

HOW CAN WE ACHIEVE HIGH QUALITY DATA RELATED TO MEDICAL TECHNOLOGIES?

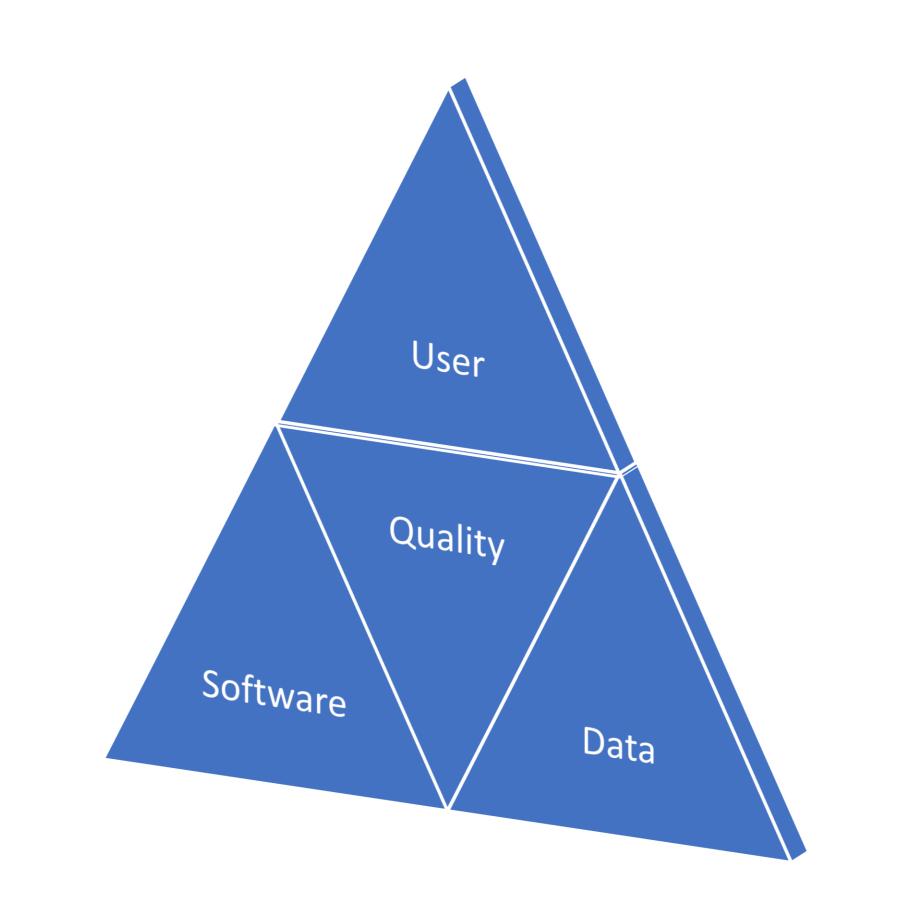
Prof. dr. Pascal Coorevits – beMedTech & i~HD Health Data Quality Seminar - May 17th 2022





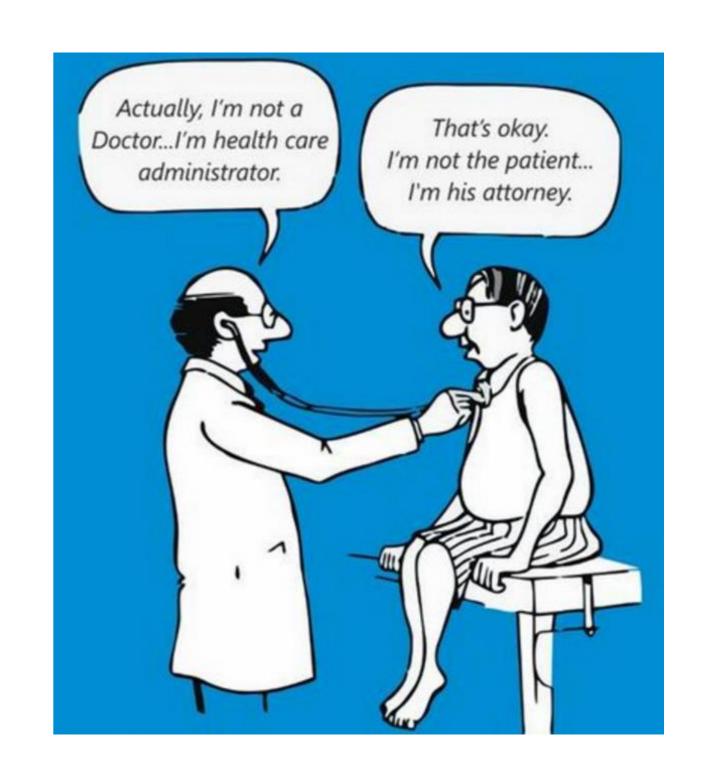






Quality of systems and data quality

- Depending on the use-case (e.g. providing daily routine care for patients, clinical research, big data analytics, ...) a number of functionalities are needed (e.g. security, confidentiality, trustworthiness, ...)
- Functions are required to ensure e.g. data correctness, completeness, accuracy, ...
- Quality assurance is essential
- Quality labelling & certification are needed





What is data quality?

 A thing you think about briefly while you start data cleaning procedures after data has been collected



- A complex scientific discipline
 - → Fit for use
 - → Multi-dimensional
 - → No consensus on exact definition, meaning and assessment methodology



Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research

Nicole Gray Weiskopf, Chunhua Weng

A Harmonized Data Quality Assessment Terminology and Framework for the Secondary Use of Electronic Health Record Data

Michael G. Kahn

Secondary Use of EHR: Data Quality Issues and Informatics Opportunities

Taxiarchis Botsis^{a,b}, Gunnar Hartvigsen^{a,c}, Fei Chen^b, Chunhua Weng^b

A practical framework for data management processes and their evaluation in population-based medical

M. SARIYAR¹, A. BORG¹, O. HEIDINGER² & K. POMMERENING¹

A Pragmatic Framework for Single-site and Multisite Data Quality Assessment in Electronic Health Record-based Clinical Research Michael G. Kahn, MD, PhD,*† Marsha A. Raebel, PharmD,†§ Jason M. Glanz, PhD, MS,†|| Various Diodlings MDH MT (ASCP) & and John F. Stoiner MD MPH† Karen Riedlinger, MPH, MT (ASCP), ¶ and John F. Steiner, MD, MPH;

A Data Quality Assessment Guideline for **Electronic Health Record Data Reuse**

Nicole G. Weiskopf, PhD; Suzanne Bakken, RN, PhD; الله George Hripcsak, MD, MS; Chunhua Weng, PhD الم

Applying probabilistic temporal and multisite data quality control methods to a public health mortality registry in Spain: a systematic approach to quality control

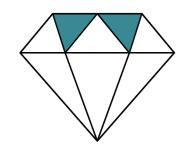






Carlos Sáez^{1,2}, Oscar Zurriaga^{3,4,5}, Jordi Pérez-Panadés³, Inma Melchor³, Montserrat Robles¹ and Juan M García-Gómez^{1,6} of repositories

i~HD Data Quality Assessment



9 data quality dimensions



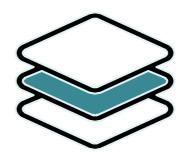
Designed for patient care, organisational learning and research



For health data providers, users and supporters



Developed by Data Quality
Task Force



Based on scientific literature



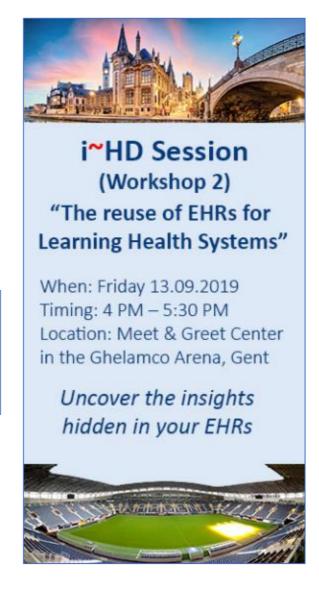
Approved by 70 hospital representatives



i~HD Hospital Network of Excellence Data Quality Workshop
Towards better data quality in hospitals

Tuesday 23rd May 2017 - Wednesday 24th May 2017







A two-day workshop run by the *i*~HD
Hospital Network of Excellence and Data Quality Task Force,
in collaboration with

Gaining the Benefits of Improved Health Data Quality

















Data Quality dimensions

Completeness

Data values are present

Consistency

Data satisfy constraints

Correctness

Values are true and unbiased

Uniqueness

Patient records are not duplicated

Stability

Data are comparable among sources and over time

Timeliness

Data is promptly processed and up-to-date

Contextualisation

Data are annotated with acquisition context

Trustworthiness

Data can be trusted based on owner's reputation

Representativeness

Data are representative of population

PatientID	Date-of- admission	Date-of- birth	Sex-at- birth	Weight- kg	Height- cm	Medication- Insulin	Glucose- blood-mg/dL	Glucose- blood-fasting	Prior MI
2310	05/03/2020	17/06/1976	F			0			0
10003	12/05/2020	24/11/1965	M	77	181	1	86	Yes	1
10003	23/08/2020	24/11/1965	М	76	181	1	91	Yes	1
10003	02/10/2020	24/11/1965	M	78	181	1	121	No	0
811	06/11/2020	01/26/1990	С	"55kg"	1.68	0	76	Yes	
345	23/01/2020	02/08/1939	F	53	162	0	134		
6786	11/08/2020	11/09/1946	М	68	177	0			1
6786	11/08/2020	11/09/1946	М	68	177	0			1
6786	11/08/2020	11/09/1946	М	83	177	0	95	Yes	1
10009	16/05/2020	24/02/1953	F	93	165	1	221	No	

Incomplete

Inconsistent

Duplicate

Incorrect

Correctness — "Values are true and unbiased"

Osteoporos Int

DOI 10.1007/s00198-016-3635-2

ORIGINAL ARTICLE

Clinical height measurements are unreliable: a call for improvement

A. L. Mikula 1 · S. J. Hetzel 2 · N. Binkley 3 · P. A. Anderson 4

"Fifty percent of clinic staff reported they on occassion enter patient reported height into the EHR rather than performing a measurement"

Bron: Carlos Saez and Juan M Garcia Gomez, UPV

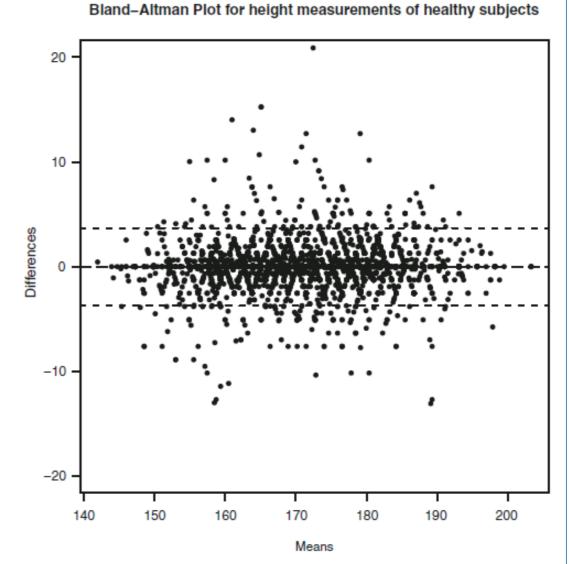


Fig. 4 Bland-Altman plot for height measurements of subjects. Each data point represents a single patient. *X axis* represent mean patient height in centimeters. *Y axis* represents difference between the first and the last height measurement for the individual patients in centimeters. The *dotted lines* represent 95 % CI

CORRECTNESS — "VALUES ARE TRUE AND UNBIASED"

Published in final edited form as:

J Nutr Health Aging. 2009 March; 13(3): 284–288.

THE ACCURACY OF MONTHLY WEIGHT ASSESSMENTS IN NURSING HOMES: IMPLICATIONS FOR THE IDENTIFICATION OF WEIGHT LOSS

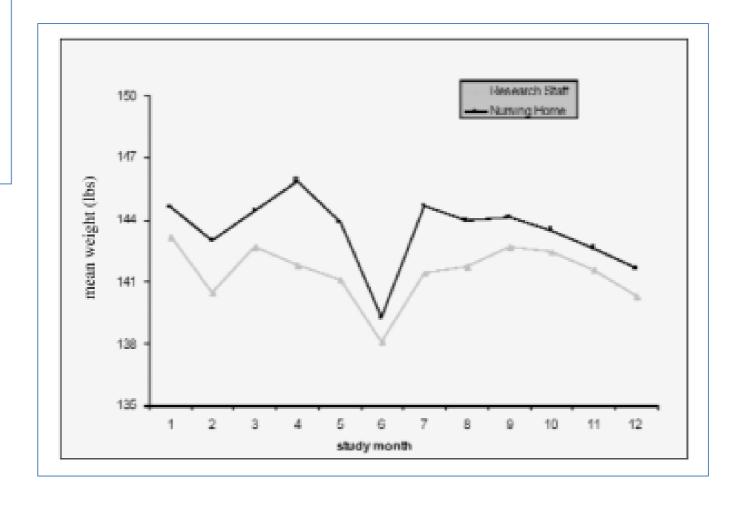
S.F. SIMMONS^{1,2}, E.N. PETERSON¹, and C. YOU¹

¹Vanderbilt University, School of Medicine, Division of General Internal Medicine and Public Health, Center for Quality Aging, Nashville, TN

²Veterans Administration Tennessee Valley Healthcare System; VA Geriatric Research, Education, and Clinical Center, Nashville, TN

Comparison of weight measurements between:

- Trained research staff -> Gold standard
- Nursing homes staff -> Biased



Bron: Carlos Saez and Juan M Garcia Gomez, UPV

COMPLETENESS — "DATA VALUES ARE PRESENT"

Incompleteness in clinical trials (EHR4CR standardized data inventory)

Data Group	Data Item	Avg. usage	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 9	Site 9
Demographics	Gender	100%	100,00%	100,00%	100,00%	100,00%	100,00%	100%	100%	100,0%	100,00%
Demographics	Case Status	96%	99,87%	100,00%	60,00%	100,00%	100,00%	100,00%	100%	100,0%	100,00%
Demographics	Date of Birth	89%	100,00%	100,00%	99,00%	NA	100,00%	100%	100%	100,0%	100,00%
Demographics	Admission date	84%	100,00%	100,00%	100,00%	NA	100,00%	99,53%	58%	100,0%	100,00%
Diagnosis	Diagnosis Text	81%	50,46%	84,02%	100,00%	100,00%	98,05%	100,00%	14%	100,0%	80,98%
Diagnosis	Diagnosis Code	81%	50,46%	84,02%	100,00%	100,00%	98,05%	100,00%	14%	100,0%	80,98%
Demographics	Discharge date	7 5%	100,00%	100,00%	100,00%	NA	100,00%	100,00%	58%	100,0%	14,18%
Diagnosis	Diagnosis Date	70%	50,46%	84,02%	100,00%	100,00%	100,00%	NA	13%	100,0%	80,98%
Medication	Dosage	25%	20,36%	0,00%	NA	NA	94,43%	95%	NA	NA	12,21%
Findings	Weight	25%	29,56%	18,24%	NA	NA	89,17%	27,20%	36%	7,5%	
Laboratory Findings	Platelets Blood	48%	52,78%	33,14%	63,73%	NA	100,00%	100%	45%	NA	33,88%
Laboratory Findings	SGPT (ALT) in serum	47%	33,61%	22,29%	100,00%	NA	100,00%	100%	47%	NA	21,86%
Laboratory Findings	Total Protein in serum	46%	52,37%	14,96%	86,53%	NA	100,00%	100%	47%	NA	16,34%
Laboratory Findings	Total Bilirubin in serum	46%	33,03%	16,99%	100,00%	NA	100,00%	100%	47%	NA	19,58%



Variables such as Weight are quite frequently not present

Doods et al. Trials 2014, 15:18 http://www.trialsjournal.com/content/15/1/18



RESEARCH

Open Access

A European inventory of common electronic health record data elements for clinical trial feasibility

Justin Doods¹, Florence Botteri², Martin Dugas¹, Fleur Fritz^{1*} and on behalf of EHR4CR WP7

Bron: Carlos Saez and Juan M Garcia Gomez, UPV

- 20% of scientific papers with supplementary data in Excel contain errors
 - Cause: automatic
 conversion of gene symbols
 in dates and numbers by
 Excel

CONSISTENCY — "DATA SATISFIES CONSTRAINTS"

Bron: Carlos Saez and Juan M Garcia Gomez, UPV

Ziemann et al. Genome Biology (2016) 17:177 DOI 10.1186/s13059-016-1044-7

Genome Biology

COMMENT



Gene name errors are widespread in the scientific literature

Mark Ziemann¹, Yotam Eren^{1,2} and Assam El-Osta^{1,3*}

Abstract

The spreadsheet software Microsoft Excel, when used with default settings, is known to convert gene names to dates and floating-point numbers. A programmatic scan of leading genomics journals reveals that approximately one-fifth of papers with supplementary Excel gene lists contain erroneous gene name conversions.

Keywords: Microsoft Excel, Gene symbol,

Supplementary data

Abbreviations: GEO, Gene Expression Omnibus;

JIF, journal impact factor

The problem of Excel software (Microsoft Corp., Redmond, WA, USA) inadvertently converting gene symbols to dates and floating-point numbers was originally described in 2004 [1]. For example, gene symbols such as SEPT2 (Septin 2) and MARCH1 [Membrane-Associated Ring Finger (C3HC4) 1, E3 Ubiquitin Protein Ligase] are converted by default to '2-Sep' and '1-Mar,' respectively. Furthermore, RIKEN identifiers were described to be automatically converted to floating point numbers (i.e. from accession '2310009E13' to '2.31E+13'). Since

frequently reused. Our aim here is to raise awareness of the problem.

We downloaded and screened supplementary files from 18 journals published between 2005 and 2015 using a suite of shell scripts. Excel files (.xls and.xlsx suffixes) were converted to tabular separated files (tsv) with ssconvert (v1.12.9). Each sheet within the Excel file was converted to a separate tsv file. Each column of data in the tsv file was screened for the presence of gene symbols. If the first 20 rows of a column contained five or more gene symbols, then it was suspected to be a list of gene symbols, and then a regular expression (regex) search of the entire column was applied to identify gene symbol errors. Official gene symbols from Ensembl version 82, accessed November 2015, were obtained for Arabidopsis thaliana, Caenorhabditis elegans, Drosophila melanogaster, Danio rerio, Escherichia coli, Gallus gallus, Homo sapiens, Mus musculus, Oryza sativa and Saccharomyces cerevisiae [2]. The regex search used was similar to that described previously by Zeeberg and colleagues [1], with the added screen for dates in other formats (e.g. DD/MM/YY and MM-DD-YY). To expedite analysis of supplementary files from multi-disciplinary journals, we limited the articles screened to those that have the keyword 'genome' in the title or abstract (Science,

- Data quality issues found in a survival analysis of pancreatic cancer patients (Columbia University Medical Center, New York)
- > Information inconsistency between different EHR data sources:
 - In a few cases, pancreatitis was diagnosed as being chronic in the pathology reports but it was reported as being only acute in the clinical notes
- Information inconsistency within the same data sources :
 - Some patients received simultaneously two different ICD-9-CM codes for their diagnoses of diabetes, both 250.01 and 250.02 for type-1 and type-2 respectively

CONSISTENCY — "DATA SATISFIES CONSTRAINTS"

Summit on Translat Bioinforma. 2010; 2010: 1–5. Published online 2010 Mar 1.

PMCID: PMC3041534

Secondary Use of EHR: Data Quality Issues and Informatics Opportunities

Taxiarchis Botsis, a,b Gunnar Hartvigsen, a,c Fei Chen, b and Chunhua Wengb

Quality of Hospital Electronic Health Record (EHR) Data Based on the International Consortium for Health Outcomes Measurement (ICHOM) in Heart Failure: Pilot Data Quality Assessment Study

Hannelore Aerts ¹ ², Dipak Kalra ¹ ², Carlos Sáez ³, Juan Manuel Ramírez-Anguita ⁴, Miguel-Angel Mayer ⁴, Juan M Garcia-Gomez ³, Marta Durà-Hernández ³, Geert Thienpont ² ⁵, Pascal Coorevits ¹

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- 5 Research in Advanced Medical Informatics and Telematics (RAMIT), Ghent, Belgium.

PMID: 34346902 PMCID: PMC8374665 DOI: 10.2196/27842

Free PMC article

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ACTIONS





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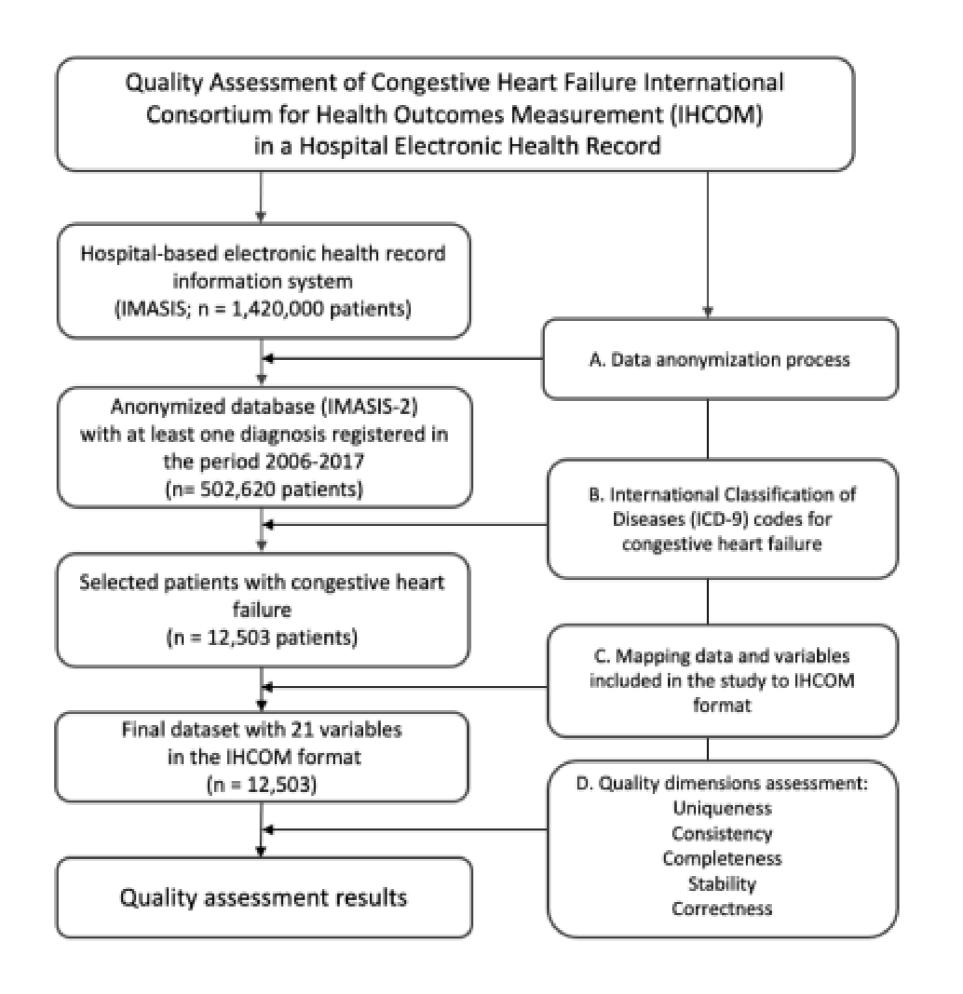
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Abstract

Conflict of interest statement

Figures



- It is essential to have considerable knowledge of the EHR (types of data available, how the data were collected or who collected it)
- The **assessment** of the data is the very first step to improve the quality of your data
- Once you know about the quality of your data, it is important to monitor it regularly
- It is of value that an **external assessment** of the data quality is performed by an independent organization
- High-quality data enhance the validity and reliability of study findings
- It is critical to ensure that **the metrics** are feasible, valid, and meaningful for a specific EHR and purpose and its quality improvement

- Multidisciplinary approach is highly recommended
- Thinking of using EHR for different purposes such as research, EHR data models would need to be expanded and redesigned and data quality assessment can assist in doing these tasks





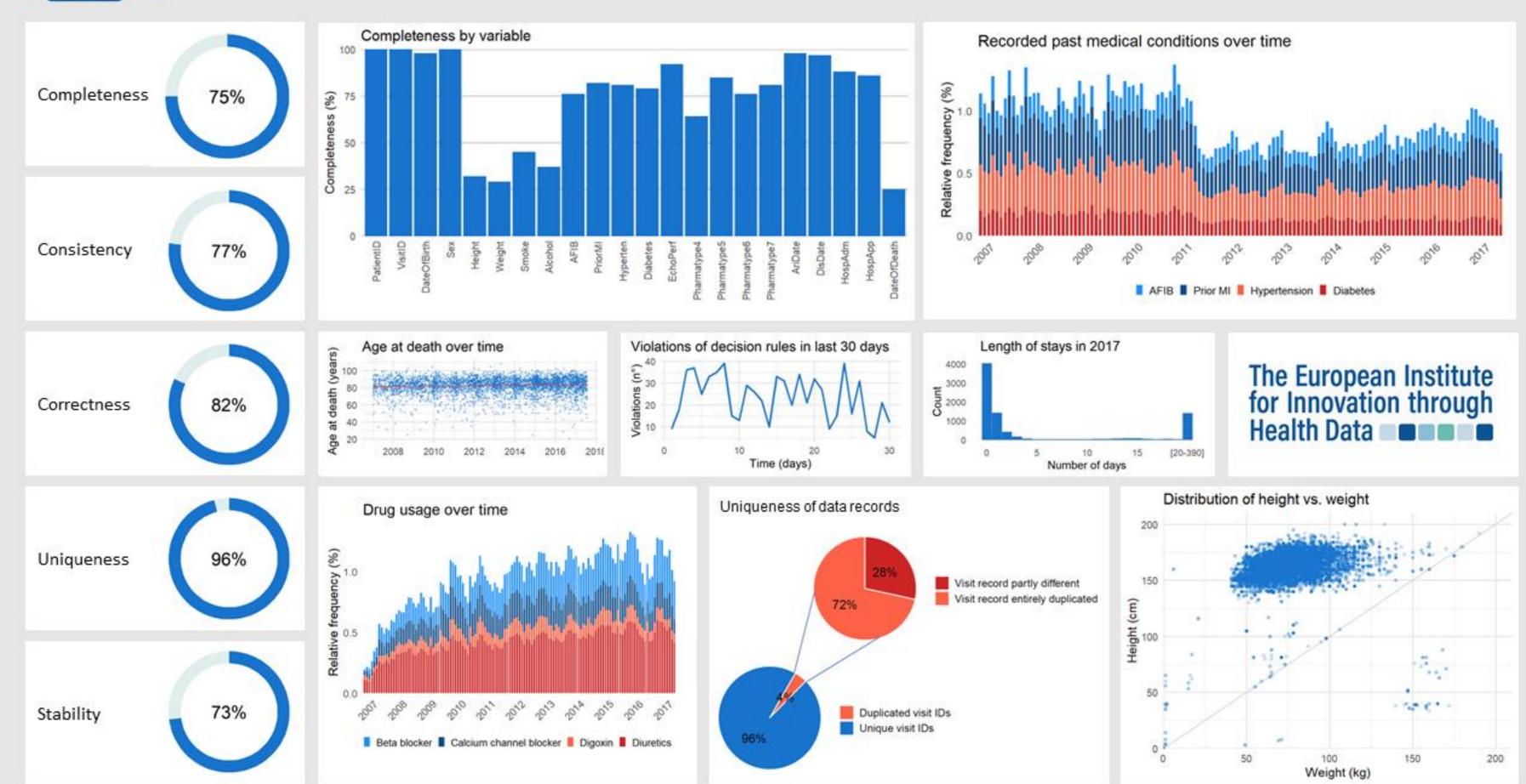








i HD ullur Data Quality Monitoring Dashboard



Thank you!



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