://www.phpc.cam.ac.uk/pcu/cprd\\_cam/codelists/](http://www.phpc.cam.ac.uk/pcu/cprd_cam/codelists/))
- 27% of patients had multimorbidity
- Patients with multimorbidity accounted for 53% of GP consultations, 79% of prescriptions and 56% of hospitalisations.

Cassell et al. (2018), British Journal of General Practice

# 2 Clustering and finding patterns

- A number of unsupervised exploratory approaches have been implemented to extract patterns from the binary matrix  $X$ :  
(cf Ng, 2014, Roso-Llorach, 2018) :
  - Hierarchical Clustering,
  - Exploratory Factor Analysis,
  - Bi-clustering.
- Typically these exploratory approaches rely on a sequence of processing steps
  - Many ad hoc choices in terms of analysis strategy, choice of similarity metric, number of clusters, etc.
  - Problems of interpretation.

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# 2 Clustering and finding patterns

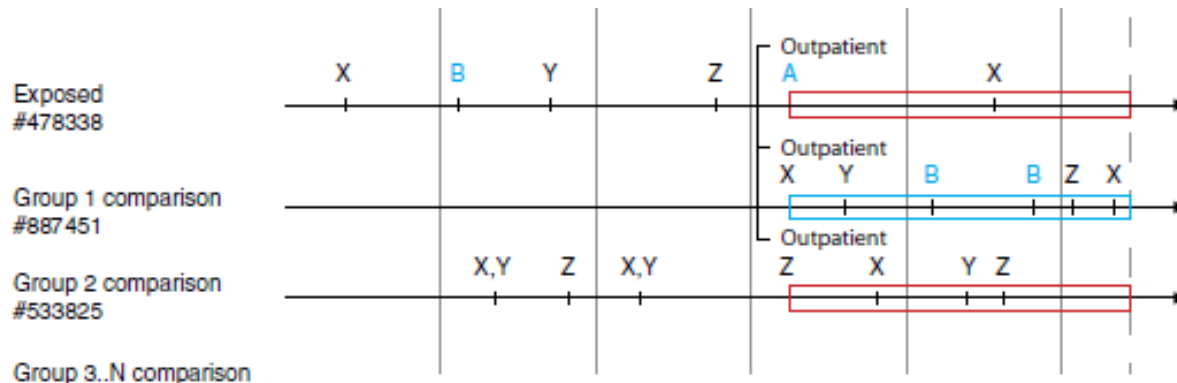
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Would be useful to take a probabilistic perspective on how to learn the decomposition of binary matrix  $X$  into **two low dimensional matrices** corresponding to latent factors/ patterns and allocations.

# Extracting patterns from longitudinal trajectories

- Longitudinal trajectories carry additional information
  - Investigate significant occurrences of pairs of diseases (A and B) and their temporality  $A \rightarrow B$ , within a specified time frame.



from Jensen et al 2014

# Extracting patterns from longitudinal trajectories

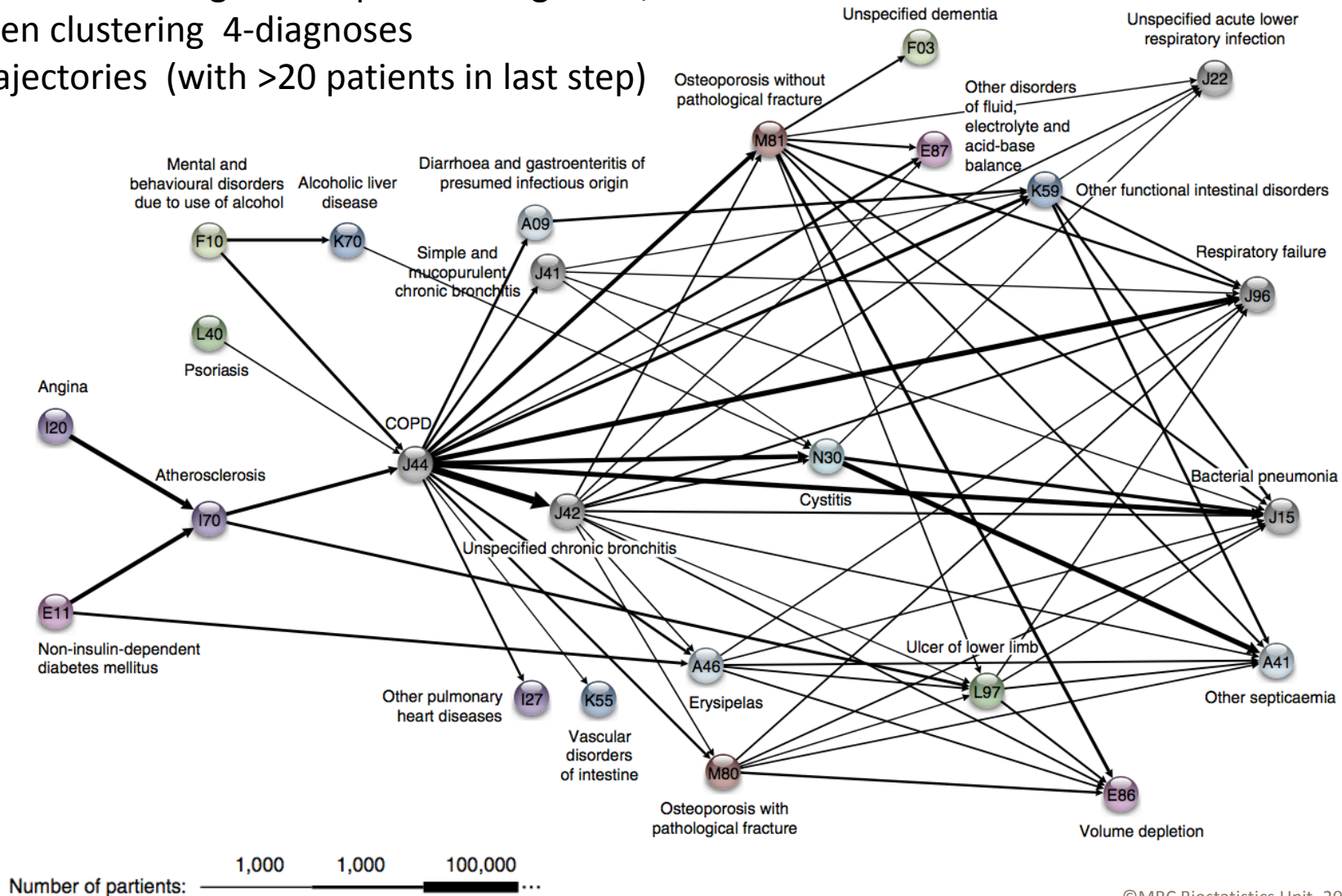
- Longitudinal trajectories carry additional information:
  - Investigate significant occurrences of pairs of diseases (A and B) and their temporality  $A \rightarrow B$ , within a specified time frame.
  - Investigate significant occurrences of  $A \rightarrow B \rightarrow C$ , within a specified time frame.
  - Quickly becomes unwieldy “combinatorially”
    - cluster the trajectories directly?
  - Main issue: defining relevant “distance function” between the trajectories to tease out meaningful patterns and groupings.

**Specific context and aims should inform the choice of distance.**

# Temporal disease trajectories condensed from population-wide registry data covering 6.2 million patients – Jensen et al., (2014)

Methodology based on piecing together time ordered significant pairs of diagnoses, then clustering 4-diagnoses trajectories (with >20 patients in last step)

**COPD disease 'trajectory cluster'**



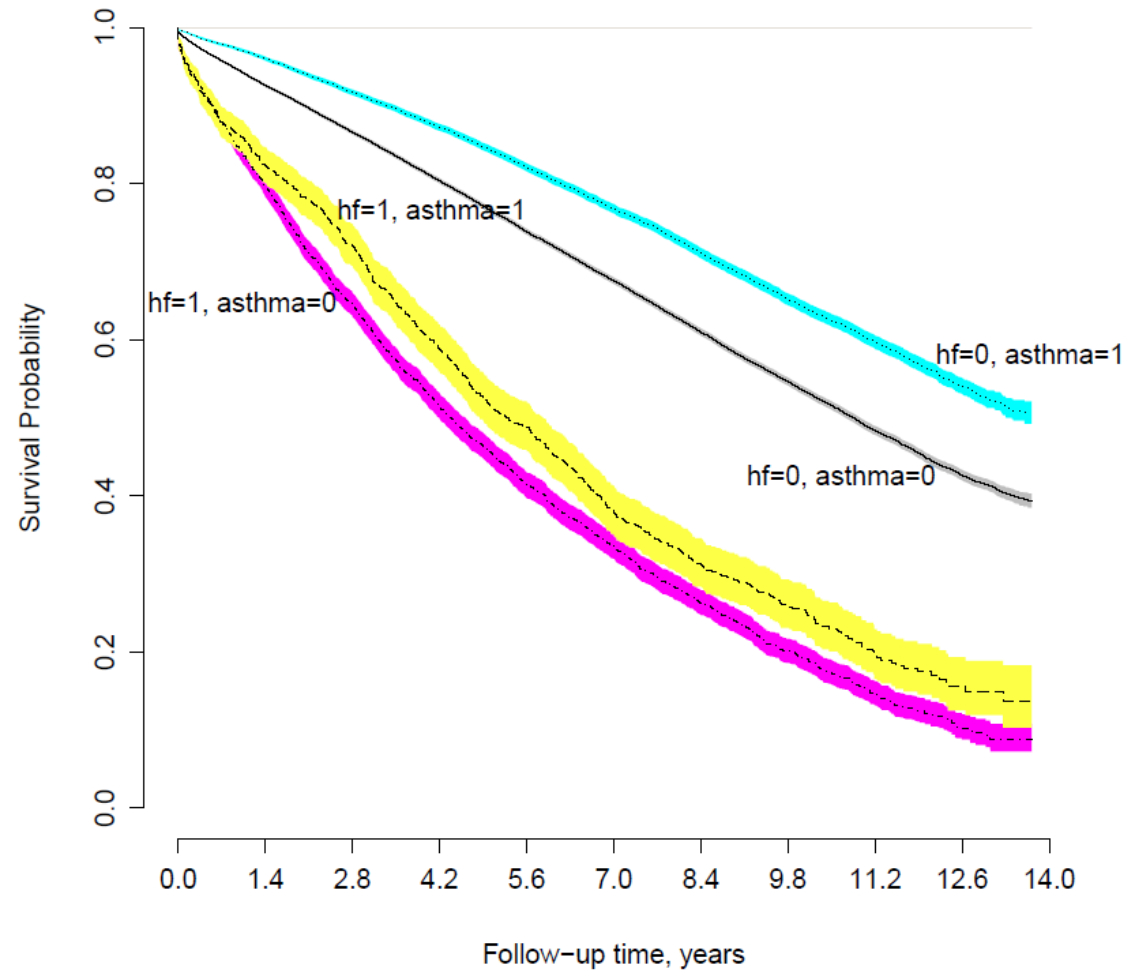
# 3 Burden

- Charlson co-morbidity Index as a summary measure of mortality risk is still popular.
  - Drawbacks
    - Additive formulation does not consider possibility of interactions between conditions,
    - Doesn't consider treatment,
    - Doesn't take into account patient history.

# 3 Burden

- Charlson co-morbidity Index as a summary measure of mortality risk is still popular.
  - Drawbacks
    - Additive formulation does not consider possibility of interactions between conditions,
    - Doesn't consider treatment
    - Doesn't take into account patient history.
- With longitudinal data, can use **survival models** to estimating link between multimorbidity and outcomes, such as death or disability.
  - Benefits: loss to follow-up is properly accounted for.
  - Survival models formulation can also be adapted to answer a number of focussed questions.
    - If the focus is on a number of index conditions, can estimate in turn the risk of developing another condition using other comorbidities as time dependent covariates.

# Survival (Weibull model) after first diagnosis of COPD, stratified by history of asthma and heart failure



**Study performed by Steven Kiddle (BSU), Hannah Whittaker & Jennifer Quint (Imperial College)**

# Burden

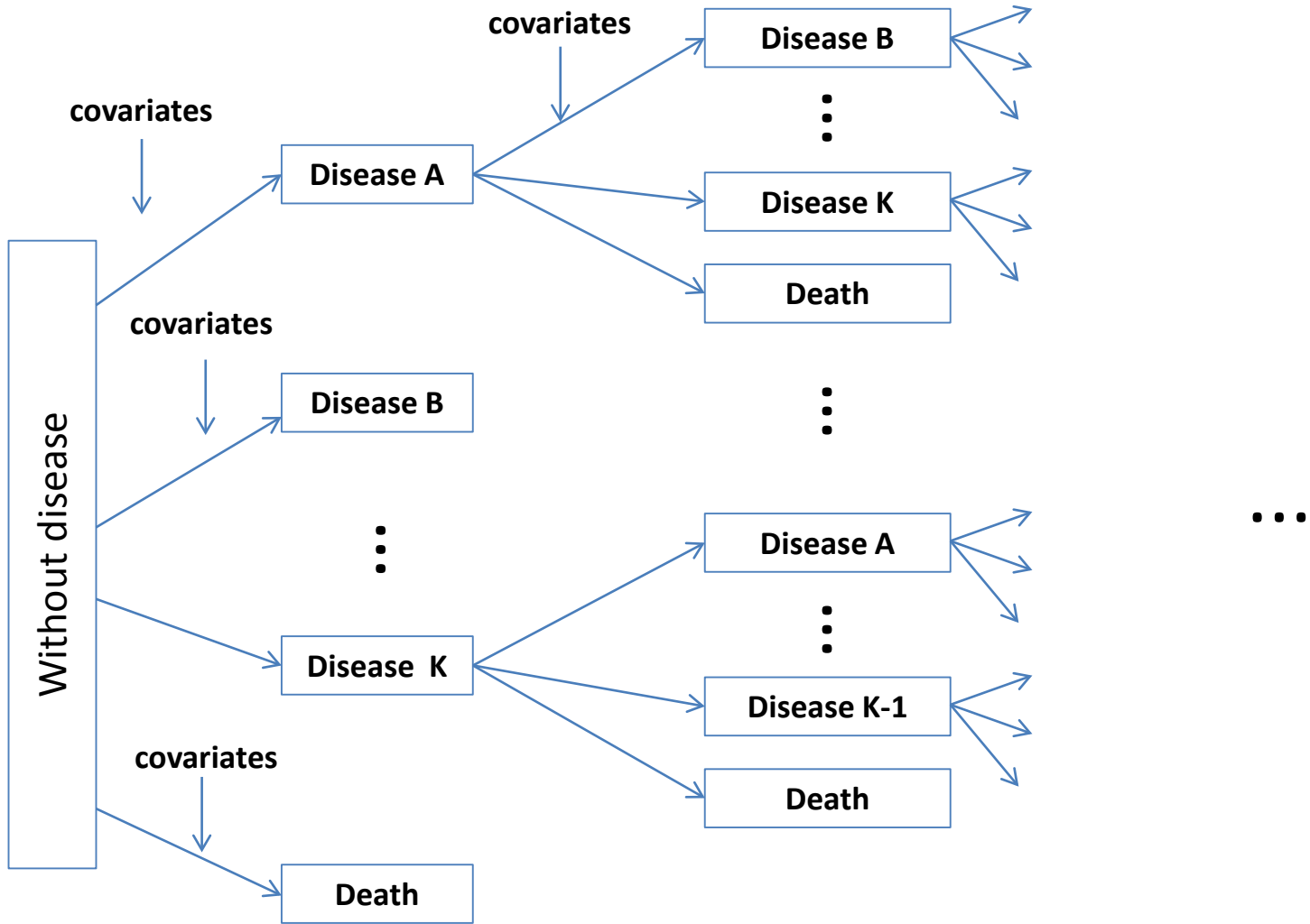
- Opportunity to use state of the art statistical modelling approaches coupled with survival models
  - to develop flexible multivariate survival models going beyond additive models and proportional hazard assumptions,
  - allowing possibility of interactions between the conditions,
  - taking into account patient history,
  - large model space to explore:
    - can benefit from advances in high dimensional regression approaches
    - model choice and validation through out-of-sample performance evaluation.



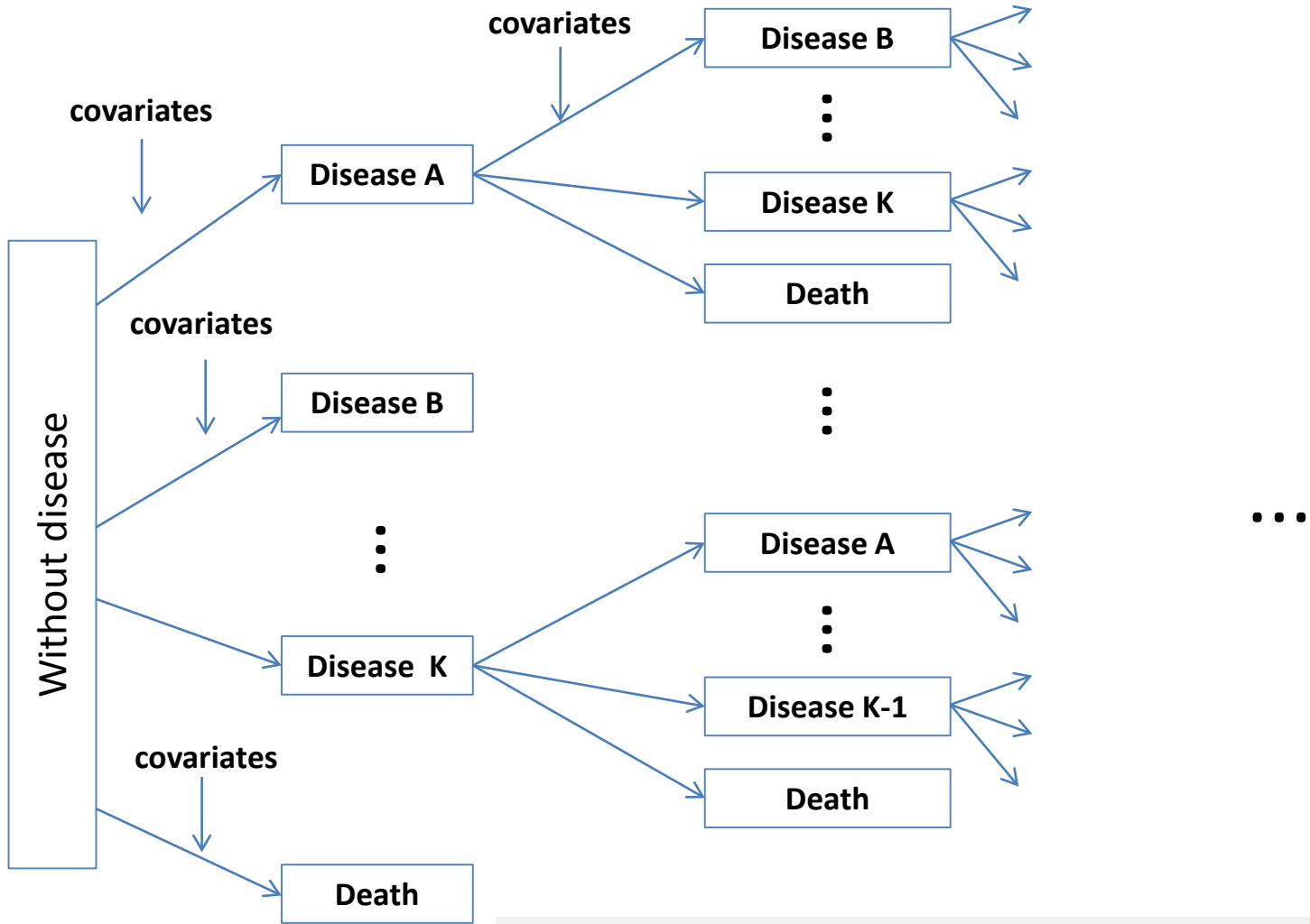
# 4 Determinants

- Best investigated using event history analysis tools, considering full history.
- In particular, multi-state models with estimation of transition rates and covariate effects on these transitions is a framework which would provide interpretable quantities.

# Generic multi state model of multimorbidity in patient trajectories



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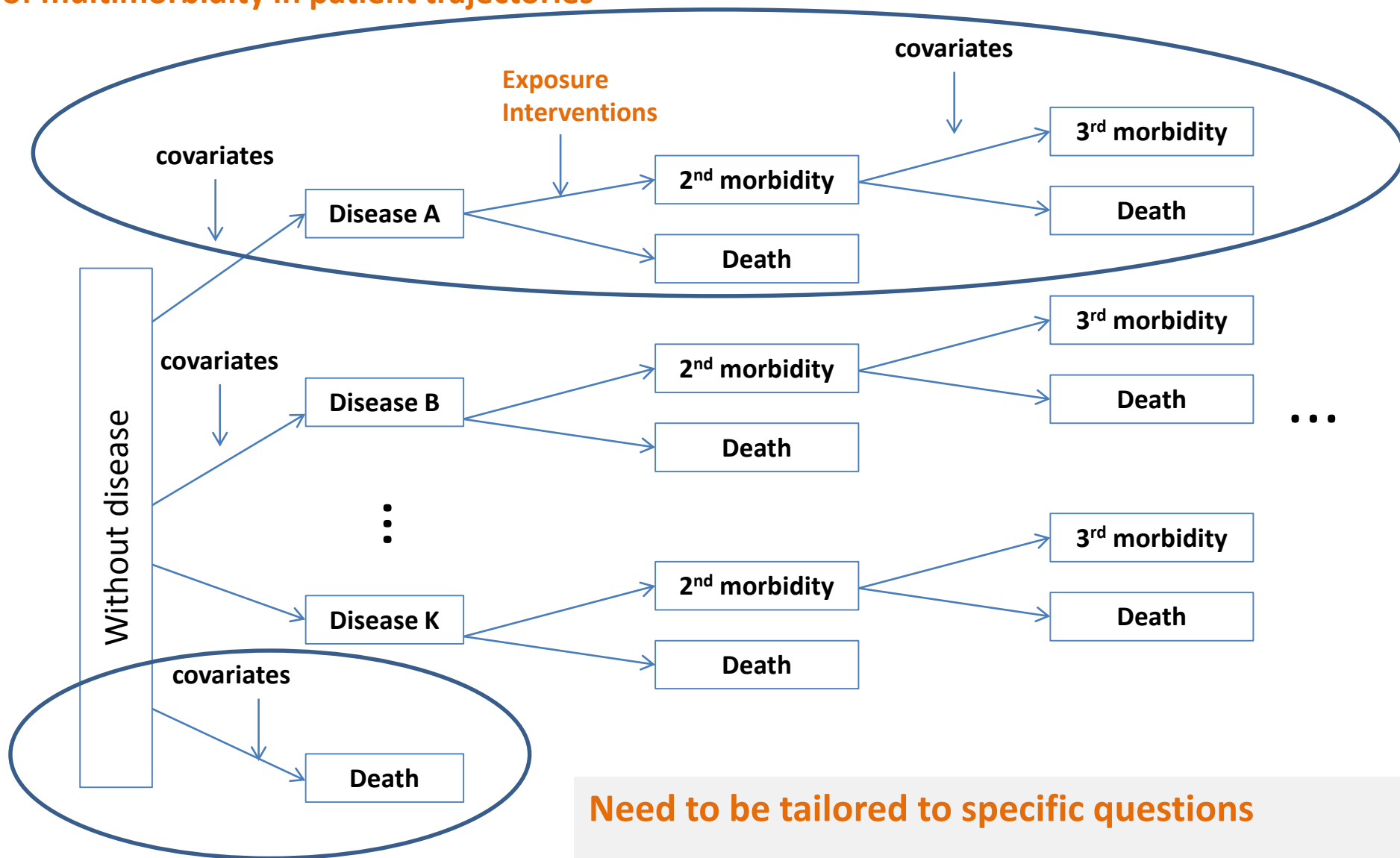


Issues of computational scalability of multistate model estimation on large data bases

# Determinants

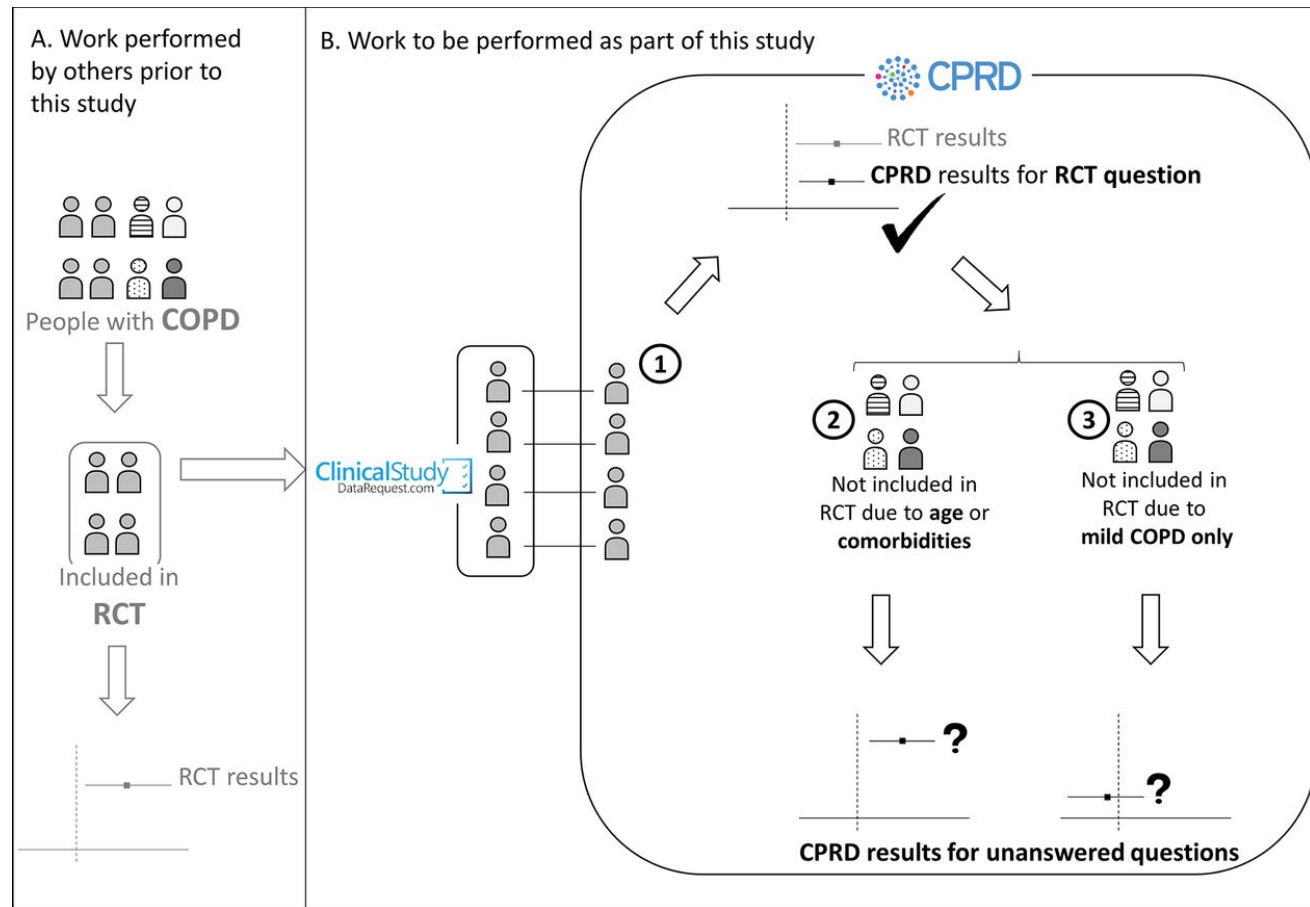
- Best investigated using event history analysis tools, considering full history.
- In particular, multi-state models with estimation of transition rates and covariate effects on these transitions is a framework which would provide interpretable quantities.
- Important issue: defining meaningful “states” and allowable transitions between these.  
→ this has to be linked closely to epidemiological and medical context.
- Potential for formulating causal hypotheses to be investigated further.

## Simplified multi state model of multimorbidity in patient trajectories



# 5 Benefits and risk of treatment in patients with multimorbidity

- Most RCTs exclude patients with multimorbidity
- Investigate trial emulation in large EHR data bases as a way to include a more realistic population of patients and address effect of treatment



# In summary

- Rich range of methodological approaches can be tailored to characterise patterns of comorbidities, and to estimate burden and disease processes.
  - Important to take into account limitations of the data,
  - Important to confront **generic statistical approaches** with specific research questions **to derive coherent analysis strategies.**
- Longitudinal analysis is key to dig deeper into processes and determinants.
- Need to prioritize important health questions related to multimorbidity that can be reasonably tackled with large electronic data bases.