How Artificial Intelligence Changes Medical Diagnosis, Treatment, and Education

Mirjana Ivanović

University of Novi Sad, Faculty of Sciences, Novi Sad, Serbia
mira@dmi.uns.ac.rs

AGENDA

- 1 Introduction 
- 2 Quality Data Aggregation in Health Domains
- 3 Data – AI/ML Models Development – Use of Models
- 4 Some Examples
- 5 Possibilities for Medical Education
- 6 Conclusions

1 Introduction

CLINICAL DATA - https://guides.lib.uw.edu/hsl/data/findclin

- **Vital resource - collected during the course of ongoing patient care** or as part of a **formal clinical trial** program

- **Six major types**:

- **Electronic health/medical records (EHR/EMR)**

  - The **purest type of electronic clinical data**, obtained at medical facility, hospital, clinic,…

  - administrative/demographic info, **diagnosis, treatment, prescription drugs, laboratory tests**, physiologic monitoring data, hospitalization, quality of life parameters (QoL), etc.

- **Administrative data, Claims data, Patient / Disease registries, Health surveys, Clinical trials data**

1 Introduction

Health terminology - "language" used to code entries in EHRs - ICD-9, ICD-10, IDC-11, LOINC, CPT, SNOMED CT, ...

- **EHRs - terminology -** key for **interoperability** between different systems and integrating data.
- **exchange data between systems** – compatibility of **codes** between systems.
- **standards** - support **mapping** of various vocabularies and smooth "**communication**" between systems

- **SNOMED CT – Systematized Nomenclature of Medicine Clinical Terms** - a comprehensive, computerized healthcare terminology.
  - **SNOMED CT - also an ontology** - defines concepts: **causes of diseases, the part of the body they affect and how they can be diagnosed ...**
  - **medical standard** for: **diagnosis, clinical findings, symptoms, procedures**, body structures, and organisms, …, **inter-relationships between concepts**.

1 Introduction

Health data models from international standards

- **HL7 FHIR – Health Level 7, Fast Healthcare Interoperability Resources**
  - **Resources** (6 major categories) for: structuring information from a patient, an adverse reaction, a procedure and an observation, …, (clinical, identification, workflow, financial,…)
  - **data model is oriented to noSQL - the content of the FHIR resources can be represented** in **XML, JSON, Turtle**, and other formats
  - The **data model include interoperability artefacts** composed of a set of modular components/ "Resources".

1 Introduction

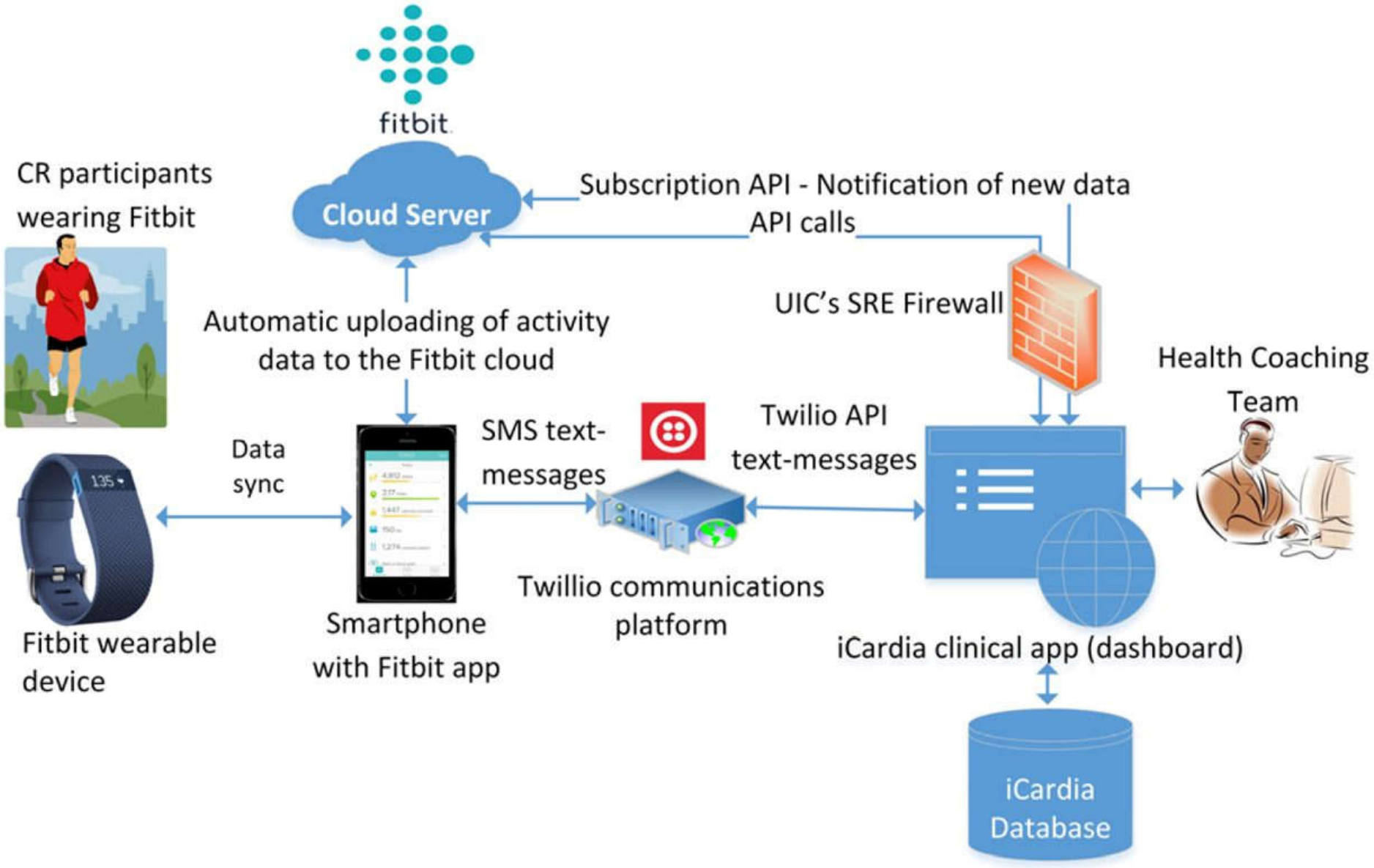
WEARABLE DEVICES - additional sources for collecting health/medical data

- **Personal health record (PHR), Remote patient monitoring (RPM)**

- **Wearable computer/device** (wristwatches , smartphones, small mobile computers) - widely used **Google FitBit**
  - **collect data to estimate a variety of metrics:** no of steps, calories burned, weight, heart rate, sleep stages, active minutes,…
  - **shows individual's statistic and progress -** used with EHR **and integrated/aggregated with other patient's data**
  - **personalized medicine** - help in **adjusting patient's therapy** in a smart way
  - **predictive analytics -** can **ensure the safety of patients** by alerting medical personnel immediately.

1 Introduction

Example: iCardia platform components and architecture - **innovative mHealth platform for remote physical activity monitoring and health coaching of cardiac rehabilitation patients (https://www.evl.uic.edu/pubs/2285)**



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2 Quality Data Aggregation in Health Domains

DATA AGGREGATION - **combining information** from multiple systems. produce **interconnective, shareable information** (sensitive health data)

AGREGATED vs INDIVIDUAL DATA

- **Individual data** - **created by patient's/doctor's interaction with the healthcare system**, physicians make **more effective treatment decisions**.

- **Data of numerous similar cases** - **anonymized aggregated data, physicians** see patient data from a **different angle**

and **make better decisions**.

- **Aggregate management**
  - important insight for **strategic planning**

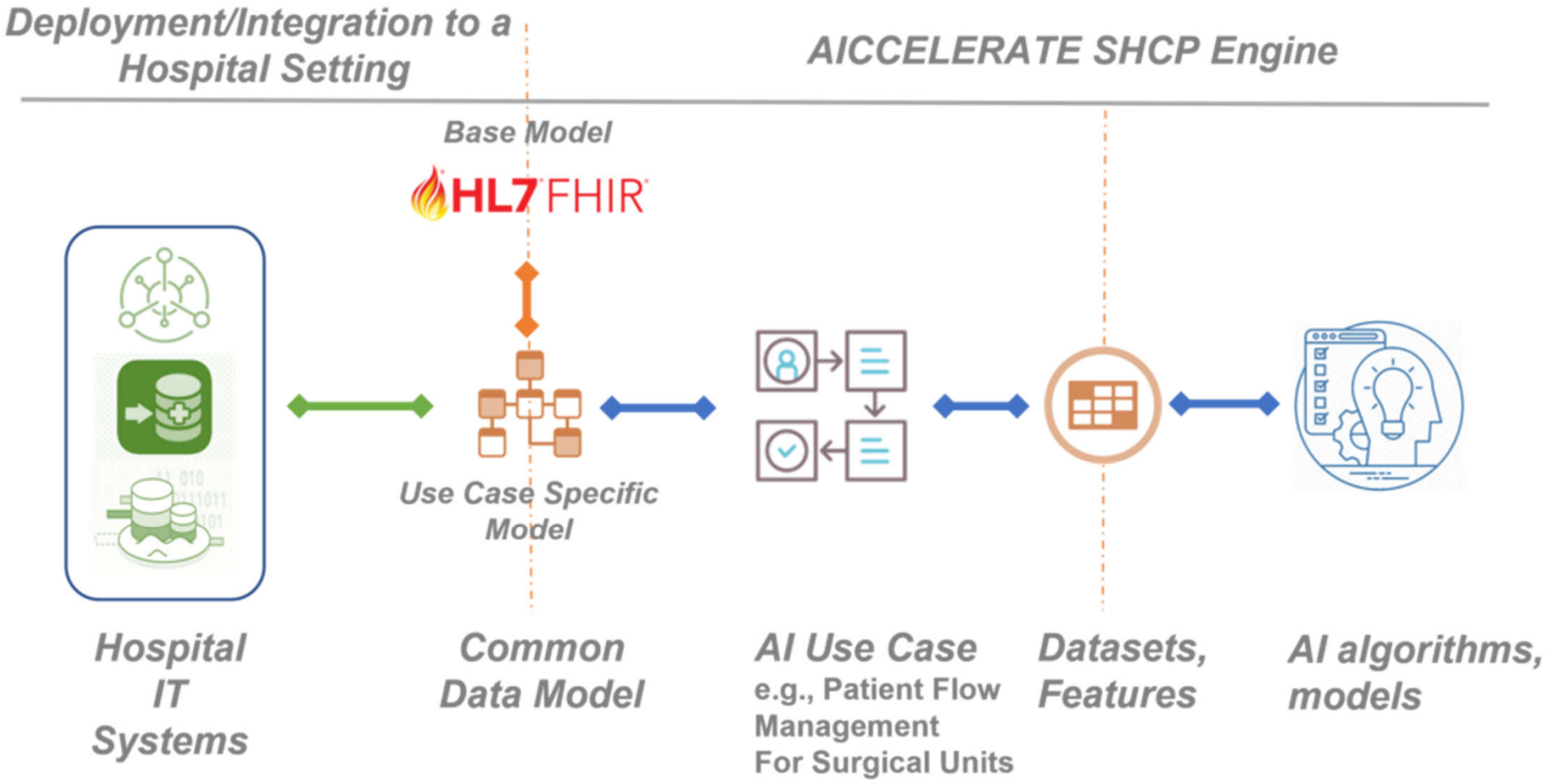
and creating health systems.

  - **by simply increasing the sample size,**

data sharing increases data quality.

2 Quality Data Aggregation in Health Domains

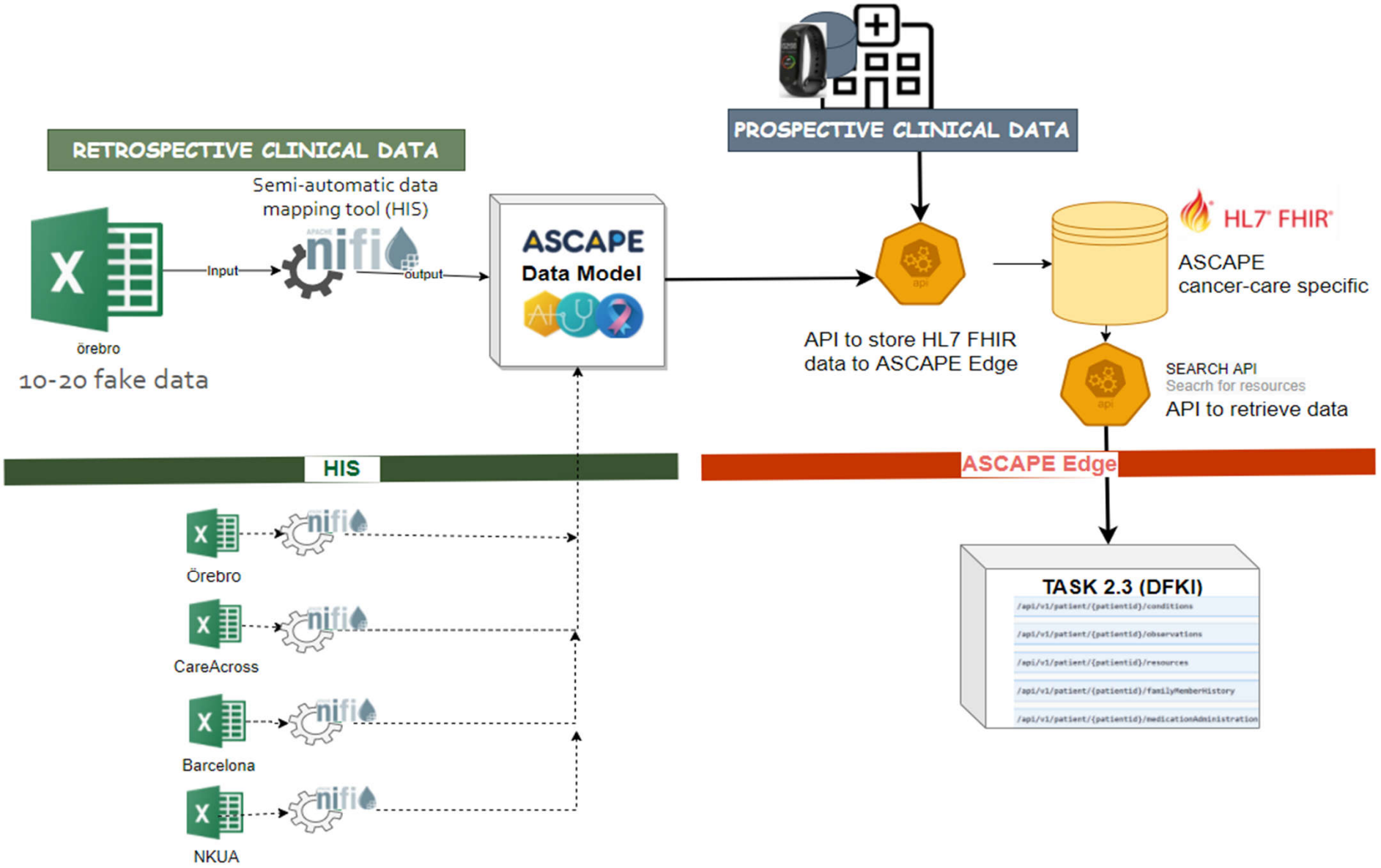
- **developing, validating, and improving a methodology based on HL7 FHIR,** interoperability.



Smart Hospital Care Pathway - https://aiccelerate.eu/health-data-preparation-for-artificial-intelligence-ai/ - (H2020)

2 Quality Data Aggregation in Health Domains

- **ASCAPE H2020 developing, validating, and improving a methodology based on HL7 FHIR,** interoperability.



2 Health Data Privacy Preserving

Important privacy preserving techniques

Privacy preserving - crucial in processing personal/patients' health data

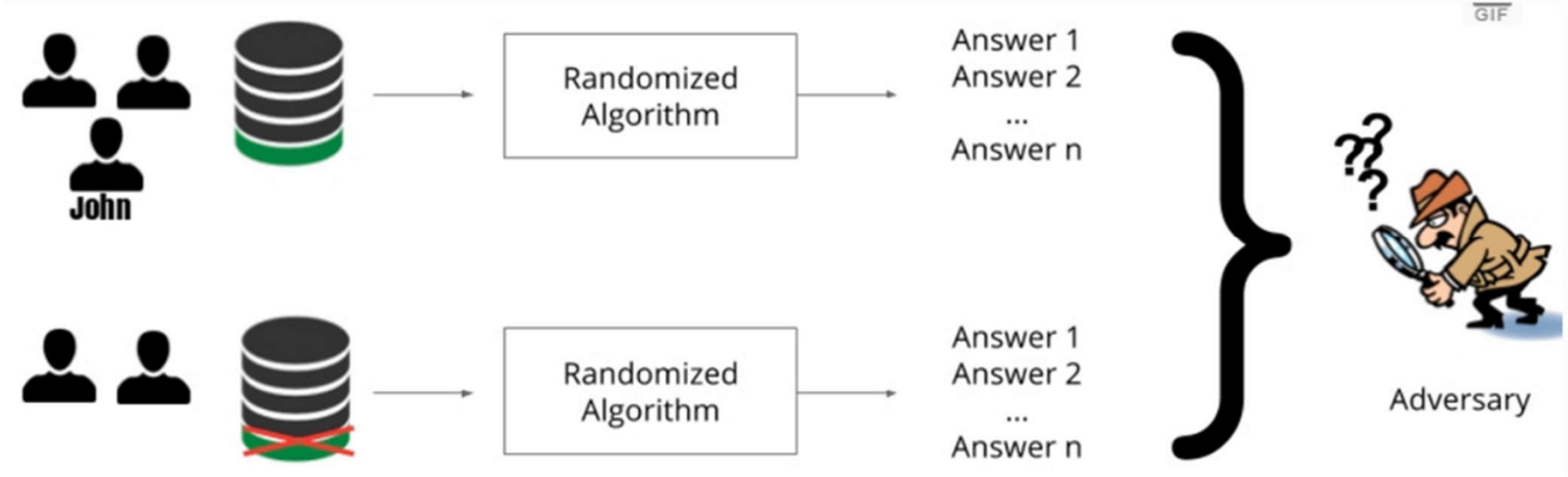
- **essential to anonymize patients' data – could not be discovered at any stage of processing**
- main techniques for **de-identification of personal info**
- **K-anonymity, L-diversity, T-Closeness,…**

- **Differential privacy** – systematic randomized **modification of a dataset or algorithm to reduce information about the single individual**.
- **Homomorphic Encryption** - **enables arithmetic operations on ciphertexts without decryption**, in distributed environments protecting data leakage from client side

2 Health Data Privacy Preserving

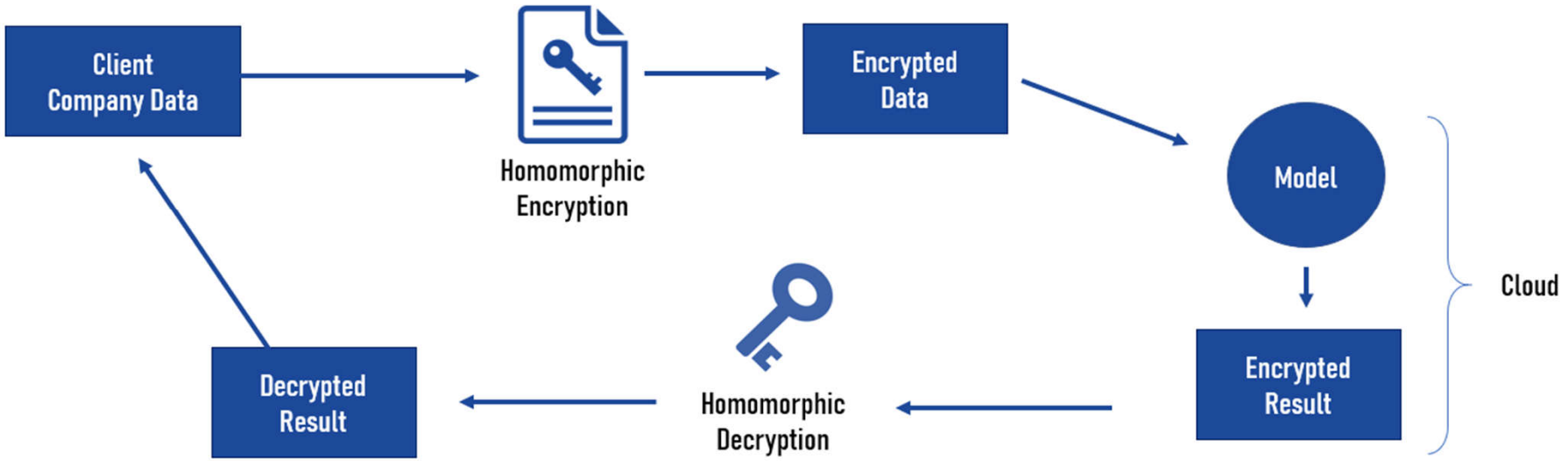
Differential privacy - **retaining the global statistical distribution of a dataset** while reducing individually recognizable information

- **Dataset is differentially private** - impossible to infer if a specific individual was used for obtaining a result
- **Implementations** - from **simple random shuffling of the input data** to the introduction of **noise to the dataset** (Gaussian/Laplacian DP, better interpretability)
- **Local DP** ensures privacy at the **source of the data**, also for **federated learning** applications (data collected by smartphones/wearable devices).



2 Health Data Privacy Preserving

- **Homomorphic Encryption** – connected to **Federated Learning** Paradigm - training is performed **without sharing sensitive local data**
- **Homomorphic Encryption** includes **multiple types of encryption schemes,** different classes of computations over encrypted data.
- ***Homomorphic* refers to homomorphism in algebra**: the encryption/decryption functions are **homomorphisms between plaintext and ciphertext spaces.**



Park, J.; Lim, H. Privacy-Preserving Federated Learning Using Homomorphic Encryption. *Appl. Sci.* **2022**, *12*, 764. https://doi.org/10.6490/app12020764

https://medium.com/data-science/homomorphic-encryption-machine-learning-new-business-models-2ba6a4f185d

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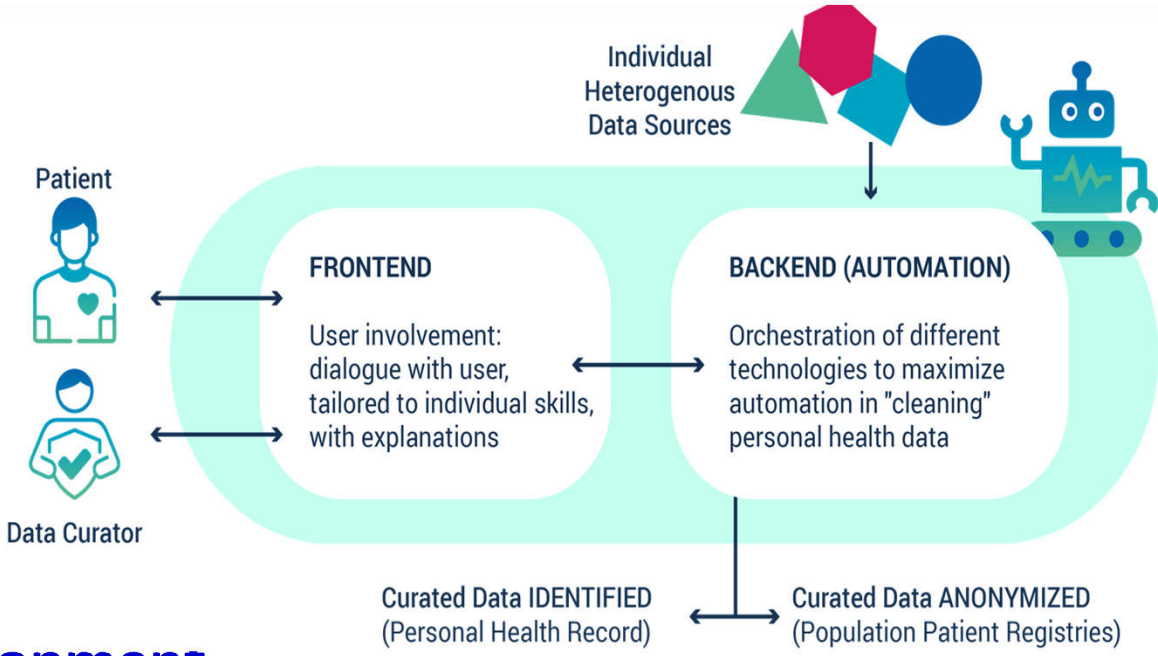
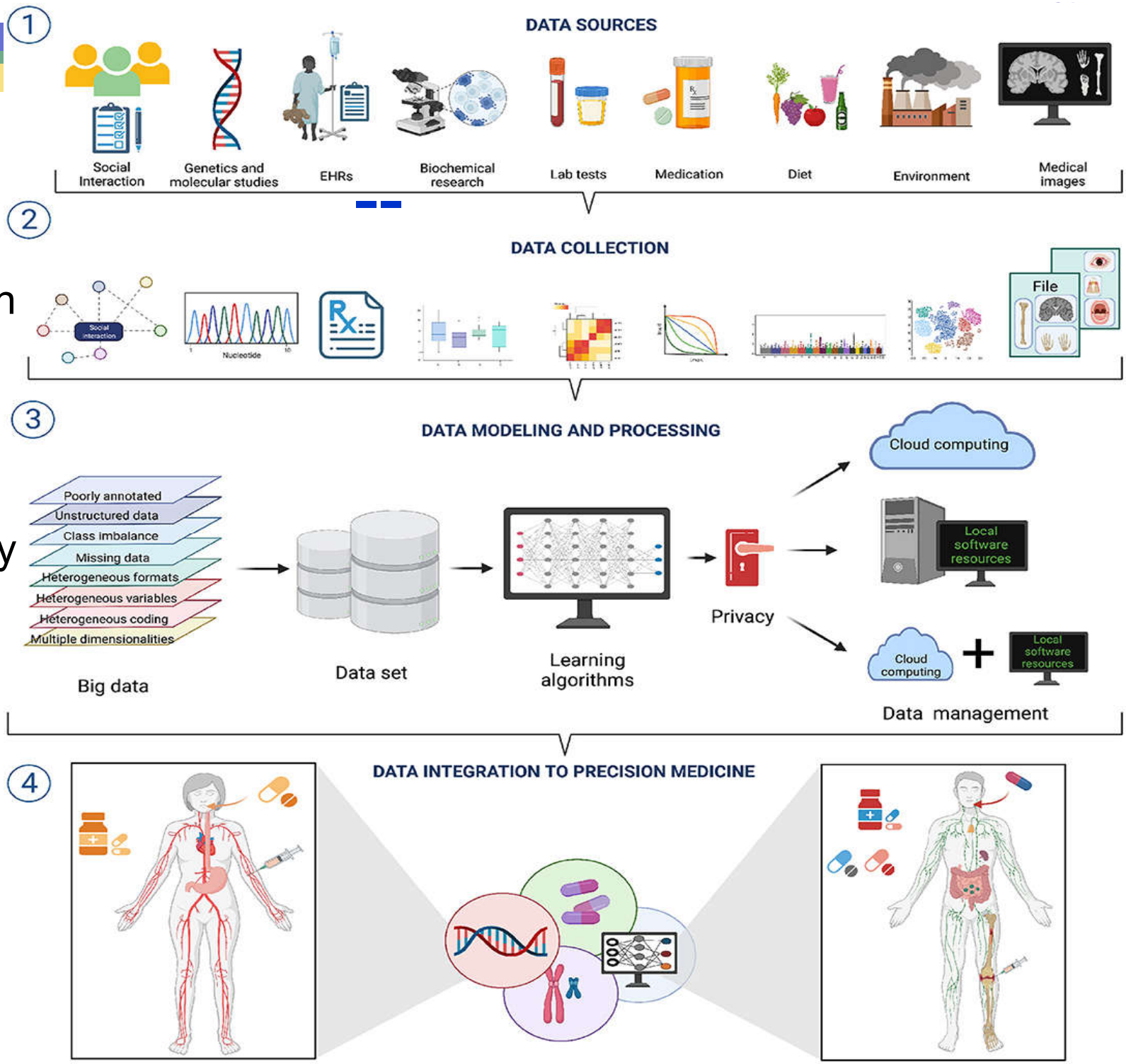
3 Data – AI/ML Models Development – Use of Models

- **Medical/Health data** – Big, Complex, collected from multiple sources
- **Data management** – **curation, aggregation, standardized representation, final datasets for AI/ML processing**
  - **Data prepared**: **New features, Imputation of missing data, Outlier detection**



- **AI/ML Predictive models development**
  - can **enhance healthcare experiences for individuals** https://aidava.eu/research/solution
  - enables the **expansion of knowledge** about diseases and treatments
  - leads to an **increase of efficiency and effectiveness of medical decisions**
  - **predictive data mining** => transformation of **Medicine from population-based to personalized practice.**

Precision medicine - "an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person."



https://www.frontiersin.org/articles/784455

3 Data – AI/ML Models Development – Use of Models

BUILDING PREDICTIVE MODELS - Modeling and evaluation (data are prepared)

- **build predictive models**
- **application of different techniques**,
- **later** - **the received results should be compared and validated**, the model **performance** are considered,
- **final stage** - use models in **real environments**, unforeseen data.

- **Classification models** **-** Different learning algorithms: NB algorithm, KNN (K-nearest neighbors), DT (decision trees), Classification And Regression Trees (CART), bagging CART, C5.0, RF (random forests), Logistic Regression (LR), Artificial Neural Network (ANN), SVM and LDA (LINEAR DISCRIMINANT analysis).

3 Data – AI/ML Models Development – Use of Models

BUILDING PREDICTIVE MODELS - Modeling and evaluation

- **Regression models** –usually used, for example **for predicting numeric values, some specific interventions or continuous variable**
  - LINEAR (linear regression), RIDGE (ridge regression), LASSO (lasso regression), ELASTICN (elastic net regression), KRIDGE (kernel ridge regression), SVM (regression by support vector machines), RF (regression by random forests), KNN (K-nearest neighbors), ADAB: AdaBoost regression, TFNN: TensorFlow Neural Network

  - **Neural networks (NN), deep learning** - techniques with a good performance, **hard to be interpreted**.
  - **Simpler techniques**: naive Bayes classifier (NB), linear discriminant analysis (LDA), support vector machines (SVM), tree-based

=> produce results that are much easier to interpret.

3 Data – AI/ML Models Development – Use of Models

- **“traditional AI (ML)”** - the **data** are usually concentrated in **the data center** (for training models).

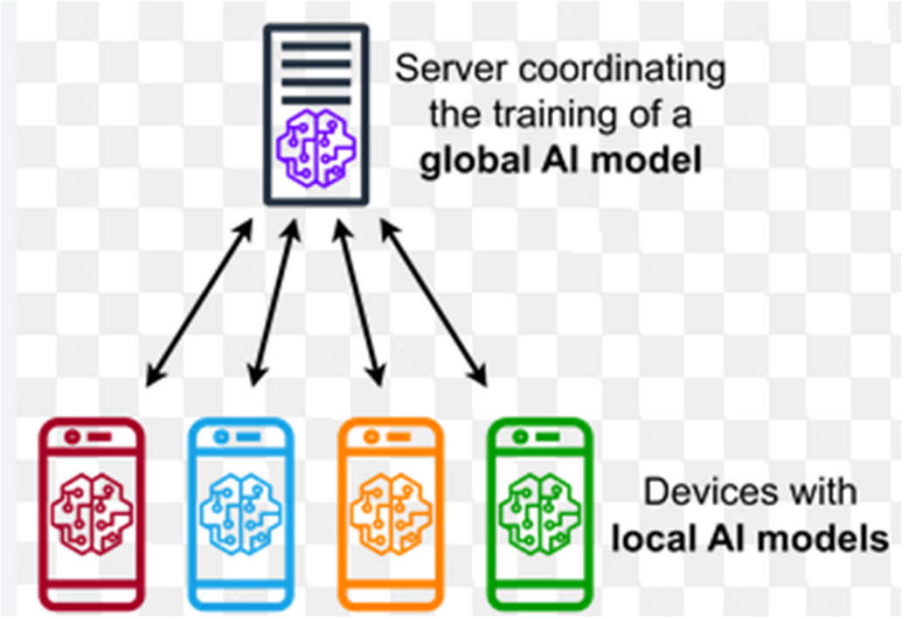
- However, when **large datasets are attacked**, the **consequences are immeasurable**.

- **Privacy is a critical concern - data** are frequently **personal,** not intended to be shared

- **Federated learning (FL)** - facilitate the **distributed training of high-quality models,** coordinating multiple clients/devices, preserving the privacy of local datasets.

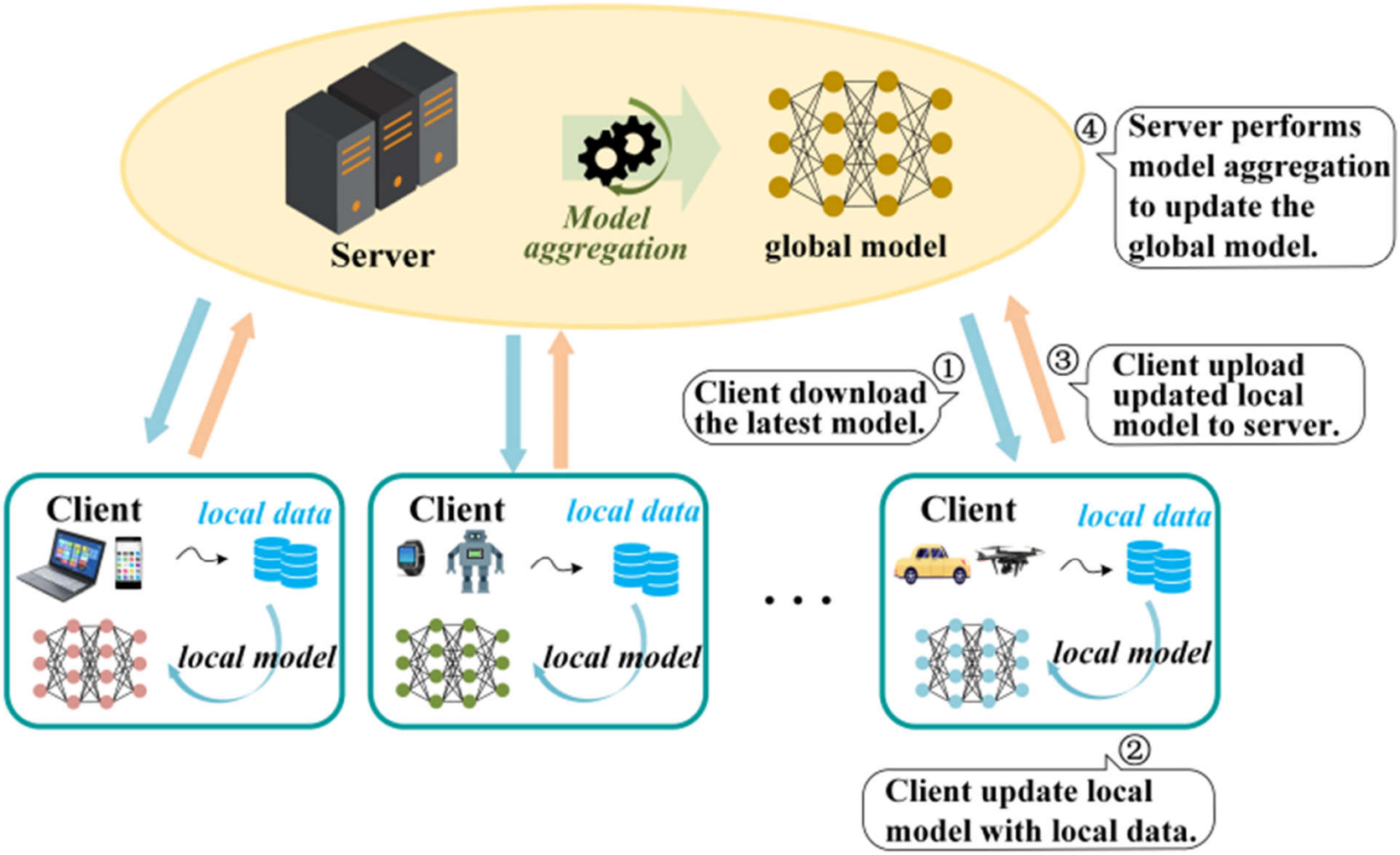
3 Data – AI/ML Models Development – Federated Learning

- **Federated Learning (FL)**
  - **Data** are (usually collected and) stored at the **edge**
  - **Training local models - computation** is done on the **edge**
    - **increased privacy**
    - **eliminated communication overhead** from data transfer
  - **Train global models** on the entirety of the **dataset in a distributed manner**
  - The **learning process** is (usually) **coordinated by a centralized server**



3 Data – AI/ML Models Development – Use of Models

- General FL framework. During the t-*th* communication round, each client downloads the latest global model from the server for initialization ① and uses its own local dataset for iterative training ②. The updated weights are uploaded to the server ③ which performs model aggregation ④ to generate a new global model. Steps are repeated.



3 Data – AI/ML Models Development – Use of Models

- **Federated Learning approaches**

(a) Incremental FL.

(b) Concurrent FL.

(c) Cyclic-incremental FL.

(d) Semi-concurrent FL.

3 Data – AI/ML Models Development – Use of Models

BUILDING PREDICTIVE MODELS – Federated Learning

- **NN** - the most natural model choice for **federated (global) models**:
  - be **incrementally updated**
  - can be **easily averaged** by averaging edge weights and biases.

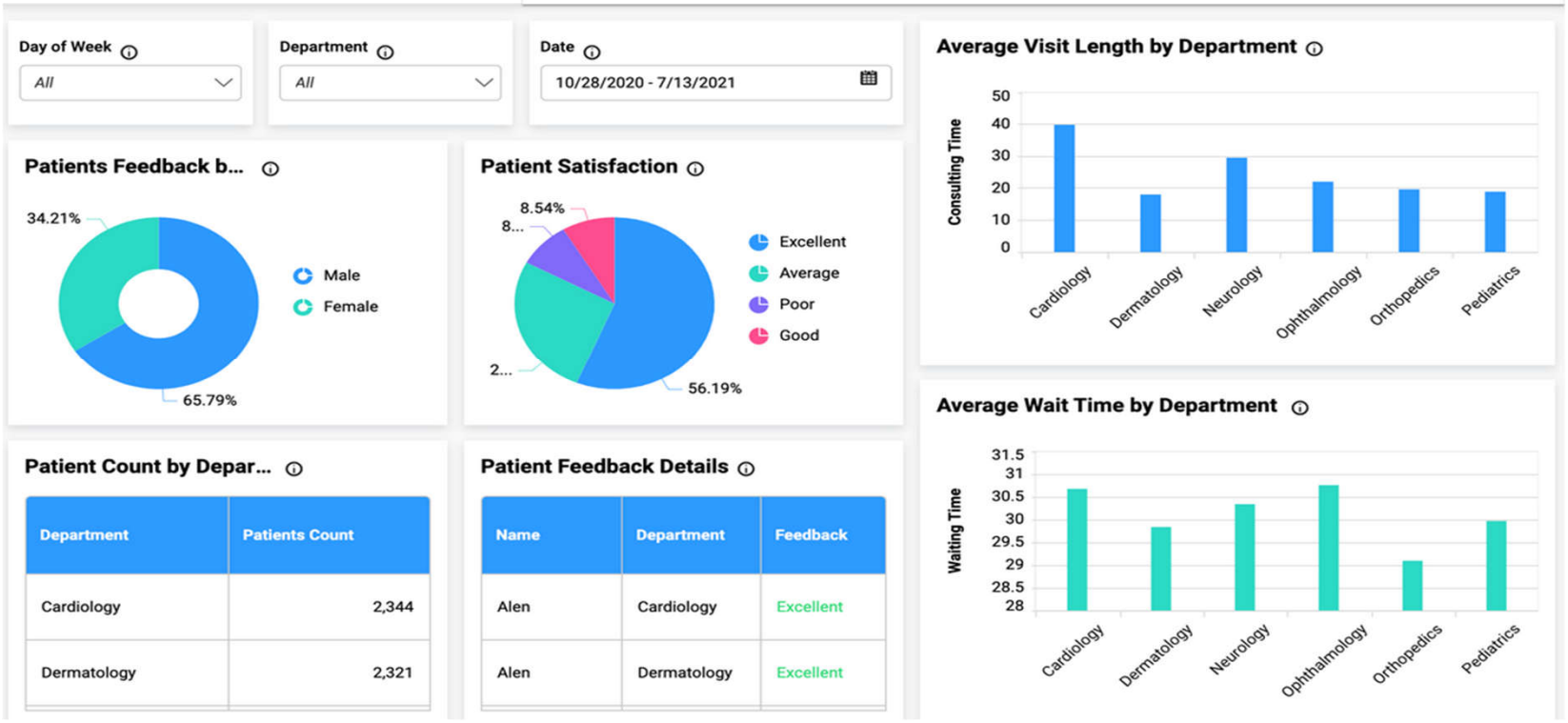
- Two types of **predictive problems, federated NN**:
  - FNN for **regression**
  - FNN for (binary) **classification**

- **Modeling and validation schema - ** After preparing the data the next step is building and validating models .

3 Data – AI/ML Models Development – Use of Models

Interpretability of the built models - Explainable Artificial Intelligence - XAI

- **allows human users to comprehend and trust the results and output of ML algorithms**
- **describes an AI model -** characterize model accuracy, fairness, transparency and outcomes in AI-powered decision making
- **comprehend and retrace how the algorithm came to a result**
- explainability helps developers **ensure that the system is working as expected**
- explaining with **Data Visualisation, Explaining with a ML model** (Logistic Regression, Decision Tree, Neural Network, …), **SHAP -SHapley Additive exPlanations**



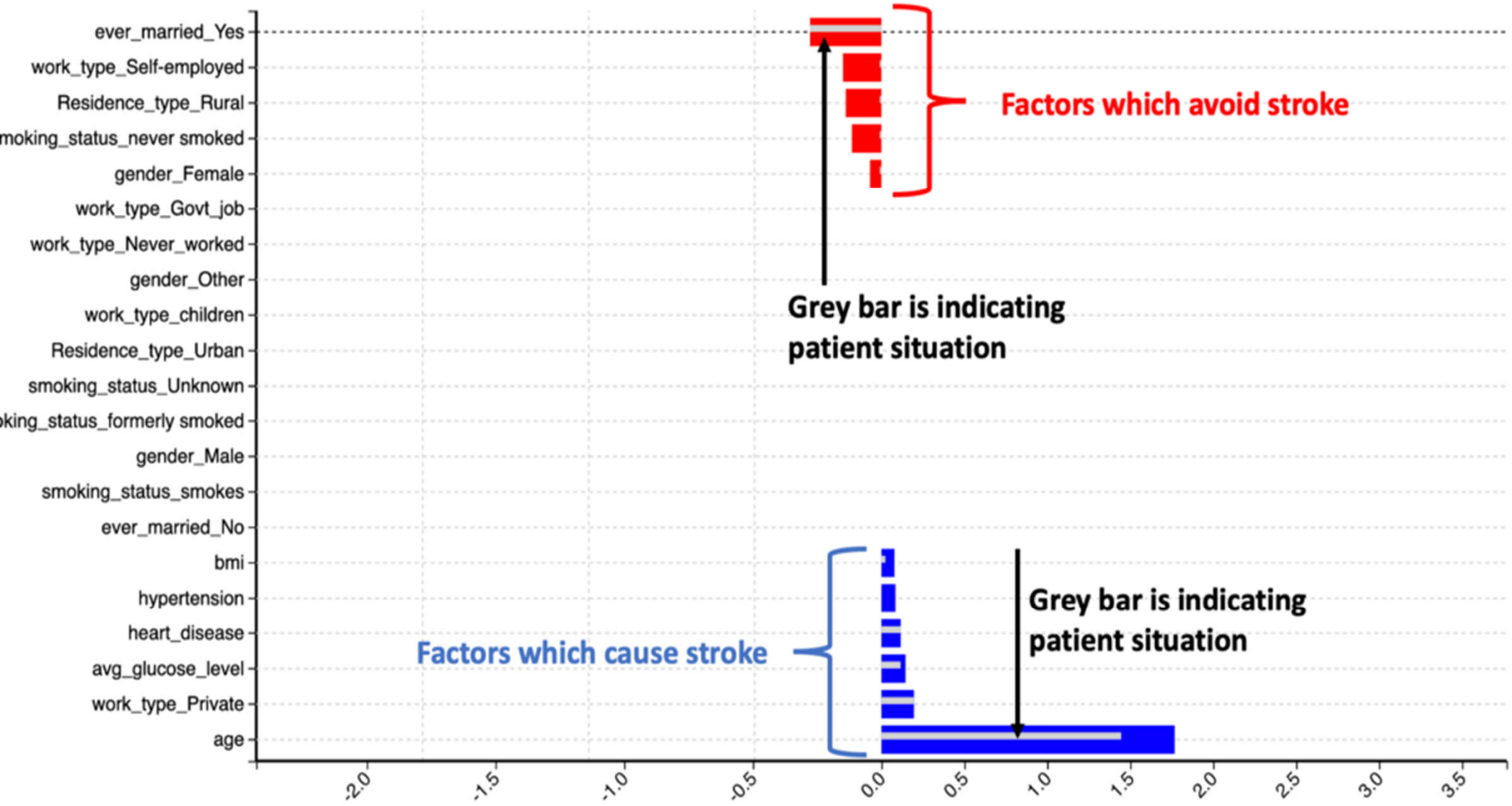
3 Data – AI/ML Models Development – Use of Models

Data Visualisation - EXAMPLE

- **take the data which was used for training AI** - data of **patients which suffered a stroke** as well as those who did not.
- **using visualization techniques** - analyze the difference between the patients who suffered/did not suffer a stroke, **understand the factors that cause a stroke**.
- **compare with the patient situation** - help to **understand why the patient is at risk**.

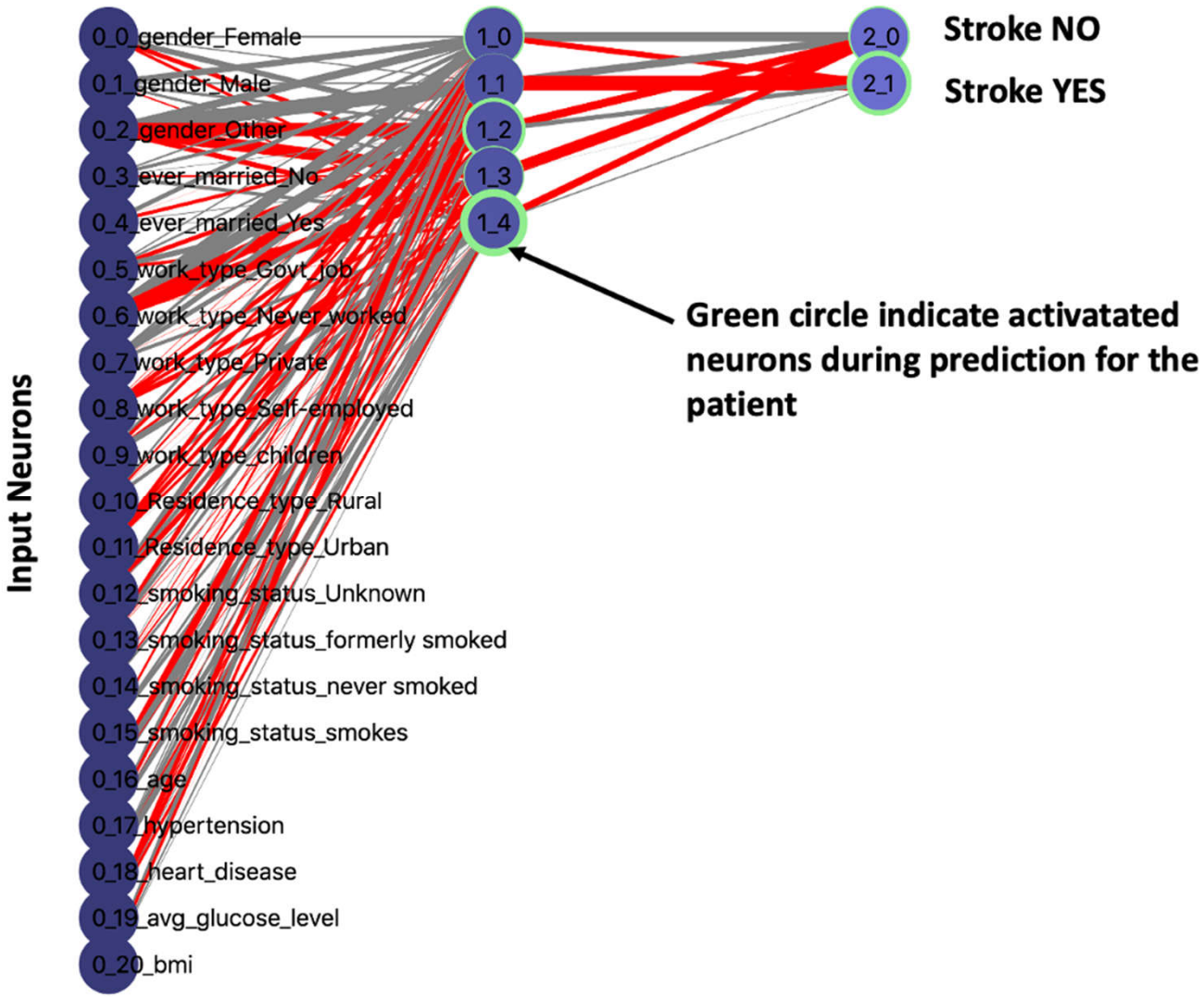
3 Data – AI/ML Models Development – Use of Models

Explaining with Logistic Regression Model - Y-axis - different factors; X-axis - the importance of the factor for a stroke condition.



3 Data – AI/ML Models Development – Use of Models

- Explaining with **NN model -** The positive signal, **negative signal**, green bordered circle - activated neurons during prediction for the patient



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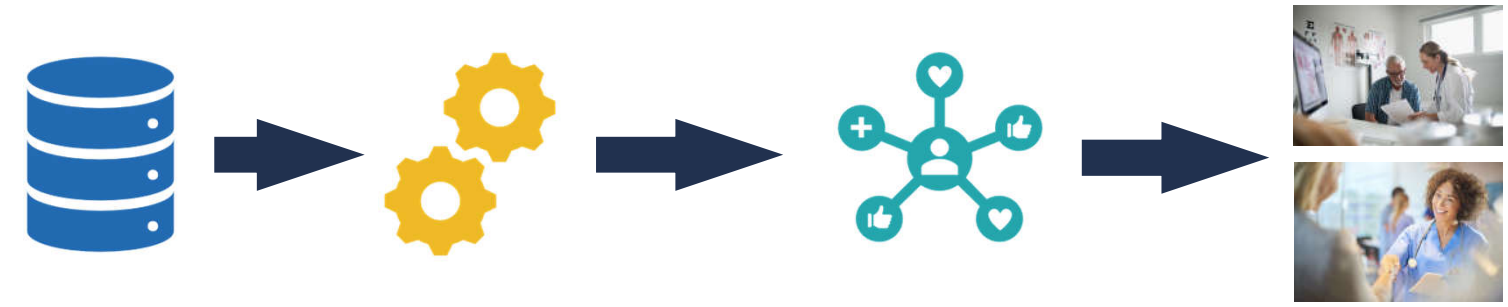
4 EXAMPLE 1: ASCAPE - Artificial intelligence Supporting CAncer Patients across Europe

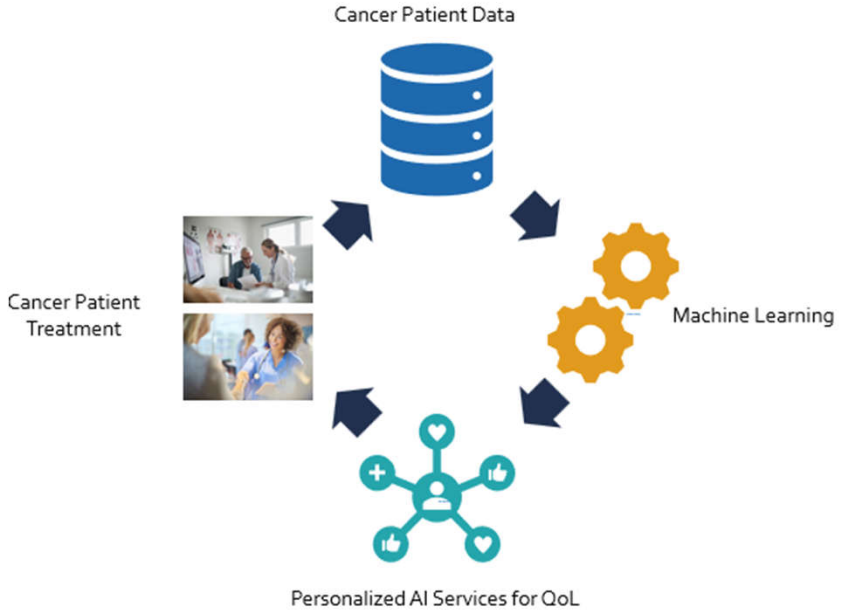
H2020: 2020-2023

Data-driven ML-based Support for Personalized Healthcare

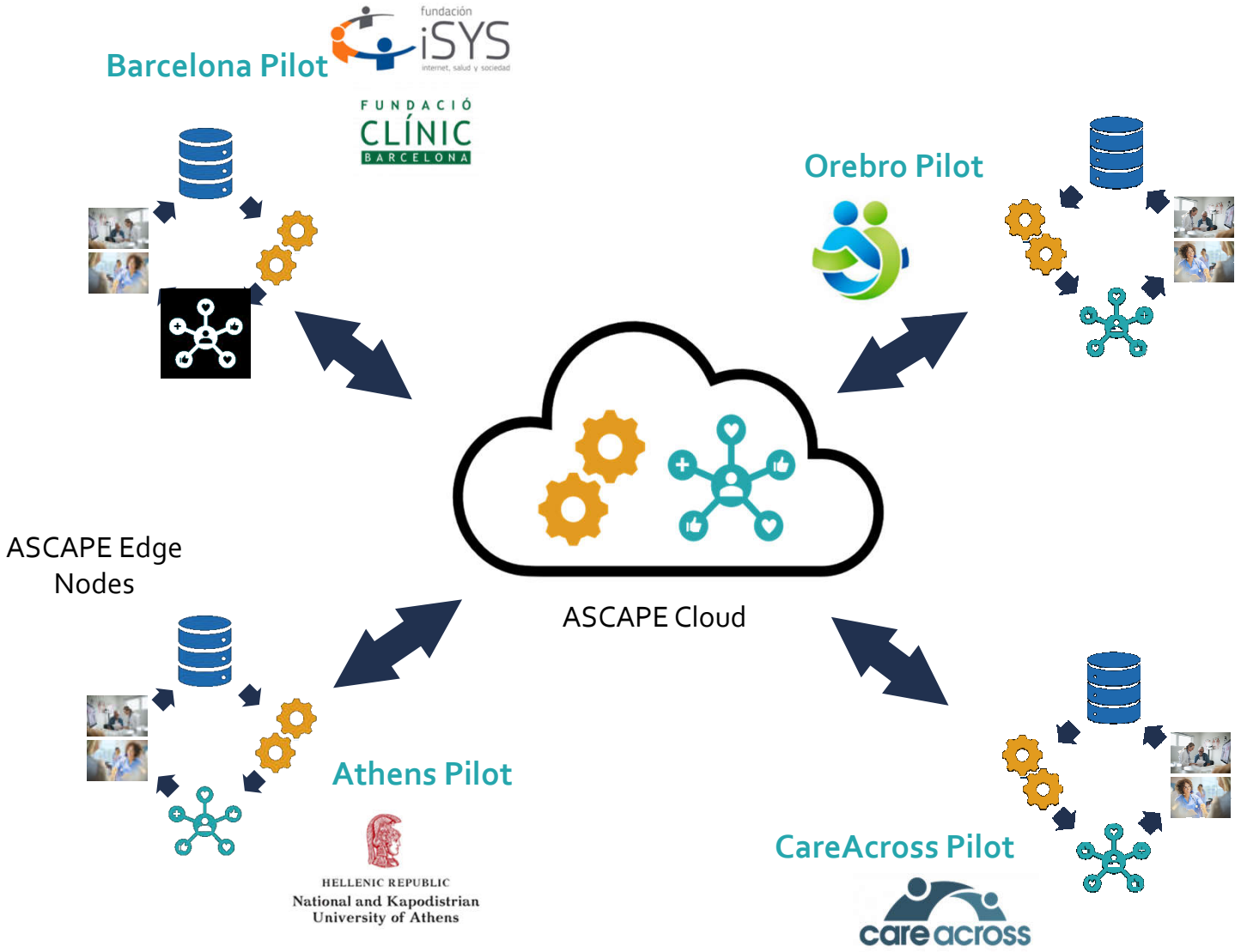


1. Patient Data collection and curation; 2. Machine Learning Model Training

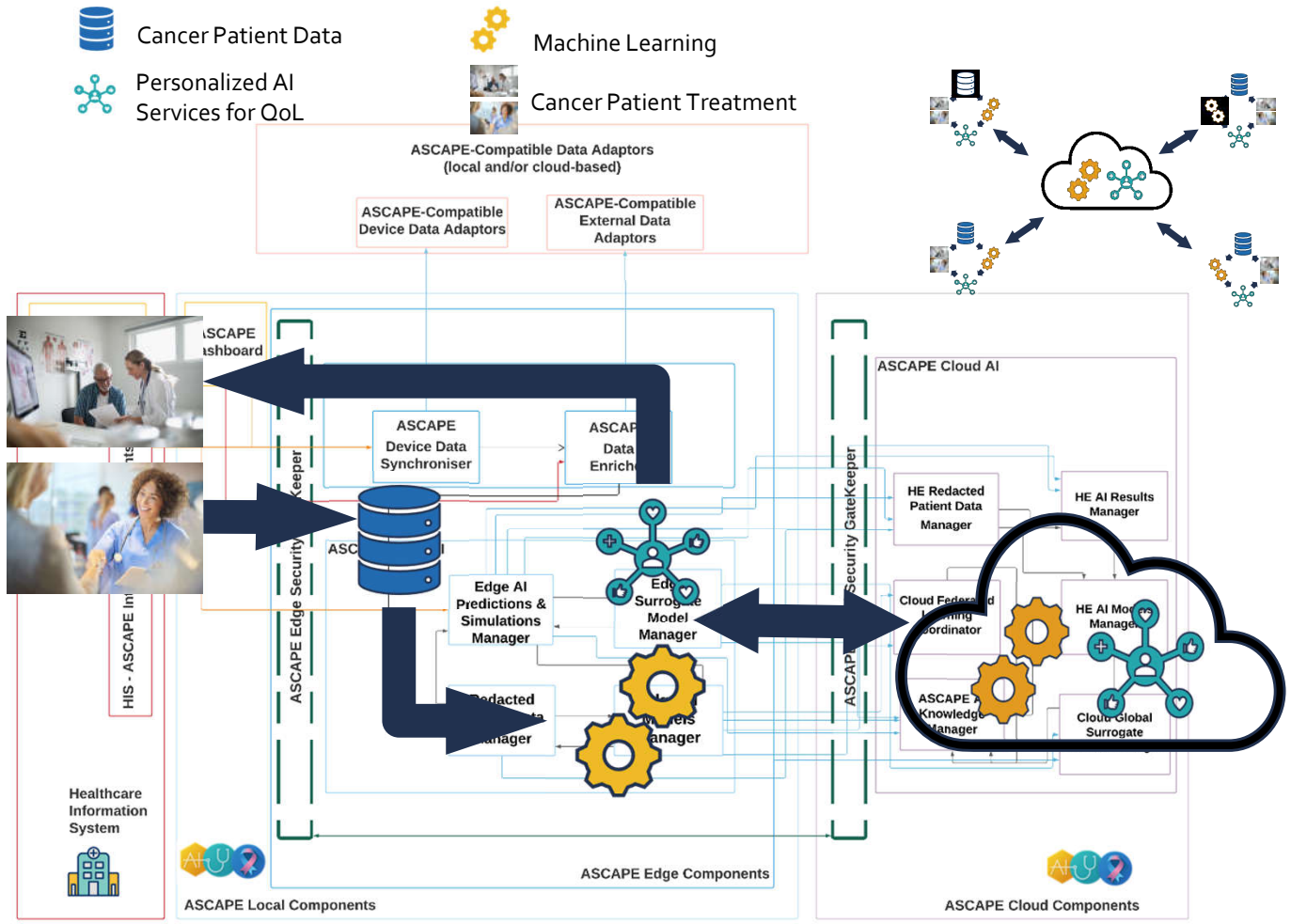
3. Clinical value of AI Services. Security of ASCAPE & Privacy of Personal Data



Cooperative.
Distributed.
Open.



From Goals and Requirements to Architecture



ASCAPE Breast Cancer Data

15 QOL Issues

Anxiety
Body changes (weight+bmi changes)
Cognitive impairment
Depression
Fatigue
Hot flushes
Body image
Dry vagina
Emotional symptoms (loneliness)
Insomnia
Joint pain
Local symptoms after surgery
Lymphedema
Neurotoxicity
Sexual dysfunction

Variables

53 Medical Variables (e.g. Patient, BodyStructure, Condition, FamilyMemberHistory, MedicationAdministration and Observation)
Nutritional
Weather (Temp,. Daylight, etc.)
Activity data from wearables

Interventions

Androgen deprivation treatment manipulation (prostate)	Progesterone / progestin (prostate)
Anti-depressants	Promotion of positive familiar and social relationship
Anti-stress techniques: Mindfulness, Yoga	Psychiatric support
Anticonvulsant agents	Psychological support
Anxiolytics	Acupuncture
Cyproterone (prostate)	Antidepressants: duloxetine
Diet	Scrambler therapy
Interventions for sleep disturbancies	Switch to another aromatase inhibitor
Movement-based relaxation techniques	Switch from aromatase inhibitor to tamoxifen
Nutrition consultation	Analgesic (NSAID or others)
Physical activity	

ASCAPE Prostate Cancer Data

12 QOL Issues

Anxiety
Body changes (weight+bmi changes)
Cognitive impairment
Depression
Fatigue
Hot flushes
Bowel dysfunction
Erectile dysfunction
Incontinence
LUTS
Loss of libido
Musculoskeletal pain

Variables

63 Medical Variables (e.g. Patient, BodyStructure, Condition, FamilyMemberHistory, MedicationAdministration and Observation)
Nutritional
Weather (Temp,. Daylight, etc.)
Activity data from wearables

Interventions

Androgen deprivation treatment manipulation (prostate)	5DE inhibitors
Anti-depressants	Androgen deprivation treatment manipulation
Anti-stress techniques: Mindfulness, Yoga	Compression devices
Anticonvulsant agents	Couple counseling
Anxiolytics	Electrical stimulation
Cyproterone (prostate)	Extracorporeal magnetic innervation
Diet	Intracavernosal injections
Interventions for sleep disturbancies	Lifestyle changes
Movement-based relaxation techniques	Other (write down the type)
Nutrition consultation	Pelvic muscle training with or without biofeedback
Physical activity	Penile prosthesis or pumps
	Slings and artificial urinary sphincters

Redacted Patient Data Manager

Redacted Patient Data Manager – 4x Pilot sites Edge Node

- HAPI FHIR Server - **ASCAPE common data model**

- HL7 FHIR structured and SNOMED CT codified
- Data: clinical data + weather + wearables + Nutrition

API for data retrieval from RPDM

Operations against **HAPI Server:**

- **Queries for clinicians**
  - No. of female/male patients, patients per pilot, patients with BMI > 30,…
  - Procedures performed between two dates

- **Output for other ASCAPE components**
  - **Gatekeeper + Synchroniser + Enricher + Data Adapters**
  - **AI algorithms**: conversion from JSON to CSV
  - **Dashboard**: adaptation from JSON to required format

queries

GET	/api/v1/{pilot}/NumberPatientsByPilot
GET	/api/v1/NumberFemalePatients
GET	/api/v1/NumberMalePatients
GET	/api/v1/NumberPatientsBMIgt30
GET	/api/v1/proceduresByDates/{FromDate}/{ToDate}

data-retrieval

GET	/api/v1/allData
GET	/api/v1/{pilot}/dataByPilot
GET	/api/v1/{cancerType}/dataByCancerType
GET	/api/v1/{patientid}/patientAllData
GET	/api/v1/{patientid}/patientDataIngestionGroup
GET	/api/v1/{patientID}/patientByID

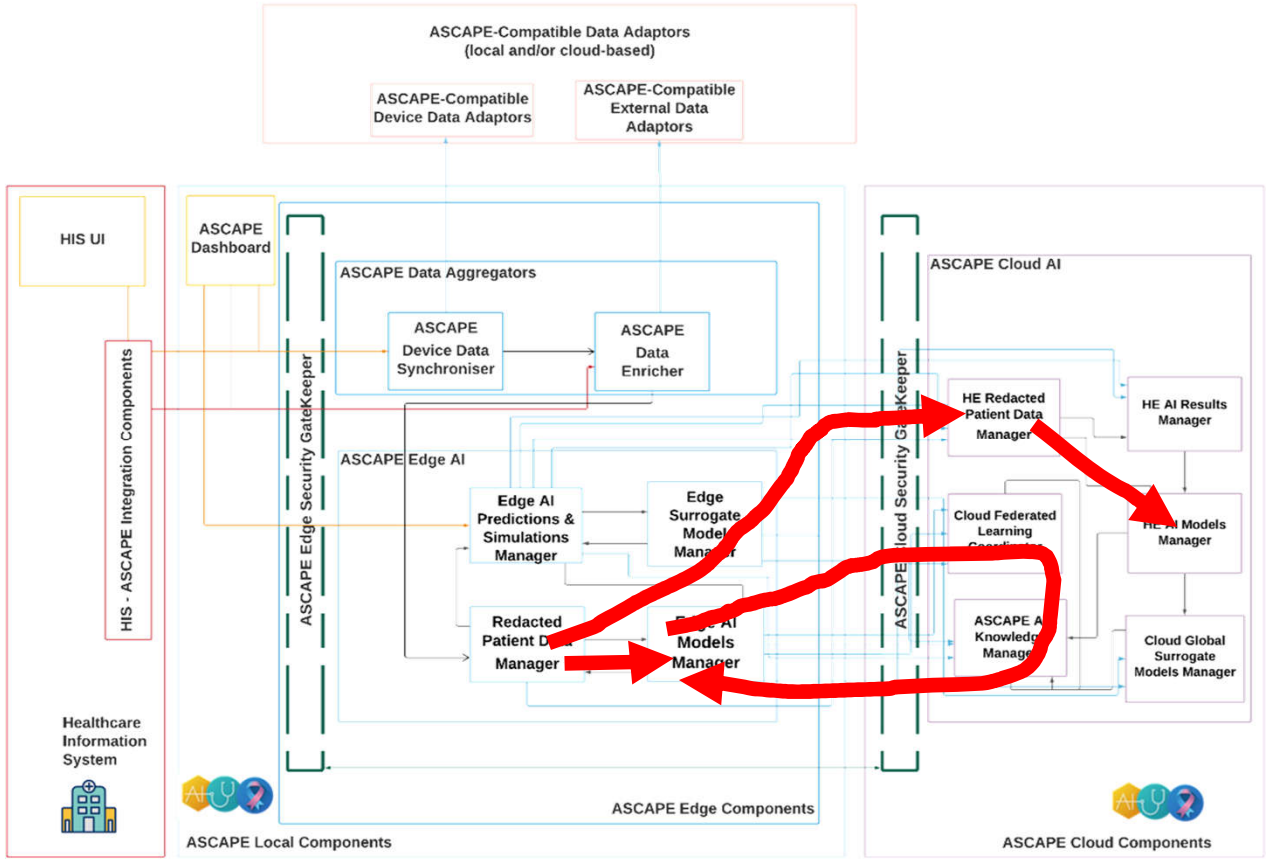
Machine Learning Model Training & Inference

- **Analysis of regression/classification algorithms for predictive QoL models**
  - **5 classification algorithms (NB** is the best **), 8 regression algorithms** (**Lasso** is the best), **10 datasets**
- **Analysis of NN for FL**
  - **FL simulator** training NN for an **arbitrary number of edge nodes**
  - **incremental and semi-concurrent** FL
- **Missing value inference approaches**
  - **simple imputer, iterative imputer**: performances are not significantly different
- **Feature analysis and evaluation of ML models after feature selection**

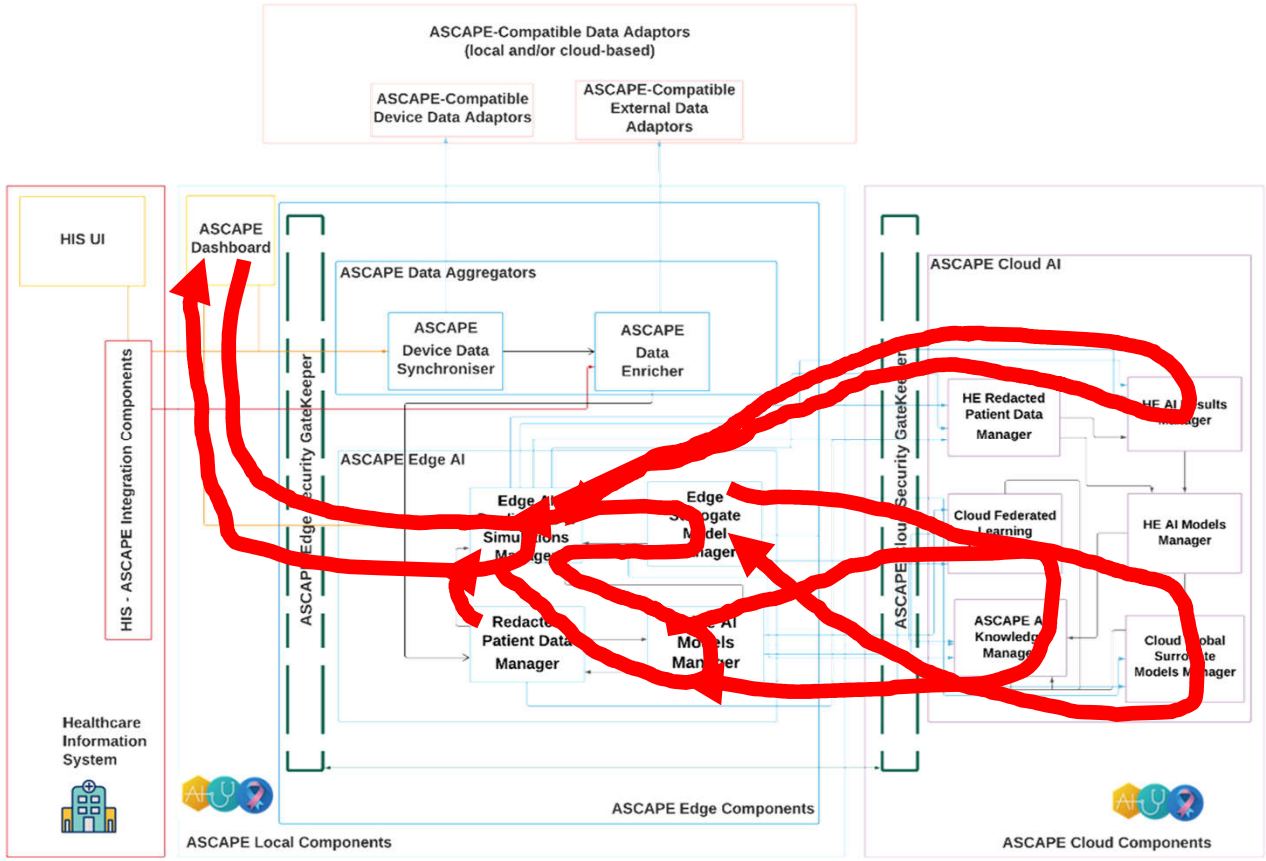
Machine Learning Model Training & Inference

- **Analysis of privacy-accuracy parameter for DP algorithm**
  - **ε parameter** - for the addition of Laplacian noise
- **Homomorphic Encryption - open source encryption libraries** - (PySyft, PyFHEL, TenSEAL, nuFHE, PHE).
- **AI Model training**
  - Selection of **algorithms for FL**
  - training, validation, selection of **the best model and inference**
- **AI Models for Homomorphic Encrypted Data**

Data Training and using models



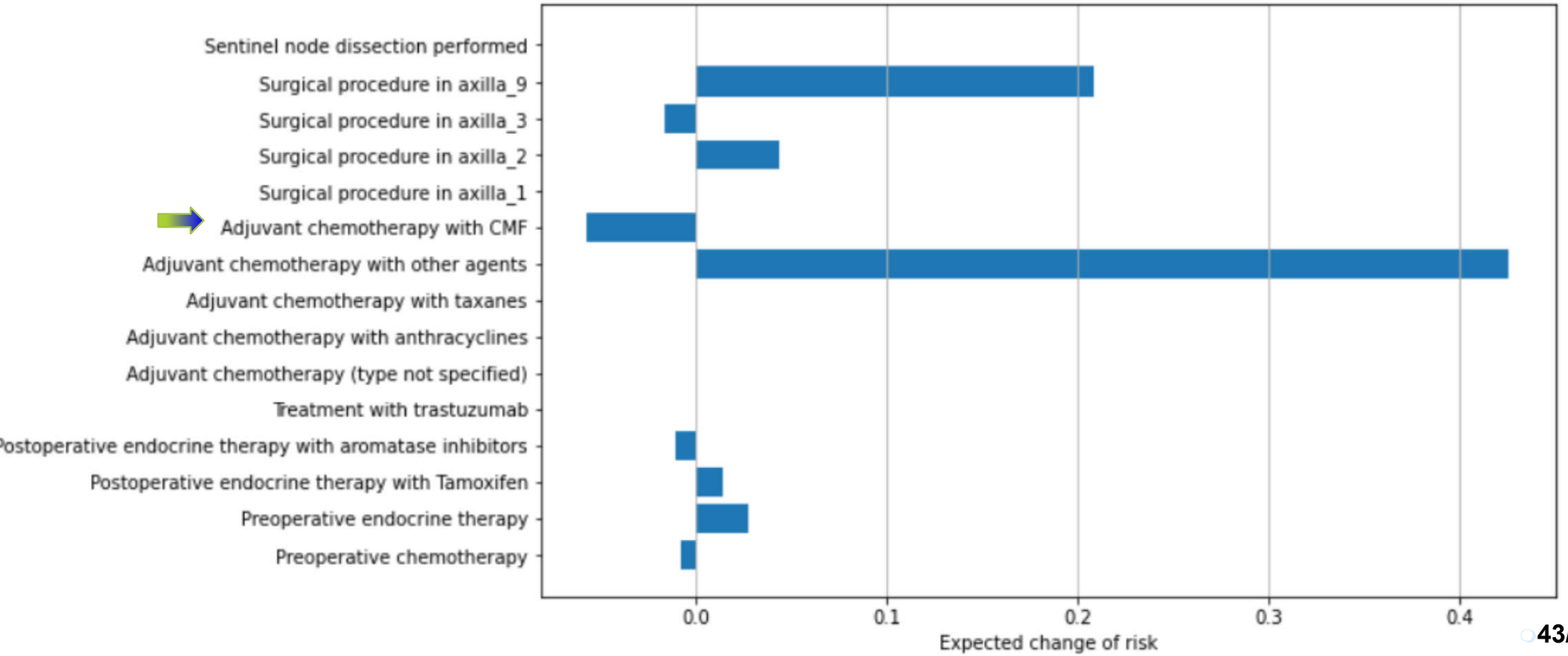
Data Training and using models – Predictions and simulation



Explanations

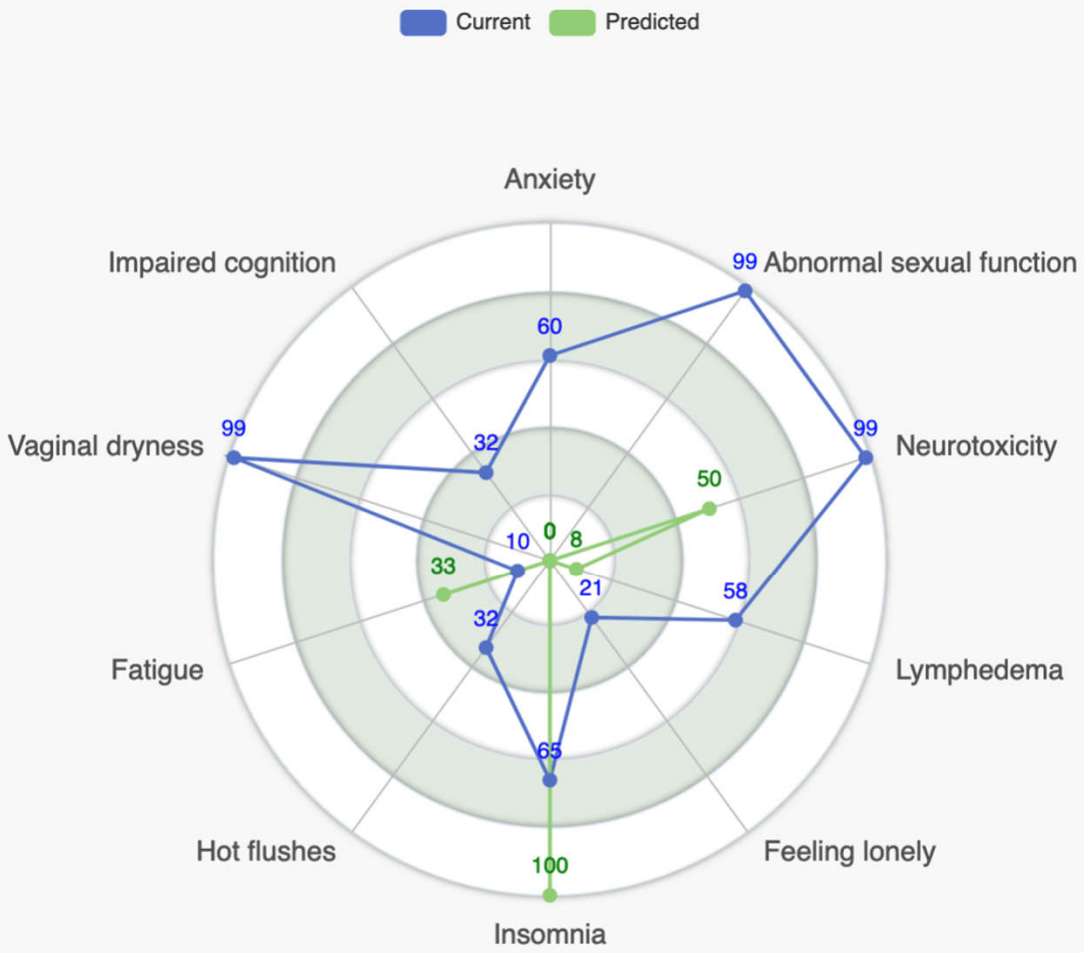
- Expected change of **risk of pain** based on **Naive Bayes classifier**

- **Example**: "Adjuvant chemotherapy with CMF" is the recommended treatment since it reduces the risk



Goal

QoL Issues



Shortcuts

No interventions

New Interventions

- ☐ Anti-stress techniques: Mindfulness, Yoga
- ☐ Movement-based relaxation techniques
- ☐ Physical activity guidance
- ☐ Promotion of positive relationship
- ☐ Emotional support
- ☐ Psychiatric therapeutic procedure
- ☐ Anxiolytic drug therapy
- ☐ Antidepressant therapy
- ☐ Dietary regime
- ☐ Counseling about nutrition
- ☐ Intervention for sleep disturbance
- ☐ Anticonvulsant therapy
- ☐ Acupuncture
- ☐ Switch to another aromatase inhibitor
- ☐ Switch from aromatase inhibitor to tamoxifen
- ☐ Analgesic technique
- ☐ Couple counseling
- ☐ Other therapy

4 EXAMPLE 2: Emergency monitoring system (EMS)

- **Platform** - integrates heterogeneous devices, storing and managing the sensed and monitored information

- **Assist the patients, help medical professionals in health monitoring** (a large number of patients and data at run-time), remote care centers

- **Sensors and devices connected** to the patient, detect and prevent emergency situations (hospital/home)

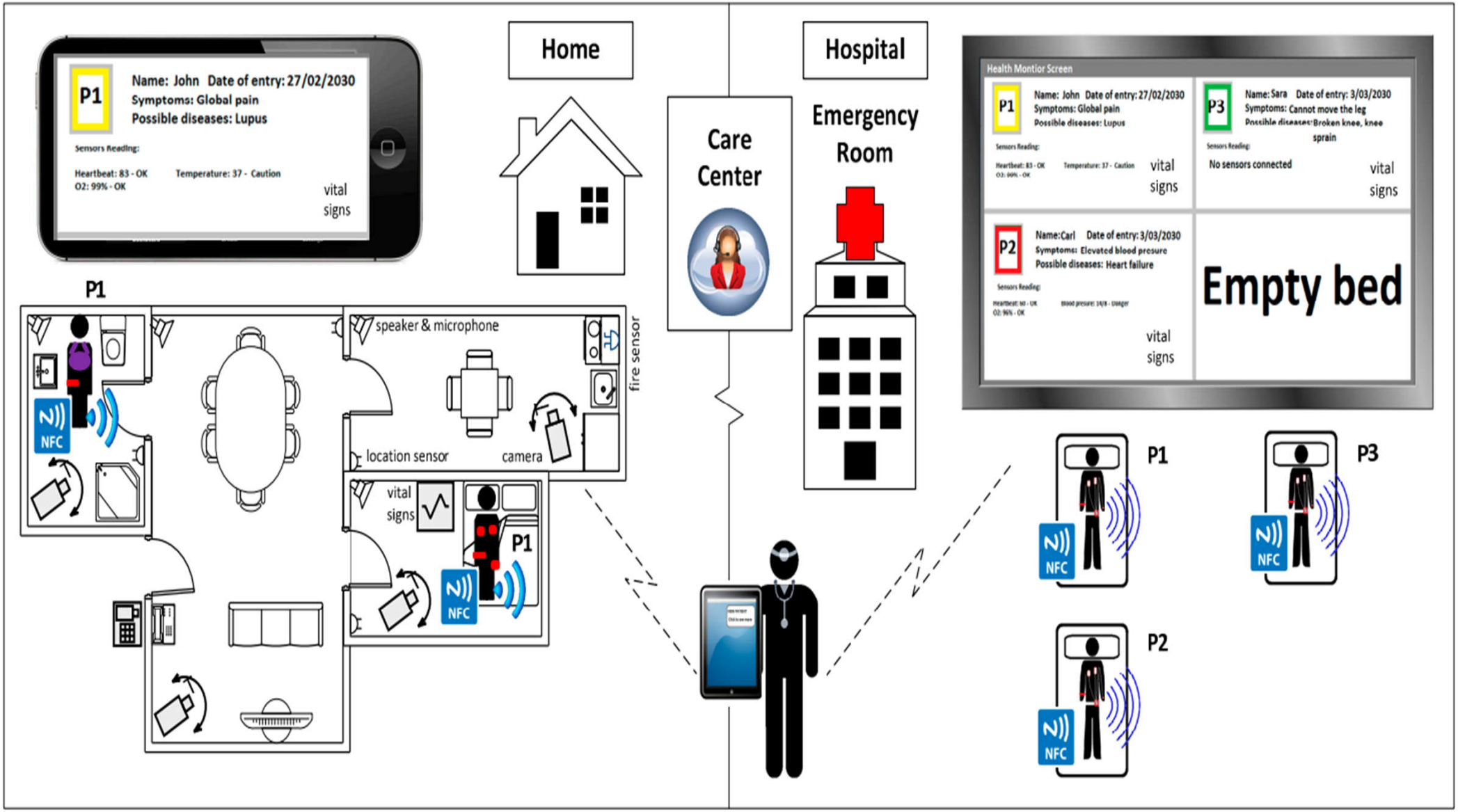
- Cubo, J.; Nieto, A.; Pimentel, E. A Cloud-Based Internet of Things Platform for Ambient Assisted Living. *Sensors* **2014**, *14*, 14070-14105. https://doi.org/10.3390/s140814070

4 EXAMPLE 2: Emergency monitoring system (EMS)

- **The system's components:**
  - **Sensor nodes** - **measure basic vital signs** - a video camera with a complex behavior, a user badge to control the movements/vital signs…
  - **Discovery application - to find the existing sensors/devices** in the environment, **connect and associate with the patients**
  - **Dashboard application** - medical professionals/care centers**, to manage the monitored information**; a cloud application for remote monitoring….
  - **Data repository** - on a cloud platform with register of the user profile (patients, specialists/people at the remote care centers), maintaining a patient's schedule.

Cubo, J.; Nieto, A.; Pimentel, E. A Cloud-Based Internet of Things Platform for Ambient Assisted Living. *Sensors* **2014**, *14*, 14070-14105. https://doi.org/10.3390/s140814070

4 EXAMPLE 2: Emergency monitoring system (EMS)



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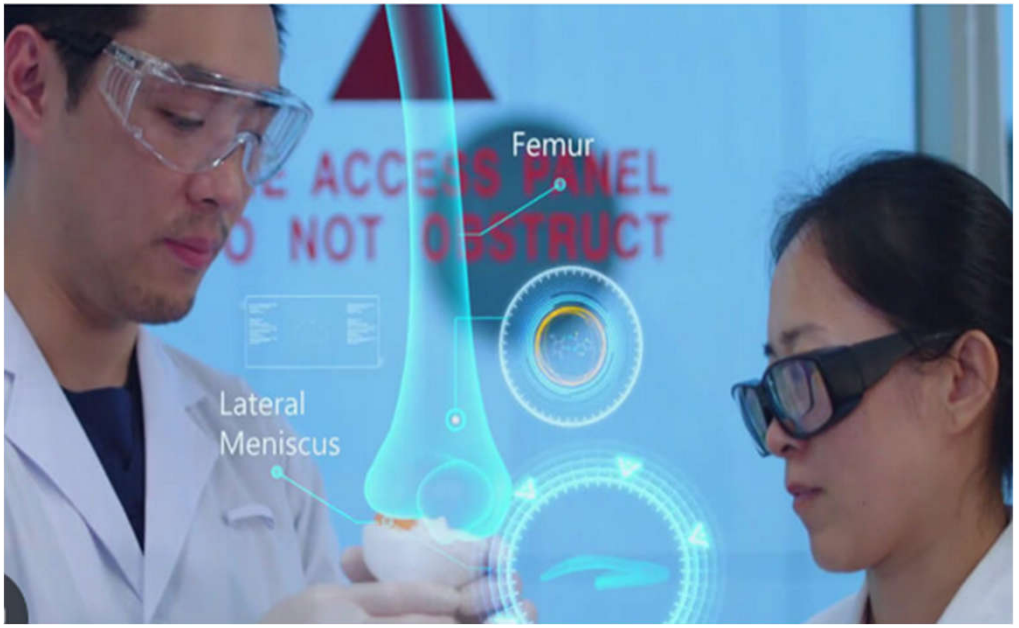
5 Possibilities for Medical Education

- **traditional medical education** - often **lacks contextual experience, limits effective application of theoretical knowledge in real-world scenarios**.
- **technology-driven changes** - transform the way medical students learn, healthcare professionals train, **the integration of XR, the metaverse and other technologies into medical education**
- **assist educators and medical practitioners** - comprehensive understanding of key factors in immersive education
- **customized simulations** - enable practice in clinical decision-making, interpersonal skills, and exposure to complex medical situations in a controlled environment.

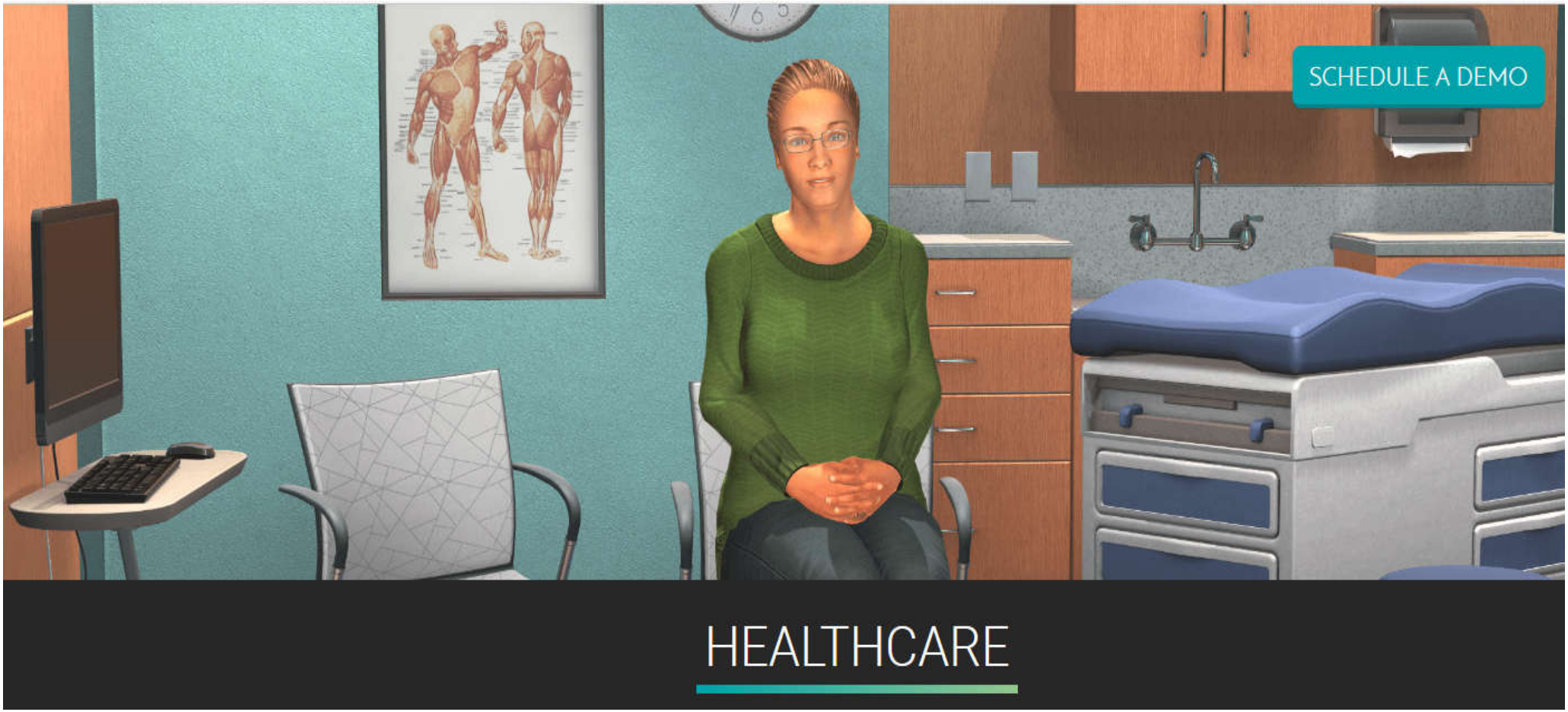


- **various disciplines** - anatomy, physiology, dentistry, pathology…, benefit from immersive learning experiences.

5 Personalized and E-coaching Medicine - Agents

MURSION®

- Virtual Standardized Patient Training & Therapy, Duke University



5 Personalized and E-coaching Medicine - Agents

- Mursion's virtual standardized patient (VSP) simulators **offer medical educators a powerful tool to enhance a blend of technical and interpersonal skills:**
  - Improving the **communication skills of a doctor** delivering a **negative diagnosis**
  - **Increasing the effectiveness of therapy skills** of psychologists
  - **Enabling prospective nurses to master giving** an **effective patient history and coaching interview**
  - **Allowing pediatric healthcare providers to train in scenarios** involving a parent and an elementary-age child
  - **Enhancing the debriefing skills** of a surgical team

5 Personalized and E-coaching Medicine - Agents

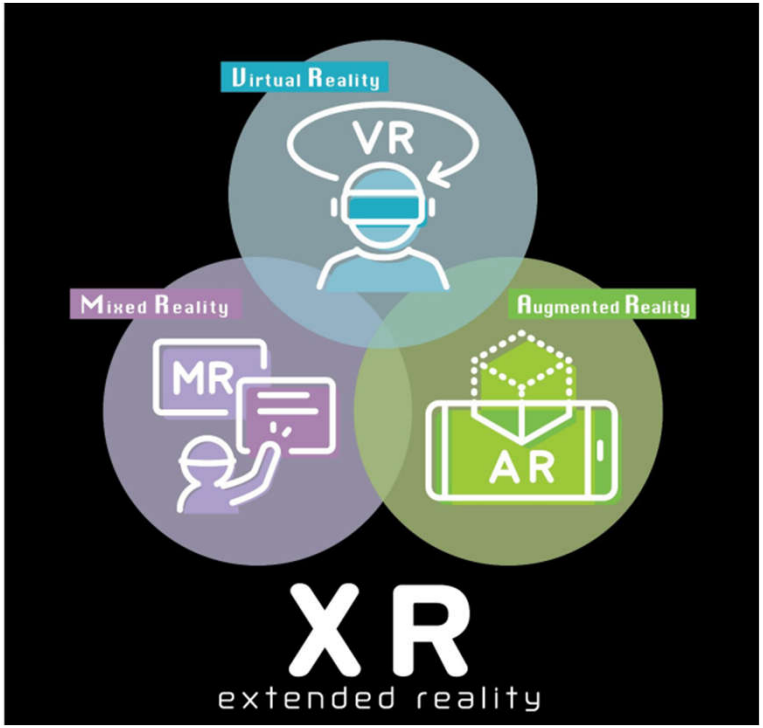
5 Personalized and E-coaching Medicine - Agents

- Advancement of **uses of virtual reality (VR) simulation technology for clinical purposes**

- **Mental health therapy, motor skills rehabilitation, cognitive assessment and clinical skills training**
  - **Mental and Behavioral Health -** assessment, training and treatment of **stress-related disorders**.
  - **Game Based Rehabilitation -** comprehensive, **evidence-based rehabilitation** training approaches for hospital, clinic, client populations.
  - **Neurocognitive Assessment and Training -** for individuals with stroke, traumatic brain injury and similar **neurological disorders**
  - **Virtual Humans - believable and more natural interactions**; simulated standardized patients for medical training, and personalized coaches for rehabilitation and wellness

5 XR in medical domains

- **XR - Extended reality** - immersive technologies, including VR – virtual reality, AR – Augmented reality, MR – Mixed reality
- **HMD – Head mounted display** – enhance interaction between the physical and virtual environments, improve and transform healthcare, benefiting patients, healthcare professionals,…
- **Applications** – accurate symptom detection, rehabilitation and physical therapy, surgical planning and training, 3D medical imaging and provisioning immersive and interactive medical training, …



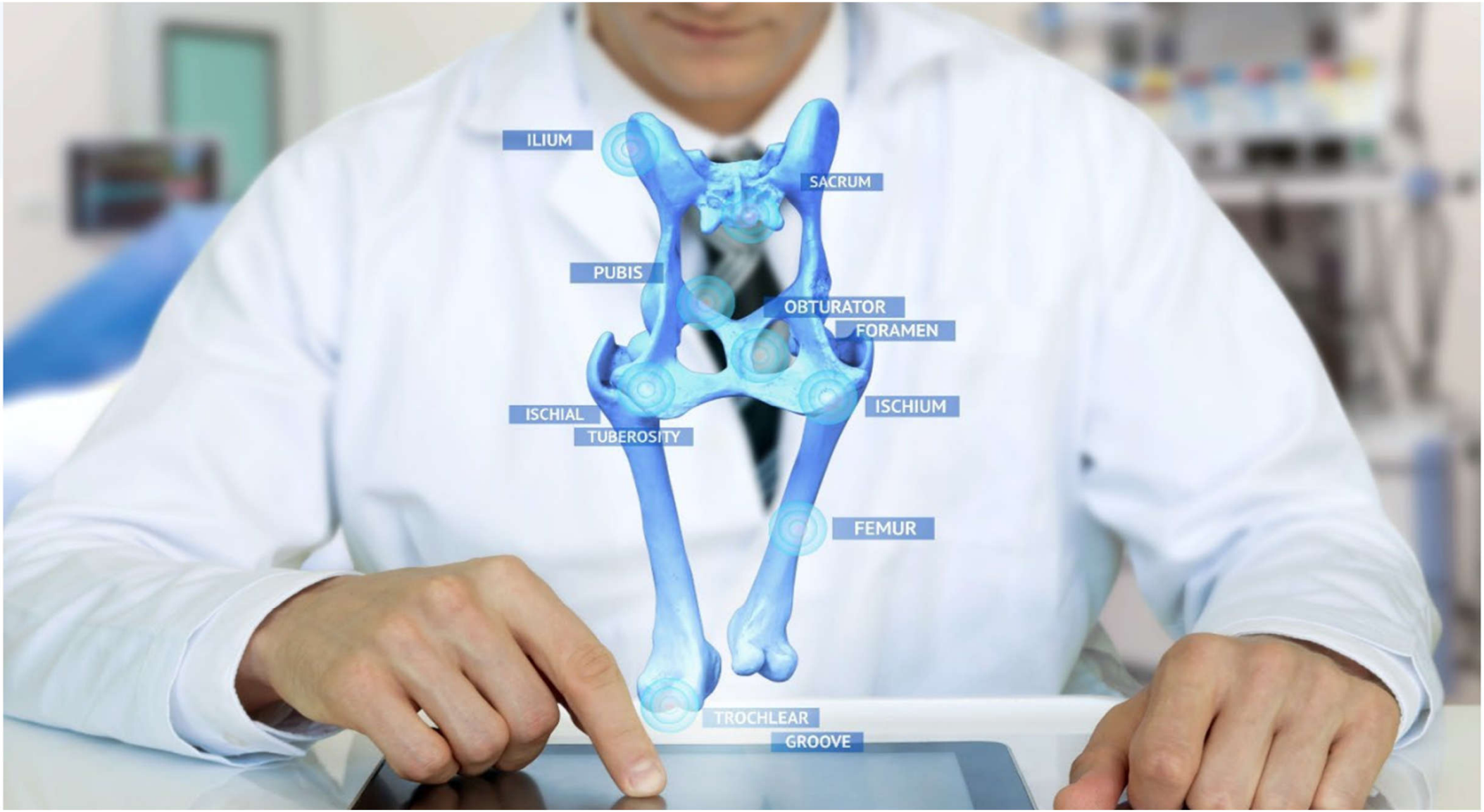
5 XR in medical domains

- **Education**
  - **Telesimulation** – telecommunication and immersive technologies can support education **for remote learners** (interaction, simulated patients, visual displays and facilitators in real time (laparoscopic surgery, robotic surgery, …);
  - **Telemonitoring** – enhancing medical education remotely**, expert provides guidance to a less experienced learner, remote consultations**, …
  - **Innovative ways for anatomical education -** students can **explore 3D views of the body** without the limitations of cadaveric teaching.
  - **XR using holograms** - teach anatomy **presenting 3D structures in the immediate learner environment**

5 XR in medical domains

5 XR in medical domains

- A Finnish company developed **SurgeryVision**, allows view of MRI and CTscans in stereoscopic 3D format, study more efficiently anatomic abnormalities



5 XR in medical domains

- **Surgery education/simulation** - offers a safe and realistic opportunity, significantly increase the quality of surgical performance in the operating room

AGENDA

- 1 Introduction
- 2 Quality Data Aggregation in Health Domains
- 3 Data – AI/ML Models Development – Use of Models
- 4 Some Examples
- 5 Possibilities for Medical Education
- 6 Conclusions

5 Conclusions

- Rapid development of range of ICT components has significant influence medicine and healthcare.
  - **Health analytics** - advanced methods and models to **analyze Big and Complex Data.**
  - **Predictive modeling - smart models** to predict behaviors, to prevent diseases and to **personalize healthcare**.
  - **Visualization of data – presentation of data** in meaningful way to **support reliable decision making**.
  - **Integration of mobile (hardware and software) technologies** – integration with data-platforms enable **automated services and tailor feedback and recommendations.**
  - **Personal communication and recommendations between patient and virtual e-coach** - agent technologies definitely could play extremely important role.

5 Conclusions

- Rapid development of range of ICT components has significant influence medicine and healthcare.
  - **XR, Metaverse, Holograms –** offer enormous potential in all aspects, for physicians, caregivers, patients; diagnoses, treatment, followups, education
  - **Large Language Models (LLMs)** - transforming medicine and healthcare by enhancing various aspects of patient care, medical research, and administrative tasks

    Enhanced Clinical Support and Diagnosis:
    - LLMs - **analyze medical literature and patient data** to provide clinicians with potential diagnoses, treatment options, and personalized care plans.
    - Med-PaLM 2 - specifically designed to **answer complex medical questions.**
    - Identify potential **drug interactions**, **suggest optimal medication dosages**, assist with personalized treatment planning based.

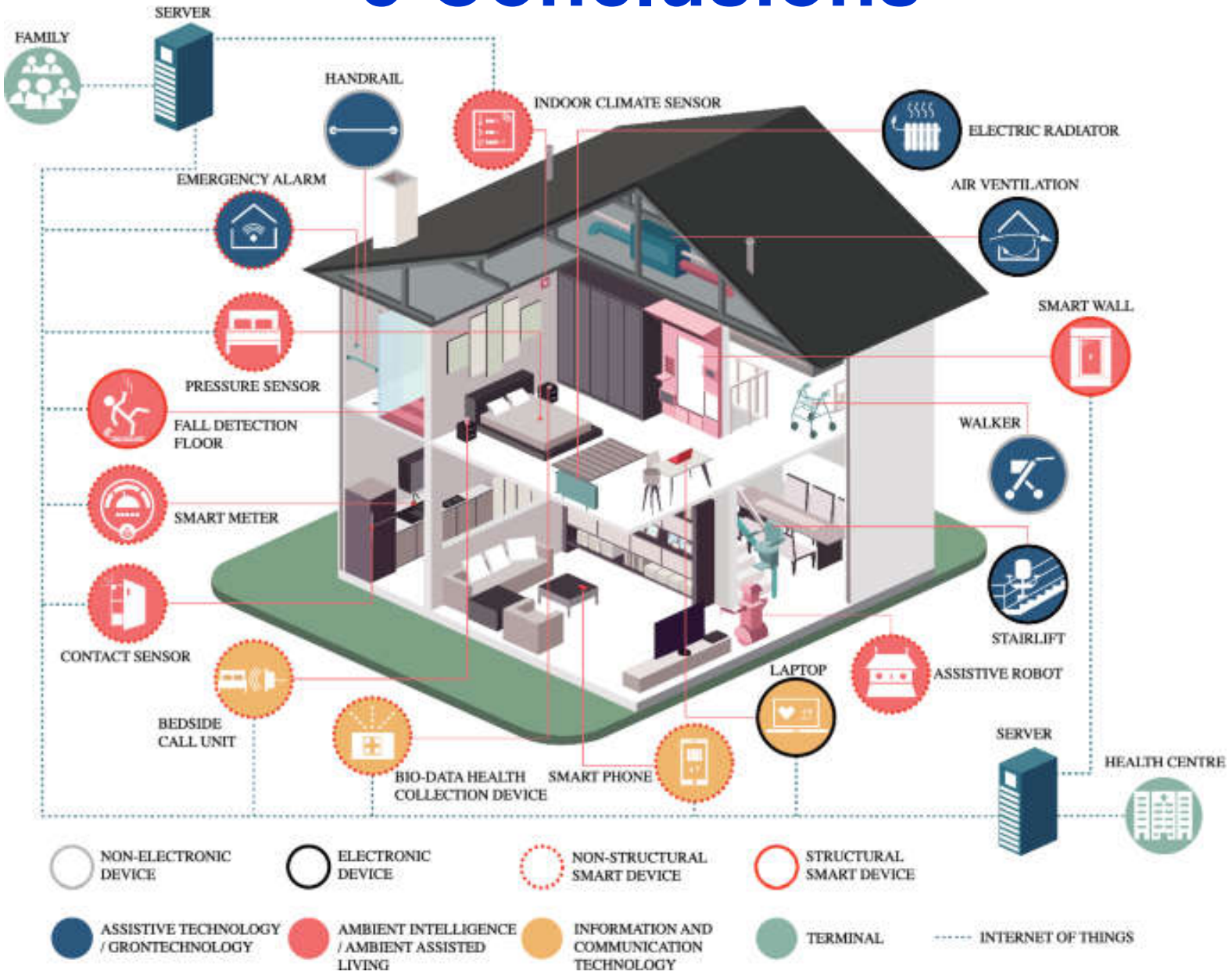
5 Conclusions

- **LLMs Ethical Considerations and Challenges**
  - **Data privacy and security** – crucial protecting sensitive patient data, access controls, secure storage.
  - **Bias mitigation** - LLMs can inherit biases existing in training data, leading to skewed or unfair recommendations. Necessary: careful data curation, algorithmic adjustments, ongoing monitoring...
  - **Hallucinations and misinformation** - inaccurate or misleading information. Human oversight and validation are necessary.
  - **Over-reliance on AI** - Clinicians should not rely solely on LLM recommendations without proper validation.

5 Conclusions

Where to go further

5 Conclusions



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Mirjana Ivanović

University of Novi Sad, Faculty of Sciences, Novi Sad, Serbia
mira@dmi.uns.ac.rs