

Challenges faced by Europe in implementing a CDM

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Disclosure

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- Educational lecture fee from Roche



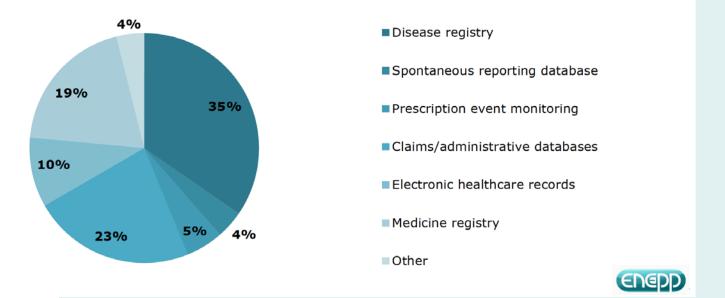
Outline

- Overview and evolution of multi-database studies in EU
- Scientific challenges distributed data networks and CDM
 - Design
 - Selection bias
 - Information bias
 - Confounding bias
 - Analysis
 - Effect estimation
 - Control for Confounding
 - Reporting



ENCePP inventory of data sources

104 Data sources (Sep 2017)



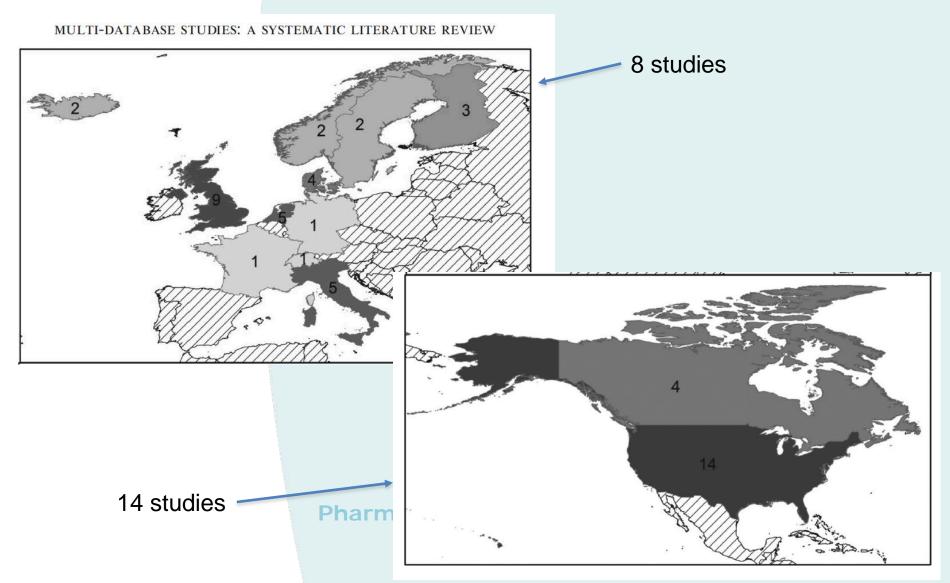
Presented by S. Perez-Gutthan at 10th Anniversary of ENCePP



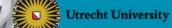
Characteristics of selected EU healthcare databases

Database	Country	Cumulative population (2008)	Data source	Coding diagnoses	Free text	Coding drugs	Coding product	Recording of drug use
BIFAP	ES	7.5 M	GP	ICPC- 2, ICD- 9	Spanish	ATC	CNF	Prescribing
SIDIAP	ES	7.0 M	GP	ICD-10	No	ATC	-	Prescribing
ARS	IT	4.0 M	Hospital claims/death	ICD-9- CM	No	ATC		Dispensing
Health Search Italy	IT	1.0 M	GP	ICD-9- CM	Italian	ATC	Brand names	Prescribing
CPRD	UK	12.5 M	GP	READ	English	BNF	Prod code	Prescribing
THIN	UK	7.8 M	GP	READ	English	BNF	Prod code	Prescribing
IPCI	NL	0.75 M	GP	ICPC	Dutch	ATC	HPK	Prescribing
AHC	NL	0.26 M	GP/Pharmacy	ICPC	Dutch	ATC	НРК	Prescribing + dispensing
PHARMO	NL	3 M	Pharmacy/Hospi tal/Laboratory/G P	ICD-9- CM, ICPC	Dutch	ATC	НРК	Prescribing /dispensing
The Danish national registries	DK	5.2 M	Hospital/ Pharmacy/death	ICD- 8/9/10	Νο	ATC	Varenr	Dispensing
Bavarian Claims	DE	10.5 M	Claims	ICD- 10-GM	No	ATC	PZN	Dispensing
AOK Nordwest	DE	2.7 M	Claims	ICD- 10-GM	No	ATC	PZN	Dispensing
EGB	FR	0,7/60 M	Claims	ICD-10	No	ATC	CIP13	Dispensing

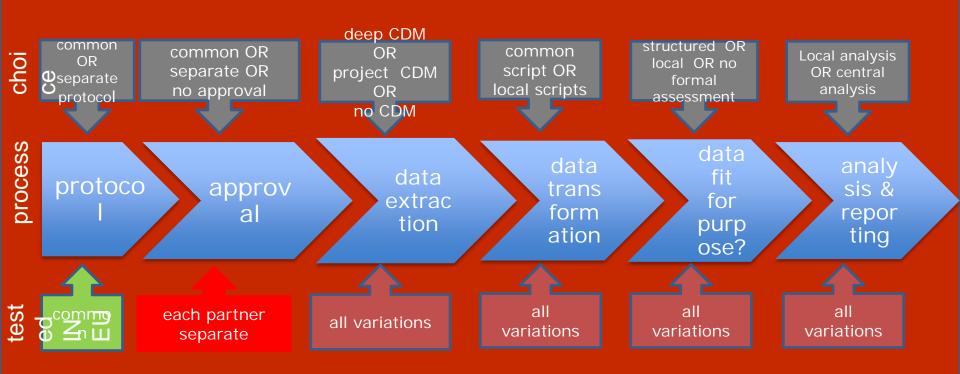




Bazelier MT, et al. Pharmacoepidemiol Drug Saf 2015;24:897-905



Process flow for multi-site drug safety studies in EU



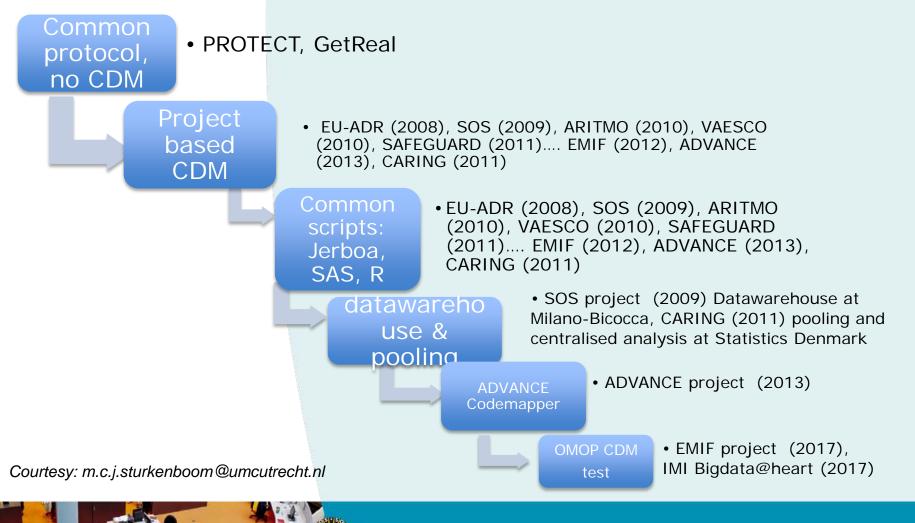
ENCePP Code of Conduct, EMIF Code of Practice, ADVANCE code of Conduct

Courtesy: M.c.j.Sturkenboom@umcutrecht.nl



'Increasing harmonization': the evolution

across FP-7 & IMI EU-funded drug safety projects



Information bias

- Misclassification of outcomes and exposures due to loss of information in mapping to a CDM
 - No mapping possible to standard vocabulary CDM
 - Different granularity source codes
 - Free text source
- Non-differential => bias towards null
- Example of acute liver injury
 - Sentinel CDM: ICD-9-CM codes
 - OMOP CDM: ICD-9-CM, LOINC codes, laboratory tests
 - PROTECT: CPRD (Read codes, laboratory tests), BIFAP (ICPC codes, laboratory tests, free text)



Classification of ALI in PROTECT

Eur J Clin Pharmacol (2014) 70:1227-1235

1229

Case status	Ia. Diagnosis of liver injury or symptoms recorded by specific codes or text ^a for liver injury	Ib. Diagnosis of liver injury or symptoms recorded by unspecific codes or text ^a indicating only positive results for liver tests	II. Complete laboratory criteria: an increase of more than two times ULN in ALT or a combined increase in AST, AP and total bilirubin provided one of them was two times ULN within 2 months of the event	III. A referral to a specialist orhospital within 2 weeks of a recorded diagnosis of liver injury
Definite	Yes	No	Yes	Yes
Probable A	Yes	No	Yes	No
Probable B	No	Yes	Yes	Yes
Possible	No	Yes	Yes	No
No case	Yes	No	No (normal LFTs or just increased values not with complete criteria)	Yes
	No	Yes	No (normal LFTs or just increased values not with complete criteria	No

ULN upper limit of normal, ALT alanine aminotransferase, AP alkaline phosphatase, AST aspartate aminotransferase

^a In BIFAP, database ICPC codes were used along with computer search of keywords in text



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Validation of ALI in PROTECT

Table 2 Computer case ascertainment and manual review process in BIFAP database

Pre-review computer case status ^a		Status after manual review of free text						
	code of ALI (<i>N</i> =19,074)	Definite-confirmed	%	Probable-confirmed	%	No-case confirmed ^b	%	
1. Definite	179	43	24.02	19	10.61	117	65.36	
2. A-Probable A	119	14	11.76	22	18.49	83	69.75	
2. B-Probable B	1,038	51	4.91	122	11.75	865	83.33	
3. Possible	1,537	16	1.04	149	9.69	1372	89.26	
4. No case	16,201	Manually reviewed a sample $n=120, 100 \%$ no case						

^aAs in Table 1

^b Reason for exclusion during manual review: other liver disease (691), cancer (23), alcohol-related problems (186), gallbladder and pancreatic disease (120), routine testing (1,322) or not confirmed cases (95)

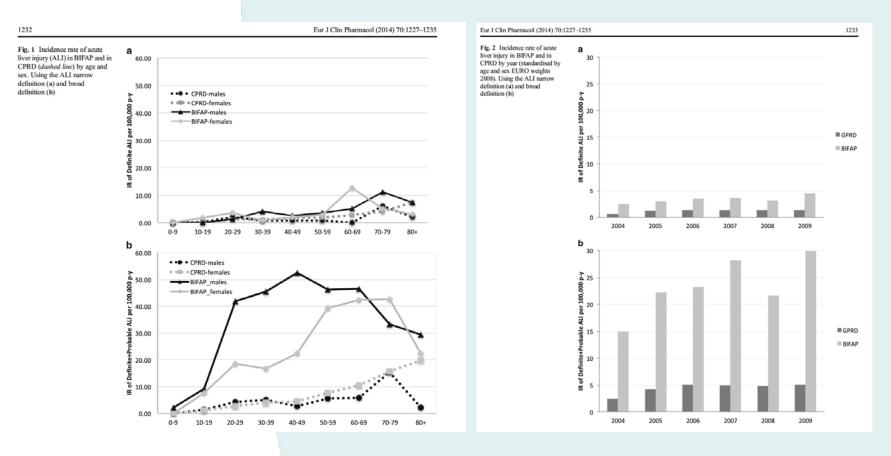
Eur J Clin Pharmacol (2014) 70:1227-1235

Table 3 Computer case ascertainment and manual review process in CPRD database

Pre-review computer case definition ^a	Sample cases to review	Status after manual review		
		Confirmed	%	
1. Definite	101 (47 with free text)	64	63.4	
2. Definite+probable	208 (59 with free text)	122	58.6	

^aAs in Table 1

Outcome definition and rates of ALI





Outcome definition and RR of ALI associated with antibiotic use

	Cohort		Case-control	
	CPRD	BIFAP	CPRD	BIFAP
Definite	10.0 [7.0-14.0]	5.8 [3.5-9.6]	5.7 [3.5-9.4]	2.6 [1.3-5.4]
Definite+ probable	8.3 [6.8-10.1]	5.1 [3.8-6.8]	3.6 [2.8-4.6]	3.1 [2.1-4.6]

Brauer R, et al. Pharmacoepidemiol Drug Saf 2016;25 (Suppl 1):29-38



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Impact of exposure misclassification

- Incomplete mapping to OMOP CDM
 - 10,3% of drug exposure records in CPRD¹
 - 7% of drug exposure records (55% of exposure terms) in THIN²
- Complex exposure definitions require adaptation to specific study/database

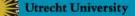
1 Matcho M, et al. Drug Saf 2014;37:945-959 2 Zhou X, et al. Drug Saf 2013;36:119-34.



Impact of confounder misclassification

- Incomplete mapping to OMOP CDM
 - 0,15% of condition records, 2,3% of procedure records in CPRD¹
 - 6% of condition records (25% of condition terms), 4% of procedures in THIN²
- Residual confounding due to incomplete measurement of confounding factors

1 Matcho M, et al. Drug Saf 2014;37:945-959 2 Zhou X, et al. Drug Saf 2013;36:119-34.



Impact of confounder misclassification

- Impact depends on:
 - strength of association between confounder-outcome and confounder-exposure
 - Type B vs Type A adverse drug reaction, intended effects
- Multilevel multiple imputation before transformation to CDM?¹

1 Jolani S, et al. Stat Med 2015;34:1841-63.



Data collection and analytical options

- 1. Aggregate level approach (e.g. PROTECT, CNODES)
 - No sharing of individual patient data
 - Overall results are collected for meta-analysis
 - Allows optimization for individual database
- 2. Semi-aggregate level approach (e.g. EU-ADR, CARING, SENTINEL)
 - Stratified datasets collected from all databases
 - Outcomes, Exposure, Covariate patterns
 - One common analysis
- 3. Individual level approach (e.g. NORPEN)
 - Individual patient data collected from all databases for one common analysis



1. Aggregate level analysis

- Decentral analysis
- Control for confounding
 - Conventional Multivariable Regression
 - Common set of confounders
 - Additional adjustment in individual databases with maximum amount of information
 - High dimensional Propensity Score
 - Disease Risk Scores
 - Distributed regression



Collaboration EMA-Health Canada

- Framework contract EU PE&PV (former PROTECT consortium)
 - 8 EU databases, ~47 M patients
- "Characterising the risk of major bleeding in patients with Non-Valvular Atrial Fibrillation: noninterventional study of patients taking Direct Oral Anticoagulants in the EU"
- Common protocol, statistical analysis plan/programmning instructions, no CDM
- Replicate findings in Canadian Network of Observational Drug Effect Studies (CNODES)
- Which CDM if replication is needed?

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2. Semi-aggregate level analysis

- Datasets collected from each database stratified on
 - Outcome
 - Exposure
 - Confounders
- Central privacy preserving analysis on semi-aggregated dataset
 - Control for confounding limited by number of confounders (e.g. propensity score) stratified on
 - Case-centered logistic regression



3. Individual patient level analysis

- Individual patient data collected from each database on
 - Outcome
 - Exposure
 - Confounders
- Central analysis on individual patient dataset
 - Control for confounding limited by number of confounders that are common to each database
 - Can be complemented by meta-analysis utilizing siteoptimized estimates



Reporting of (multi-)database studies

- The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) Statement for Pharmacoepidemiology (RECORD-PE)
- Developed as an extension of the existing <u>STROBE</u> guidelines (STrengthening the Reporting of OBservational studies in Epidemiology), with the overall goal to enhance transparency by providing researchers with the minimum reporting requirements needed to adequately convey the methods and results of their research.

http://www.record-statement.org



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Reproducability and replicability

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WILEY

ORIGINAL REPORT

Reporting to Improve Reproducibility and Facilitate Validity Assessment for Healthcare Database Studies V1.0

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Value in Health 2017;20:1009-22 Pharmacoepidemiol Drug Saf 2017;26:1018-32



Reproducability and replicability

TABLE 1 Reproducibility and replicability

		Data	Methods
bility	Direct replication Reproduction of a specific study	Same	Same
Reproducibility	Conceptual replication Reproduction of a finding for the exposure (and comparator), outcome and estimand of interest	Different Same Different	Different

Value in Health 2017;20:1009-22 Pharmacoepidemiol Drug Saf 2017;26:1018-32



TABLE 2 Reporting specific parameters to increase reproducibility of database studies*

	Description	Example	Synonyms		
A. Reporting on data so	ource should include:				
A.1 Data provider	Data source name and name of organization that provided data.	Medicaid Analytic Extracts data covering 5 states from the Centers for Medicare an Medicaid Services.			
A.2 Data extraction date (DED)	The date (or version number) when data were extracted from the dynamic raw transactional data stream (e.g. date that the data were cut for research use by the vendor).	The source data for this research study was cut by [data vendor] on January 1st, 2017. The study included administrative claims	Data version, data pull		
A.3 Data sampling	The search/extraction criteria applied if the source data accessible to the researcher is a subset of the data available from the vendor.	from Jan 1st 2005 to Dec 31st 2015.			
A.4 Source data range (SDR)	The calendar time range of data used for the study. Note that the implemented study may use only a subset of the available data.		Study period, query period		
A.5 Type of data	The domains of information available in the	The administrative claims data include			
	source data, e.g. administrative, electronic health records, inpatient versus outpatient capture, primary vs secondary care, pharmacy, lab, registry.	enrollment inform outpatient diagno procedure (ICD9) well as outpatient for 60 million live The electronic he diagnosis and pro- records, problem prescription and l results, inpatient i well as unstructur		typically available	We used Surveillance, Epidemiology, and End Results (SEER) data on prostate cancer cases from 1990 through 2013 linked to Medicare and a 5% sample of Medicare enrollees living in the same regions as the identified cases of prostate cancer over the same period of time. The linkage was created through a collaborative effort from the National Cancer Institute (NCI), and the Centers for Medicare and Medicaid Services (CMS).
		notes and reports encounters at AB system.	inconsistencies. This may be at the data source level or the decisions can be made on a project specific basis.		Global cleaning: The data source was cleaned to exclude all individuals who had more than one gender reported. All dispensing claims that were missing day's supply or had 0 days' supply were removed from the source data tables. Project specific cleaning: When calculating duration of exposure for our study population, we ignored dispensation claims that were missing or had 0 days' supply. We used the most recently reported birth date if there was more than one birth date reported.
		A.8 Data model conversion	Format of the data, including decisions used to convert d Common Data Model (CDN	ata to fit a	The source data were converted to fit the Sentinel Common Data Model (CDM) version 5.0. Data conversion decisions can be found on our website (http://ourwebsite). Observations with missing or out of range values were not removed from the CDM tables.

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Conclusions

- Characterise loss-of-information when different EU databases are transformed into CDM
- Assess impact of transformation into CDM on effect estimates from analytic studies
 - Empyrical studies comparing original database studies vs CDM based studies
- Complete CDM (eg OMOP) for all EU databases versus basic CDM for EU databases enhanced with study/database specific variables
- Further development and assessment of analytic methods for distributed data networks/multi-database studies



Key publications regarding methods & tools

- Trifirò G, Coloma PM, Rijnbeek PR, Romio S, Mosseveld B, Weibel D, Bonhoeffer J, Schuemie M, van der Lei J, Sturkenboom M. Combining multiple healthcare databases for postmarketing drug and vaccine safety surveillance: why and how? J Intern Med. 2014 Jun; 275(6):551-61.
- Gini R, Schuemie M, Brown J, Ryan P, Vacchi E, Coppola M, Cazzola W, Coloma P,Berni R, Diallo G, Oliveira JL, Avillach P, Trifirò G, Rijnbeek P, Bellentani M, van Der Lei J, Klazinga N, Sturkenboom M. **Data Extraction and Management in Networks of Observational Health Care Databases for Scientific Research: A Comparison of EU-ADR, OMOP, Mini-Sentinel and MATRICE Strategies**. EGEMS (WashDC). 2016 Feb 8;4(1):1189.
- Klungel OH, Kurz X, de Groot MC, Schlienger RG, Tcherny-Lessenot S, GrimaldiL, Ibáñez L, Groenwold RH, Reynolds RF. Multi-centre, multi-database studies with common protocols: lessons learnt from the IMI PROTECT project. Pharmacoepidemiol Drug Saf. 2016 Mar; 25 Suppl 1:156-65.
- Bazelier MT, Eriksson I, de Vries F, Schmidt MK, Raitanen J, Haukka J,Starup-Linde J, De Bruin ML, Andersen M. Data management and data analysis techniques in pharmacoepidemiological studies using a pre-planned multi-database approach: a systematic literature review. Pharmacoepidemiol Drug Saf. 2015Sep;24(9):897-905.
- But A, de Bruin ML, Bazelier MT,
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- Kurz X, Bauchau V, Mahy P, Glismann S, van der Aa LM, Simondon F; ADVANCE consortium. The ADVANCE Code of Conduct for collaborative vaccine studies. Vaccine. 2017 Apr 4;35(15):1844-1855.

