LUDWIG BOLTZMANN INSTITUTE Digital Health and Prevention

CBmed BIOMARKER RESEARCH

Medizinische Universität Graz

Digital Biomarkers for Precision Medicine

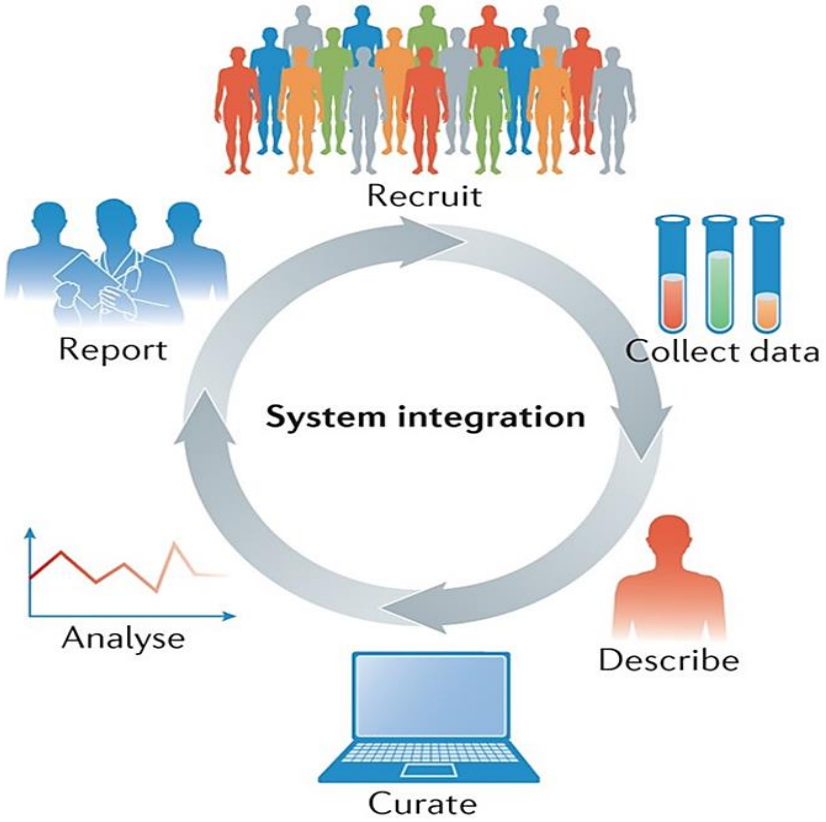
Stefan Schulz
Medical University of Graz, Institute for Medical Informatics, Statistics and Documentation
Rada Hussein
Ludwig Boltzmann Institute for Digital Health and Prevention, Salzburg

PhD program AMBRA – Jan 17, 2022

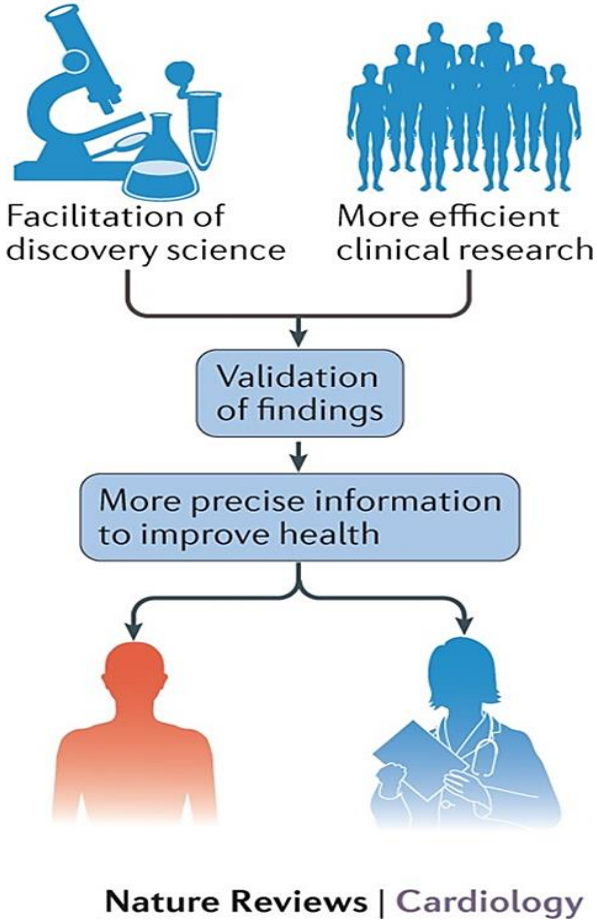
Digital Biomarkers for **Precision Medicine**

Precision Medicine

A precision medicine system



Precision medicine goals



Source: Precision Medicine in Cardiology. *Nature*

Precision Medicine (PM) is data-centred

Precision Medicine

- Treat every patient as an individual case,
- Incorporating a **range of** personalized **data**

Artificial Intelligence
- Clinical Prediction
- Decision Support

Research Support
- Retrospective analyses
- Cohort building

Enhanced use of clinical data at point of care
- Filtering
- Visualisation
- Content retrieval
- Quality assessment

David J. Duffy. Problems, challenges and promises: perspectives on precision medicine. Briefings in Bioinformatics, Volume 17, Issue 3, May 2016, Pages 494–504, https://doi.org/10.1093/bib/bbv060

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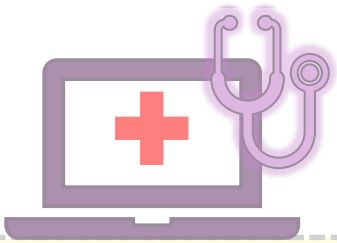

Precision Medicine

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Artificial Intelligence

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Findable
Metadata and data should be findable for both humans and computers

Interoperable
Data needs to work with applications or workflows for analysis, storage and processing

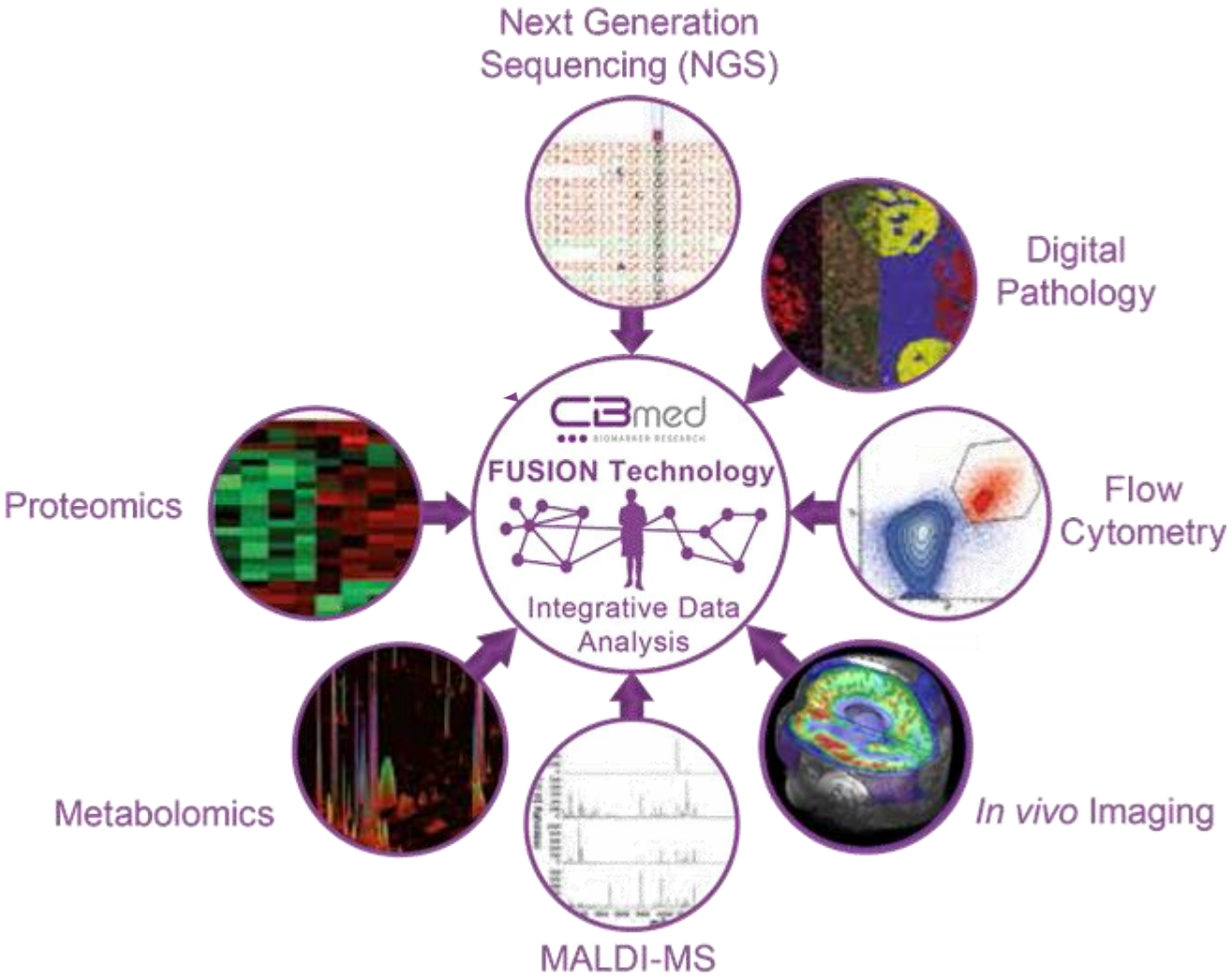
F **A** **I** **R**

Accessible
Once found, users need to know how the data can be accessed

Reusable
The goal of **FAIR** is to optimise data reuse via comprehensive well-described metadata

https://www.go-fair.org/fair-principles/

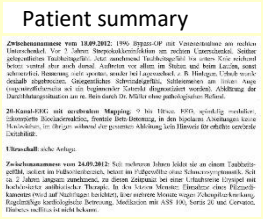
Data sources for precision medicine



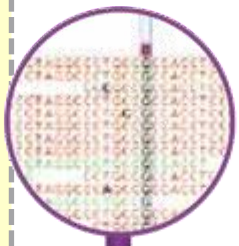
Source: CBmed – Center for Biomarker Research in Medicine, Graz, Austria

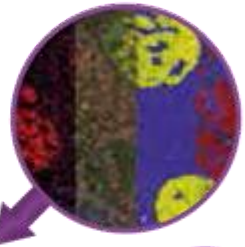
Data sources for precision medicine

- Phenotype
- Environment
- Lifestyle
- Clinical History



Next Generation Sequencing (NGS)





Digital Pathology

Proteomics

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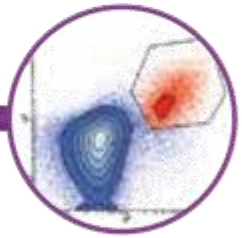
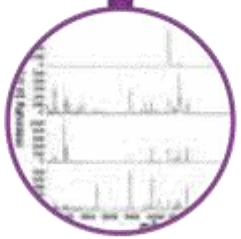
FUSION Technology

Integrative Data Analysis

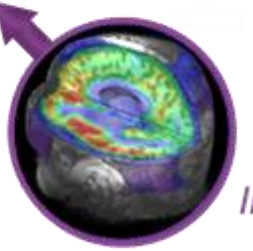


Flow Cytometry

Metabolomics



MALDI-MS



In vivo Imaging

Source: CBmed – Center for Biomarker Research in Medicine, Graz, Austria

Digital Biomarkers for Precision Medicine

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Digital Footprints

Clinical routine data

In clinical information systems: Electronic health records contain data about diagnoses, therapies etc.

Patient-reported outcomes

Health-related data created and recorded by or from patients outside of the clinical setting to help address a health concern

Research Challenges: From Digital Footprints to Digital Biomarkers (Patient-generated data)

New from the *Weekly Spark*

Work-Related Perceptions and Suicide
March 09, 2018

Sexual Orientation Discordance Puts Adolescents at Greater Risk for Nonfatal Suicidal Behaviors
March 09, 2018

WYOMING: With Church Donation, Wyoming Organization to Create Info Packets for Families Affected by Suicide
March 09, 2018

INTERNATIONAL: Twitter Updates Its Policy on Tweets that Encourage Self-Harm and Suicide
March 09, 2018

Technology and Suicide Risk: Moving Beyond Fear to Opportunity
March 02, 2018

The *Weekly Spark*
Stay Connected!
Subscribe

Can Facebook's Machine-Learning Algorithms Accurately Predict Suicide?

March 10, 2017

News Type: Weekly Spark, Weekly Spark News

Scientific American

Facebook has just expanded the array of tools it provides to reach users at risk for suicide and connect them with mental health resources. The menu of options that allows Facebook users to report posts with content indicating potential thoughts of suicide or self-harm will now be available for Facebook live streams as well. The social media company is also piloting a pattern recognition algorithm that it hopes will automatically identify posts of concern even if they have not yet been reported by users. According to Facebook spokesperson William Nevius, the algorithm will use words or phrases related to suicide or self-harm in a user's post, and in comments added by friends, to determine if the person may be at risk. The system will automatically alert Facebook's Community Operations team about posts of concern so that the team can quickly review them. If the team determines that support is warranted, they will ensure that information about helping resources will appear in the user's news feed.

Spark Extra! Check out a community guide for Facebook users.

Planning and Implementing: New and Social Media

Research Challenges: From Digital Footprints to Digital Biomarkers (Clinical data)

Alerts | Author Instructions | Submit | About

JAMIA

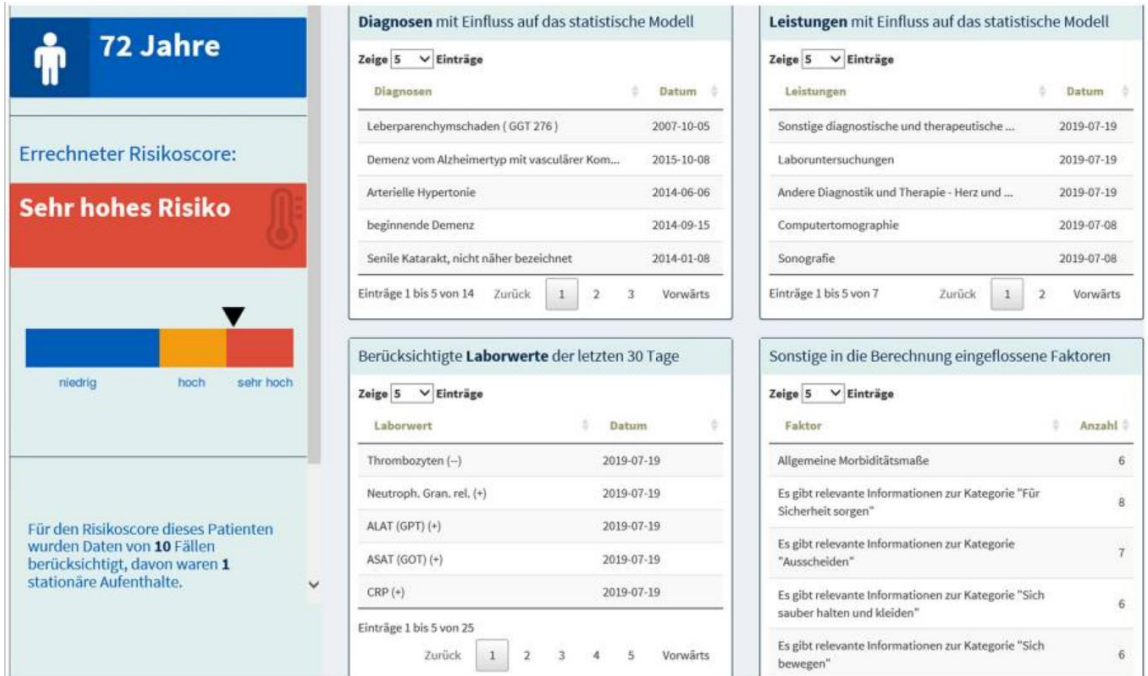
Journal of the American Medical Informatics Association

J Am Med Inform Assoc. 2020 Sep; 27(9): 1383–1392.
Published online 2020 Sep 24. doi: 10.1093/jamia/ocaa113

PMCID: PMC7647341
PMID: 32968811

Risk prediction of delirium in hospitalized patients using machine learning: An implementation and prospective evaluation study

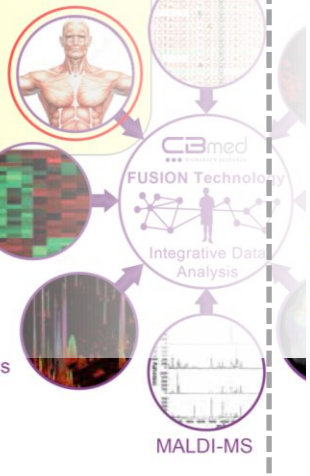
Stefanie Jauk,[1,2] Diether Kramer,[1] Birgit Großauer,[3] Susanne Rienmüller,[3] Alexander Avian,[2] Andrea Berghold,[2] Werner Leodolter,[1] and Stefan Schulz[2]

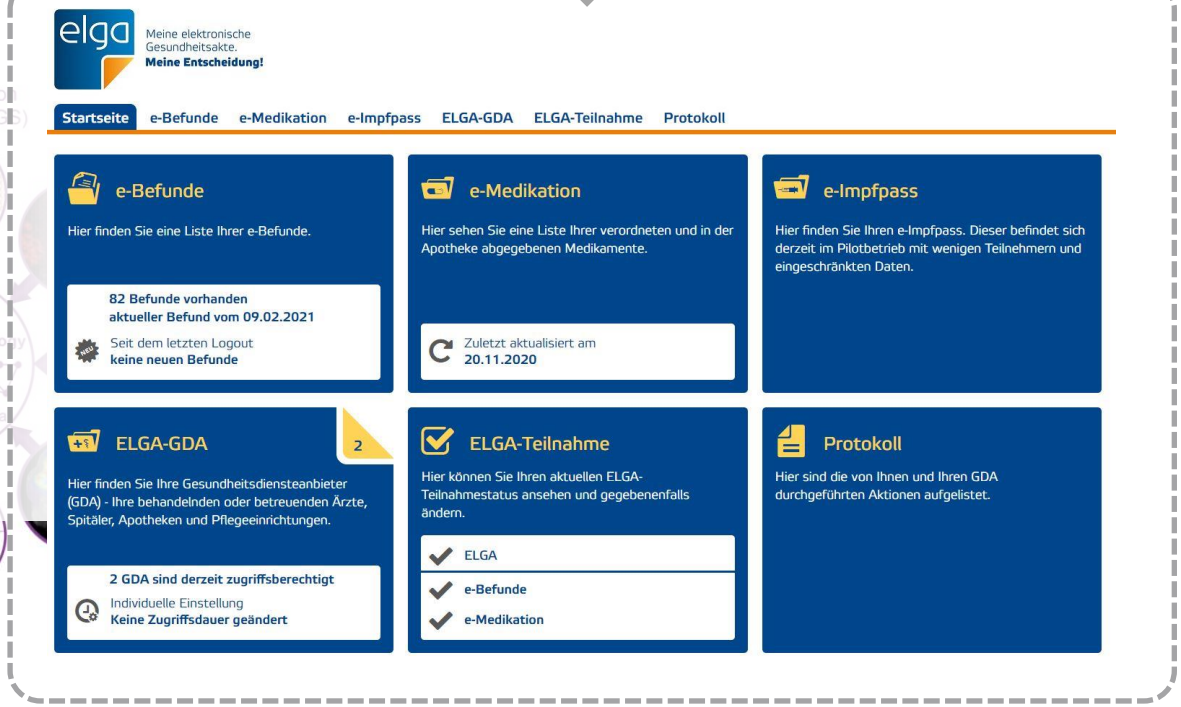


Goal: integrate all data in patient-controlled personalised record

Extracting
Cleaning
Standardising

- Phenotype
- Environment
- Lifestyle
- Clinical History





Semantic resources for interoperability

FHIR

Standardised information templates for typical documentation needs ("condition", "observation", "drug prescription"). Meaning is represented therein by codes, which come from ontology and terminology standards like

SNOMED CT
The global language of healthcare

Huge ontology that provides codes and definitions for a broad range of concepts referred to by health records

LOINC®
from Regenstrief

LOINC, a vocabulary for standardising observable entities like lab parameters.

Basic technology: information extraction using Natural Language Processing

- **Large amounts of data only as free-text**
  - Clinical data
  - Social network data

CABG n HWI
Polenallergie
Fischgerät im Hals
ZW. EBA PAE re. ,TVT. li
Acutes Coronar Syndrom
Nagelkranzfraktur Damen li
V. mors fel dig IV man dex
chron perfor. Gabla DD: Gabla CA
Bursitis Olecrani sin mit begl.Erisypel
Zst.n.Lux. Daumensattelgel.protese li.
Bulli-Trauma: Rippenserienfraktur links
Außenmeniscusscheibenmeniscusdeformität
Zahnex in AN bei Entwichklungsret. unkl.Genese
St. post Pneumonektomie links propter Neo Bronchi
Intervalle, in denen die Beschwerden nahezu beschwerdefrei sind
St.p.TE eines exulc. sek.knot.SSM li US dors. 5/11 Level IV 2,4mm TD. Sentinnel LK ing. li. tumorfr.

- bad spelling
- typing errors
- transcription errors
- spelling variants
- grammatical errors
- ambiguous acronyms
- ad hoc compounds
- ad hoc abbreviations
- elliptic style
- local contexts
- idiosyncrasies, mannerisms
- non-native authors

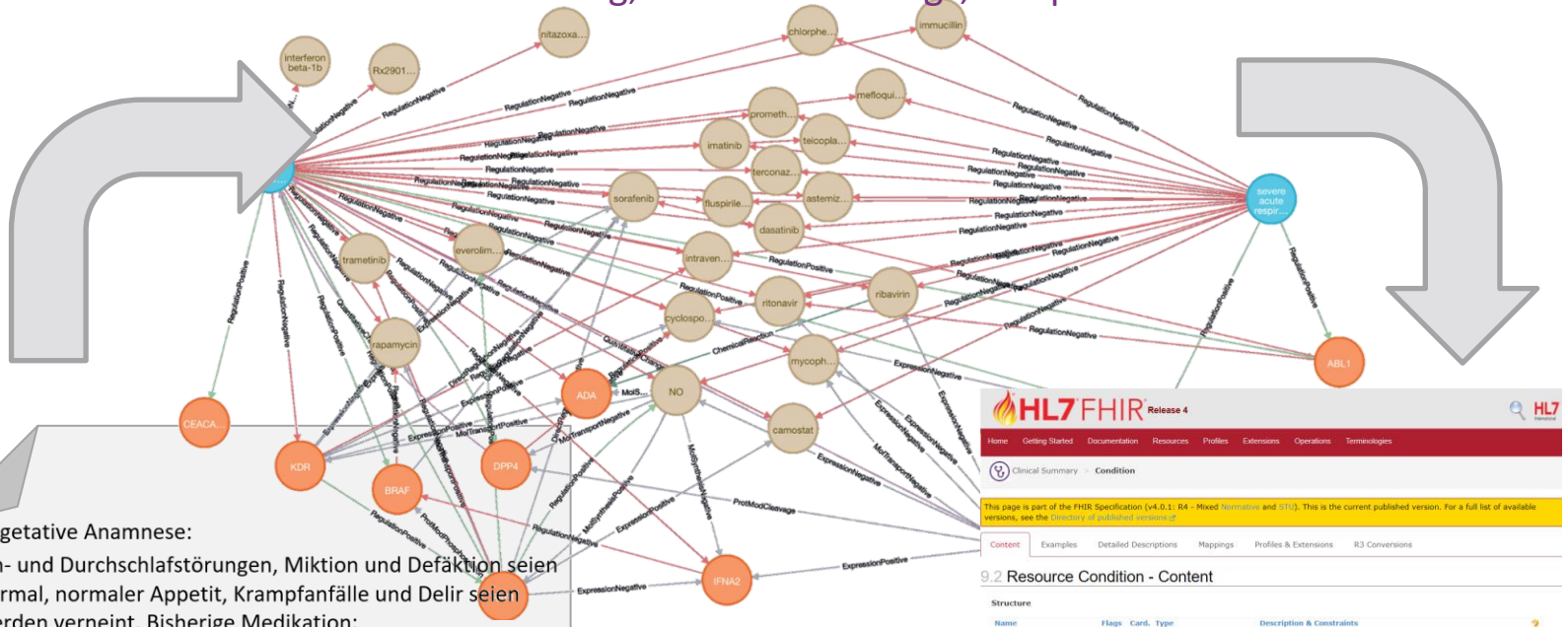
Text to knowledge graph to standards

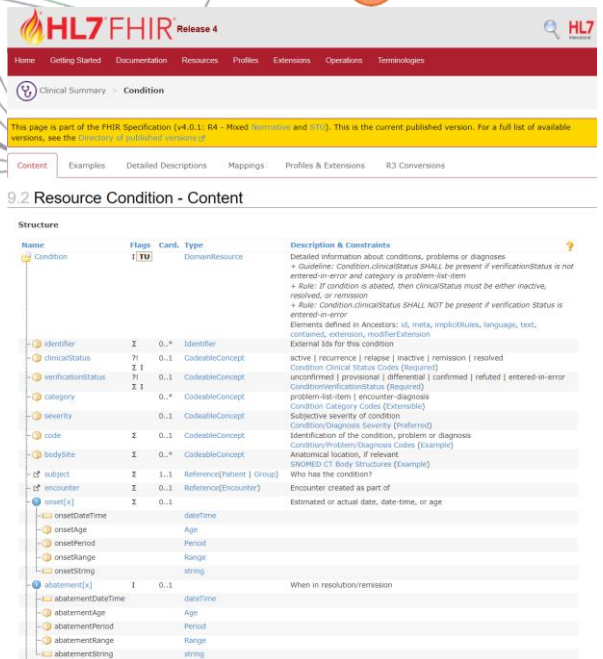
Resources:

- Ontologies, Vocabularies, Language Models

Methodology:

- Text mining, Node embeddings, link prediction





Vegetative Anamnese:

Ein- und Durchschlafstörungen, Miktion und Defäktion seien normal, normaler Appetit, Krampfanfälle und Delir seien werden verneint. Bisherige Medikation:

Seroquel Prolong 0-0-0-50 mg.

Promethazin 200 mg.

Mirtazapin 90 mg.

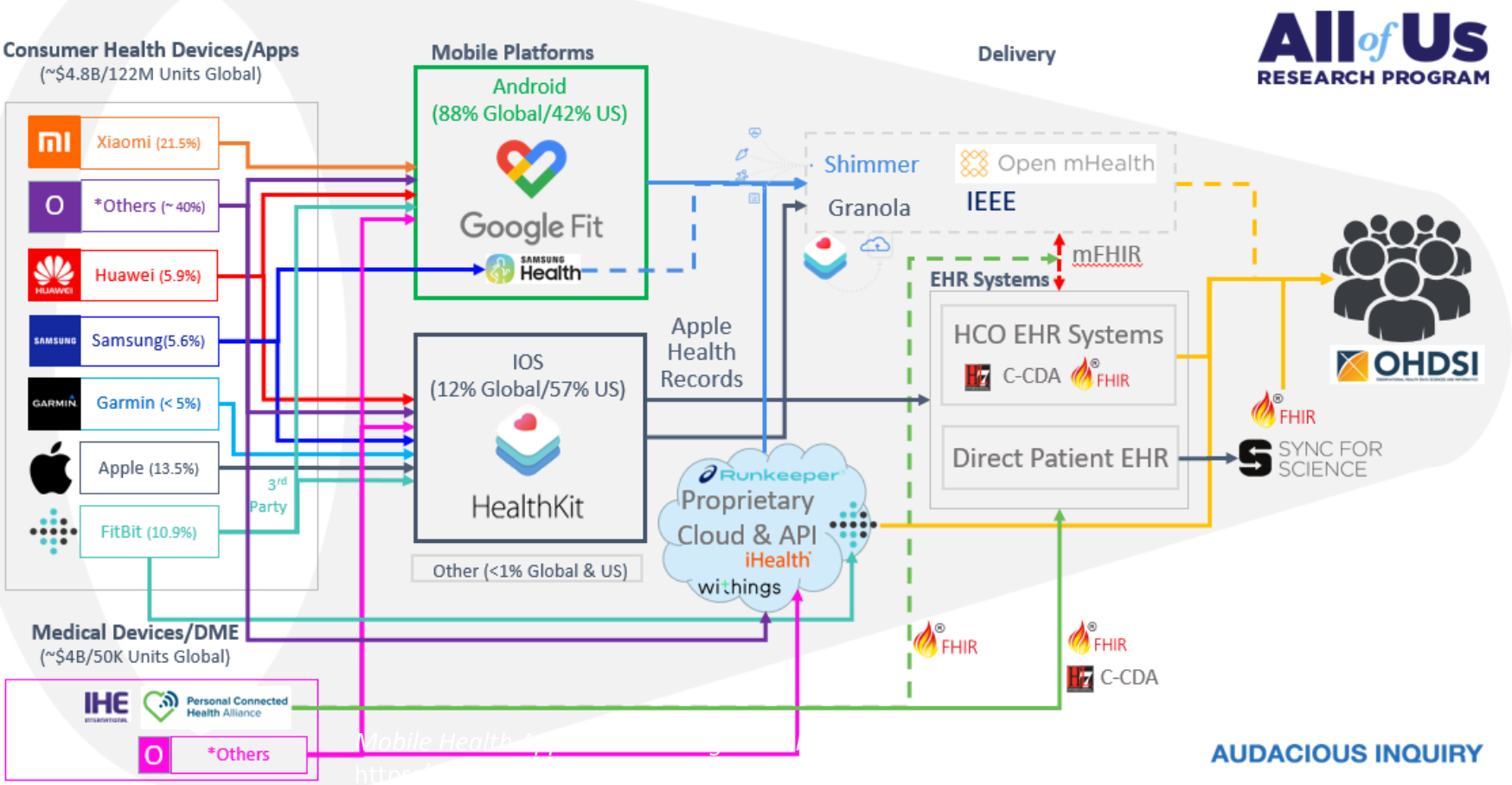
Medikamenten Unverträglichkeit / Allergien:

Heuschnupfen.

Psychische Aufnahme Bef.:

Patient ist wach, wesentlicher orientiert, kooperativ, auskunftsbereit, keine mnestische Defizite, gedrückte Stimmung, unruhig, formale Gedankengang geordnet, misstraue Gefühle, kein H. a. optische oder akustische

Sensor data from wearable apps to standards



Mobile Health App Data Exchange - Mobile Health - Confluence. https://confluence.hl7.org/display/MH/Mobile+Health+App+Data+Exchange?preview=/55939942/55939955/DataFunnel.pptx. Accessed 6 Dec. 2021.

PhD research questions

How can structured and standardised content be extracted out of unstructured clinical and patient-generated data?

How can existing standards be adapted to meet the needs to represent patient-generated data and relate them to clinical data?

How can different technical specifications and formats lead to normalised representation of sensor data output

How can interoperability be achieved from textual data in different (sub)language

How can machine learning techniques be leveraged to identify equivalent or similar FHIR instances?

How can interoperability models and standards be evaluated

To what extent formal-ontological approaches are suitable for representing contexts, provenance, temporality of this data?

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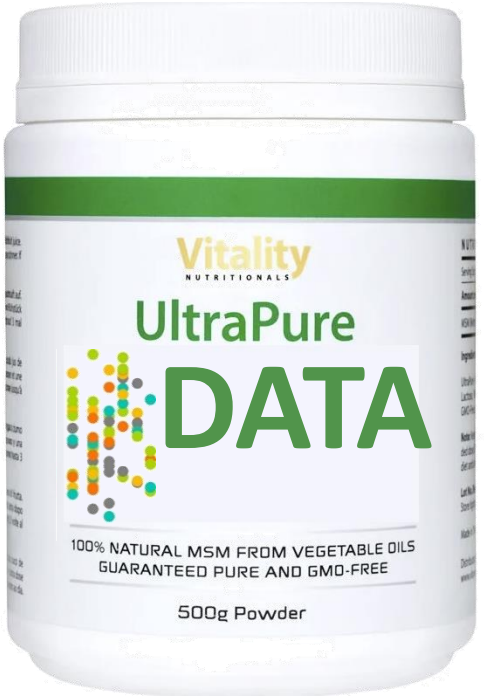
Thanks for your interest!

Stefan Schulz

Rada Hussein



Contact:
stefan.schulz@medunigraz.at
rada.hussein@dhp.lbg.ac.at