EXPLAINABLE AI IN PERVASIVE HEALTHCARE: OPEN CHALLENGES AND RESEARCH DIRECTIONS

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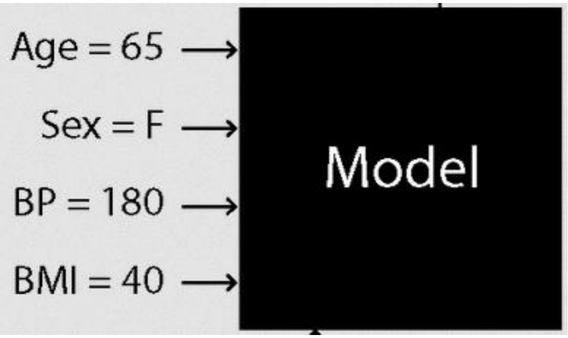
EXPLAINABLE ARTIFICIAL INTELLIGENCE

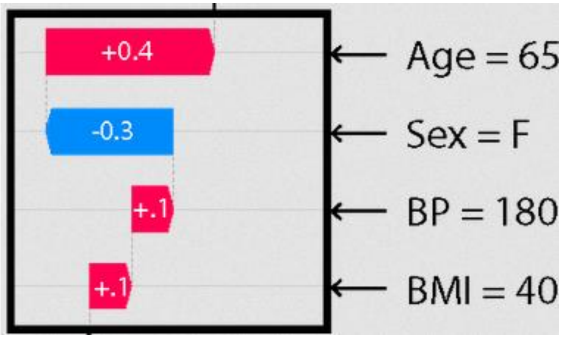
Class: Train Station
Confidence: 0.76

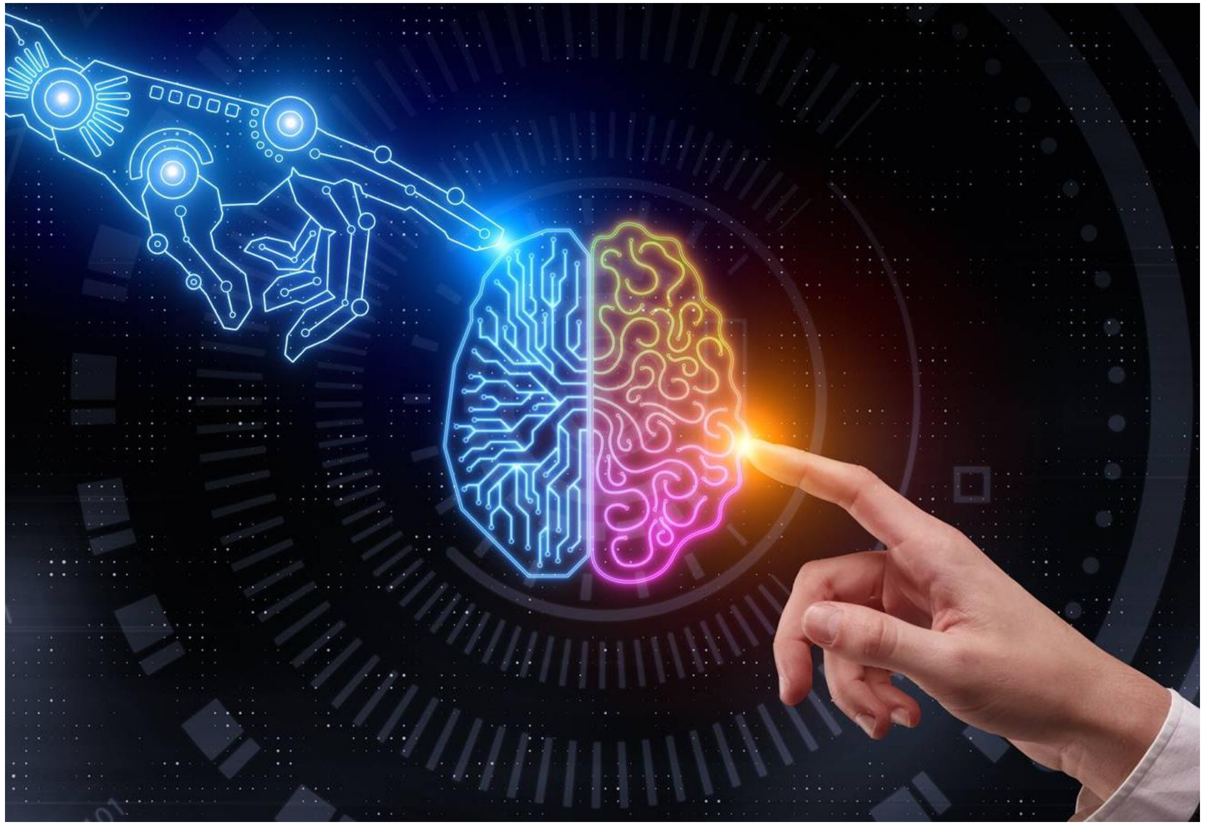
EXPLANATION



Risk factor: Low
Confidence: 0.81

EXPLANATION





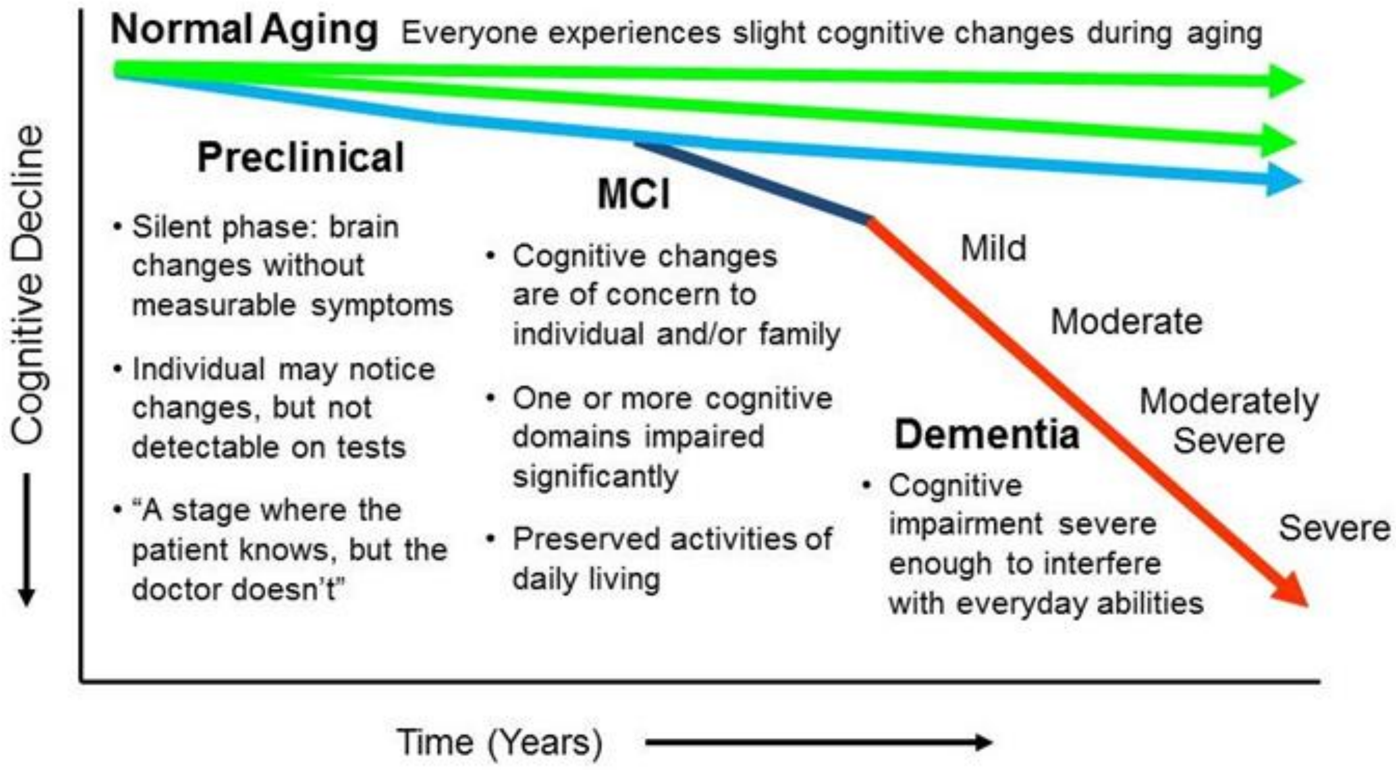
AI AND PERVASIVE HEALTHCARE

- ✓AI is more and more adopted to support several tasks in pervasive healthcare
  - ✓Ambient assisted living, supporting the diagnosis of cognitive issues…
- ✓Most current AI algorithms work as black boxes
- ✓Explainable AI may:
  - ✓increase trust in pervasive healthcare users (practitioners, patients)
  - ✓help devising more efficient and effective algorithms
  - ✓Introduce transparency and support self-care

AI FOR SENSOR-BASED COGNITIVE ASSESSMENT

- ✓AI and sensor data for early diagnosis of neurocognitive diseases
  - ✓Alzheimer, Parkinson, Huntington disease
- ✓Method: detection of abnormal behaviors, gait, locomotion patterns
- ✓Most existing systems only report an anomaly score or a black-box prediction
- ✓AI explanations may
  - ✓Help clinicians in the diagnosis
  - ✓Support patients and caregivers

THE THREE STAGES OF COGNITIVE DECLINE



NEUROPSYCHOLOGICAL ASSESSMENT

- ✓ Neuropsychological assessment is intrinsically performance-based
- ✓ Typically performed through a battery of tests about different cognitive abilities
  - ✓ memory, attention, processing speed, reasoning, spatial abilities …
- ✓ Tests can be standardized or targeted to the individual

ABNORMAL BEHAVIOR MODELS: **OVERT ERRORS**

- ✓**Omissions:** key steps of an activities are skipped
- ✓**Commissions:** key steps are performed inaccurately
  - ✓Anticipation-omission
  - ✓Perseveration
  - ✓Substitution …
- ✓**Action-additions:** actions unrelated to the activity are performed

Giovannetti, Tania, et al. "Naturalistic action impairments in dementia." Neuropsychologia 40.8 (2002): 1220-1232.

ABNORMAL BEHAVIOR MODELS: **SUBTLE INEFFICIENCIES**

Subtle disruption of functional abilities in seniors who are still capable of completing instrumental activities

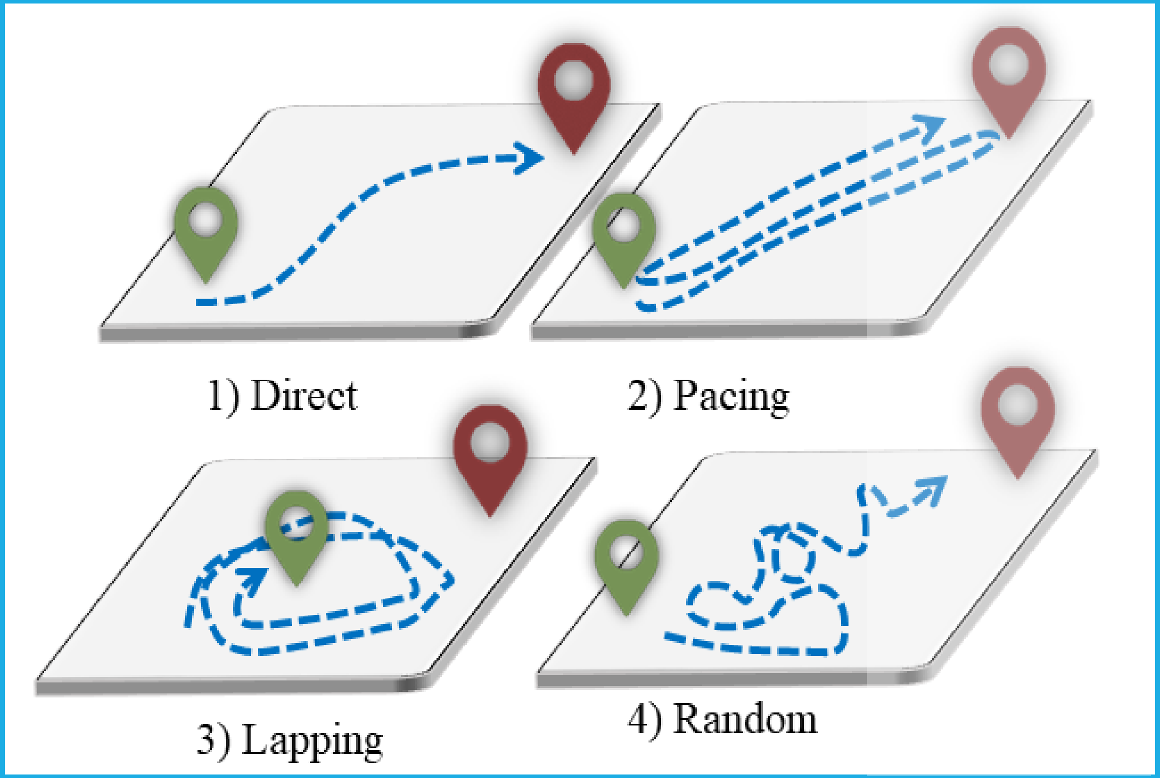
- ✓Reach, touch
- ✓Reach, no touch
- ✓Reach with object
- ✓Extra action
- ✓Sequence

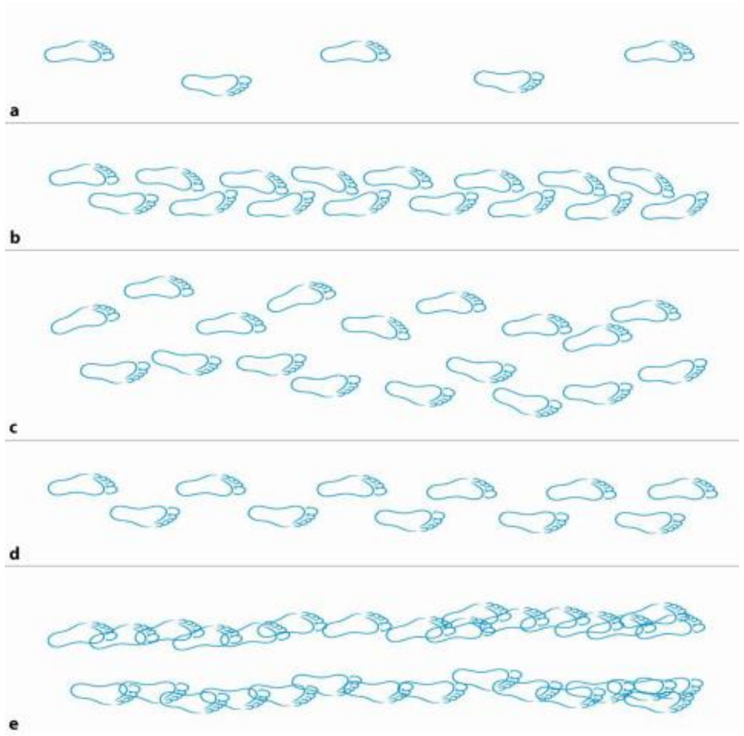
Seligman, Sarah C., et al. "A new approach to the characterization of subtle errors in everyday action: implications for mild cognitive impairment." The Clinical Neuropsychologist 28.1 (2014): 97-115

ABNORMAL LOCOMOTION MODELS: **TRAJECTORY-BASED INDICATORS**

- ✓Wandering behaviors

- ✓Martino-Saltzmann model:
  - ✓Direct (normal)
  - ✓Pacing (abnormal)
  - ✓Lapping (abnormal)
  - ✓Random (abnormal)





ABNORMAL LOCOMOTION MODELS: **LOW-LEVEL MOTION INDICATORS**

- ✓ Gait disorders

- ✓ Statistical measures
  - ✓ Jerk
  - ✓ Sharp angles
  - ✓ Straightness
  - ✓ Tortuosity
  - ✓ Fractal dimension …

AI AND SENSOR DATA FOR COGNITIVE ASSESSMENT: MODEL-BASED

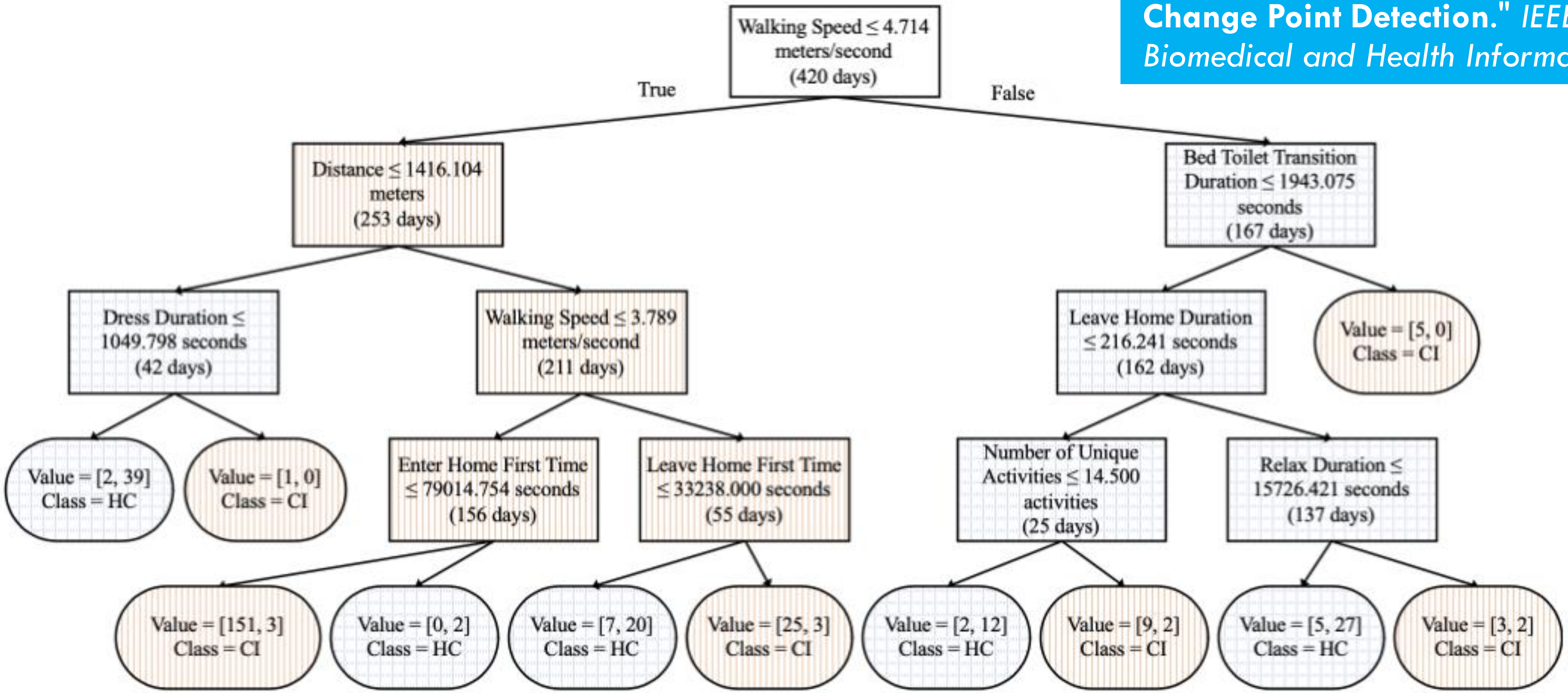
Riboni, D., Bettini, C., Civitarese, G., Janjua, Z. H., & Helaoui, R. "**SmartFaber: Recognizing fine-grained abnormal behaviors for early detection of mild cognitive impairment.**" *Artificial intelligence in medicine* (2016)

Type	Occurences in last 7 days	Occurences in last 30 days	Occurences in last 90 days
Red (most important)	6	23	44
Yellow	14	41	74
Green (less important)	13	49	97

No.	Rule	Anomaly type
1	$anomaly(cr, fridge, T_2) \leftarrow action(return, RF, S, T_1) \wedge action(close, door, S, T_2) \wedge RefFood(RF) \wedge NonRefStorage(S) \wedge (T_1 < T_2).$	Critical replacement: the patient has placed a food item that needs refrigeration inside a non-refrigerated cabinet.
2	$anomaly(nca, prepBF, T_1 + 45\ \text{min}) \leftarrow startActivity(prepBreakfast, T_1) \wedge endActivity(prepBreakfast, T_2) \wedge ((T_2 - T_1) > 45\ min).$	Non-critical anomaly: the patient spent too much time to prepare breakfast.
3	$anomaly(co, medicine, T_2) \leftarrow prescribed(M, T_1, T_2) \wedge not((action(retrieve, M, C, T) \wedge MedCabinet(C) \wedge (T_1 \leq T \leq T_2).$	Critical omission: the patient has not retrieved a prescribed medicine in due time.
4	$anomaly(wa, medicine, T) \leftarrow not(prescribed(M, T_1, T_2)) \wedge action(retrieve, M, C, T) \wedge MedCabinet(C) \wedge Medicine(M).$	Wrong activity: the patient has taken a medicine that was not prescribed.

AI AND SENSOR DATA FOR COGNITIVE ASSESSMENT: STATISTICS-BASED

Sprint, Gina Lee, Diane J. Cook, and Roschelle Fritz. "**Behavioral Differences Between Subject Groups Identified Using Smart Homes and Change Point Detection.**" *IEEE Journal of Biomedical and Health Informatics* (2020)



HEALTHXAI SYSTEM

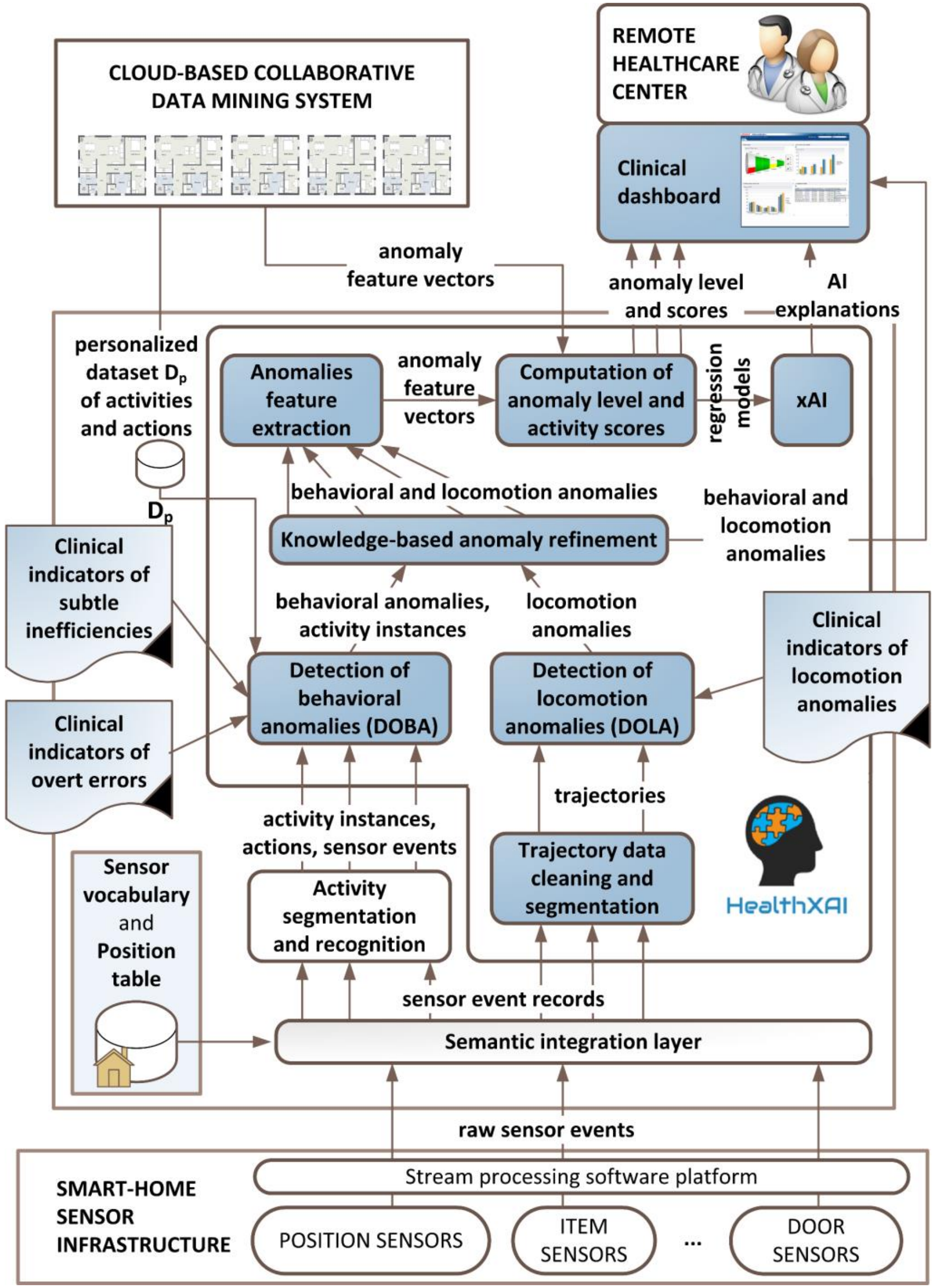
Elham Khodabandehloo, Daniele Riboni, Abbas Alimohammadi. "**HealthXAI: Collaborative and Explainable AI for Supporting Early Diagnosis of Cognitive Decline.**" *Future Generation Computer Systems* (2021).

Approach

- ✓ Based on clinical indicators of abnormal behaviors and locomotion
- ✓ Use of general rules to capture a large spectrum of anomalies
- ✓ No need for manual fine-tuning
- ✓ Natural language explanation of predictions
- ✓ User-friendly interfaces for clinicians

HEALTHXAI SYSTEM

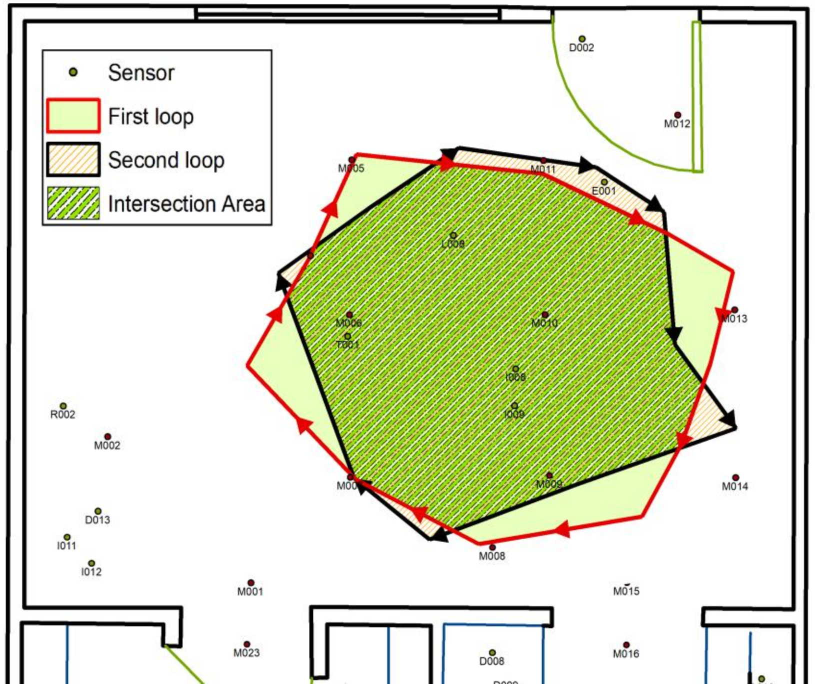
Architecture overview

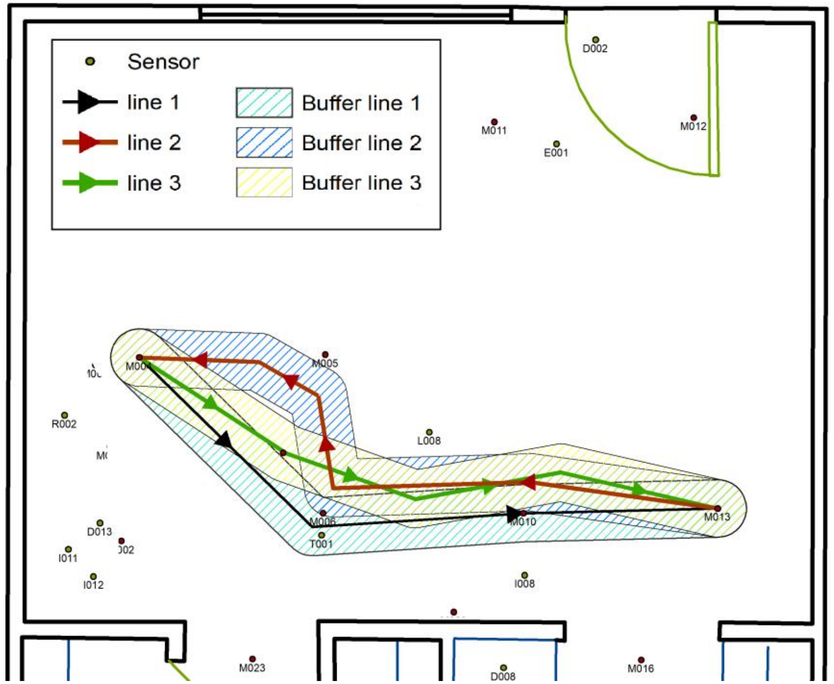


HEALTHXAI SYSTEM

Anomaly detection methods

- ✓Behavioral anomalies:
  action/activity recognition and collaborative statistics
- ✓Locomotion anomalies:
  spatio-temporal data mining





HEALTHXAI SYSTEM

Features for computing the anomaly level (0=healthy; 0.3=MCI; 1=dementia)

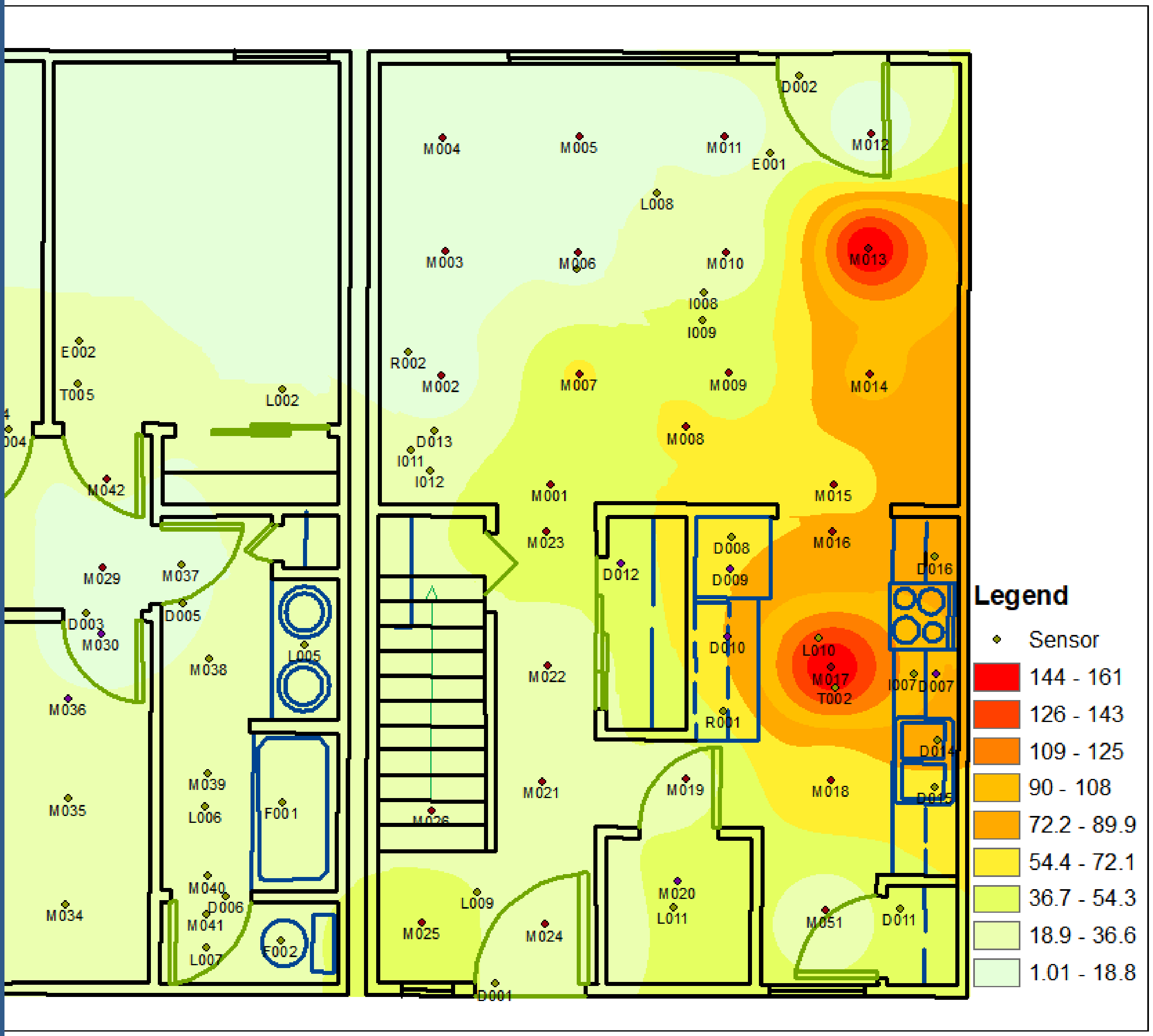
Feature name	**Description**
Additions	Number of action additions
Anticipation-Omissions	Number of anticipation-omissions
Omissions	Number of omissions
Perseverations	Number of perseverations
Reach-touch	Number of reach-touch subtle inefficiencies
Pacing	Number of pacing episodes
Lapping	Number of lapping episodes
Random	Number of random walk episodes
Jerk	Average jerk of trajectories
Straightness	Average straightness of trajectories
Sharp-points	Average number of sharp points in trajectories
Anomaly-level	Anomaly level in [01]

HEALTHXAI SYSTEM

Experiments with 192 subjects:

- ✓19 PwD
- ✓54 people with MCI
- ✓80 seniors aged 60 to 74
- ✓39 seniors aged 75 or older

Test bed: CASAS smart homes, Univ. of Washington



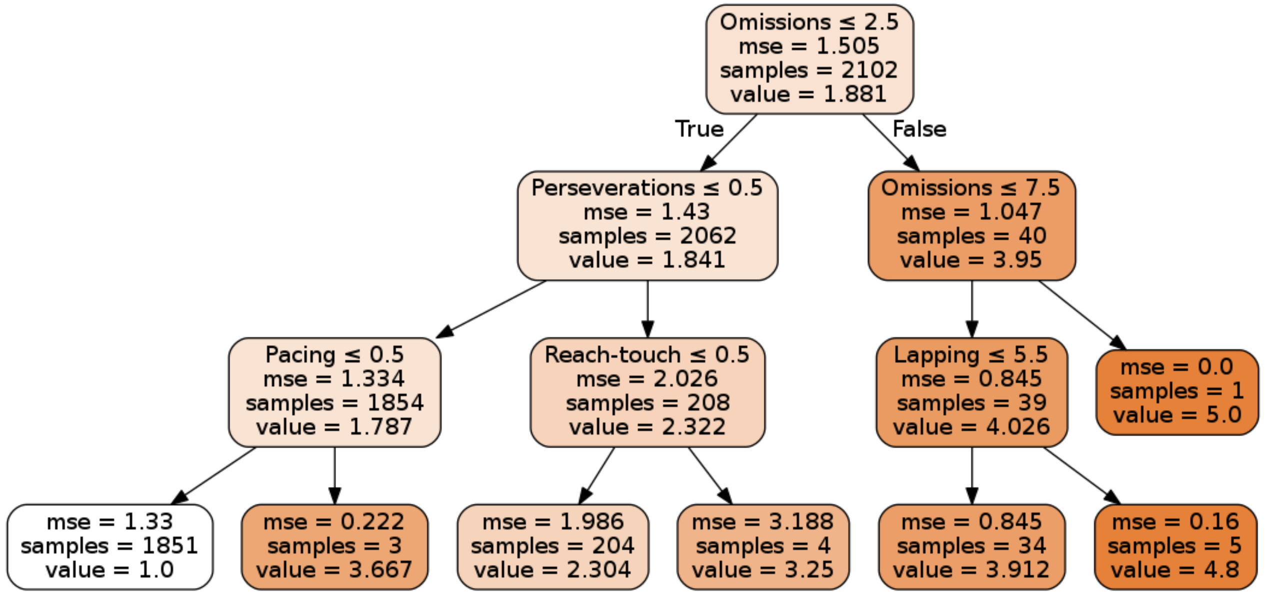
HEALTHXAI SYSTEM

Recognition of individual's anomaly level (0=healthy; 0.3=MCI; 1=dementia)

Regressor	Correl. coeff.	Mean abs. err.	Root mean squared err.
5 Nearest Neigh.	0.346	0.187	0.429
Decision stump	0.29	0.244	0.394
Decision table	0.29	0.244	0.394
Linear regression	0.579	0.218	0.329
M5 model decision tree	**0.707**	**0.161**	**0.279**
Neural Net.	0.594	0.213	0.354
Random forest	0.543	0.217	0.331
Random tree	0.309	0.217	0.463
Red. Err. Prun. dec. tree	0.546	0.186	0.333
Simple linear regr.	0.623	0.197	0.308
SVM	0.376	0.24	0.38

HEALTHXAI SYSTEM

Decision tree



AI explanation

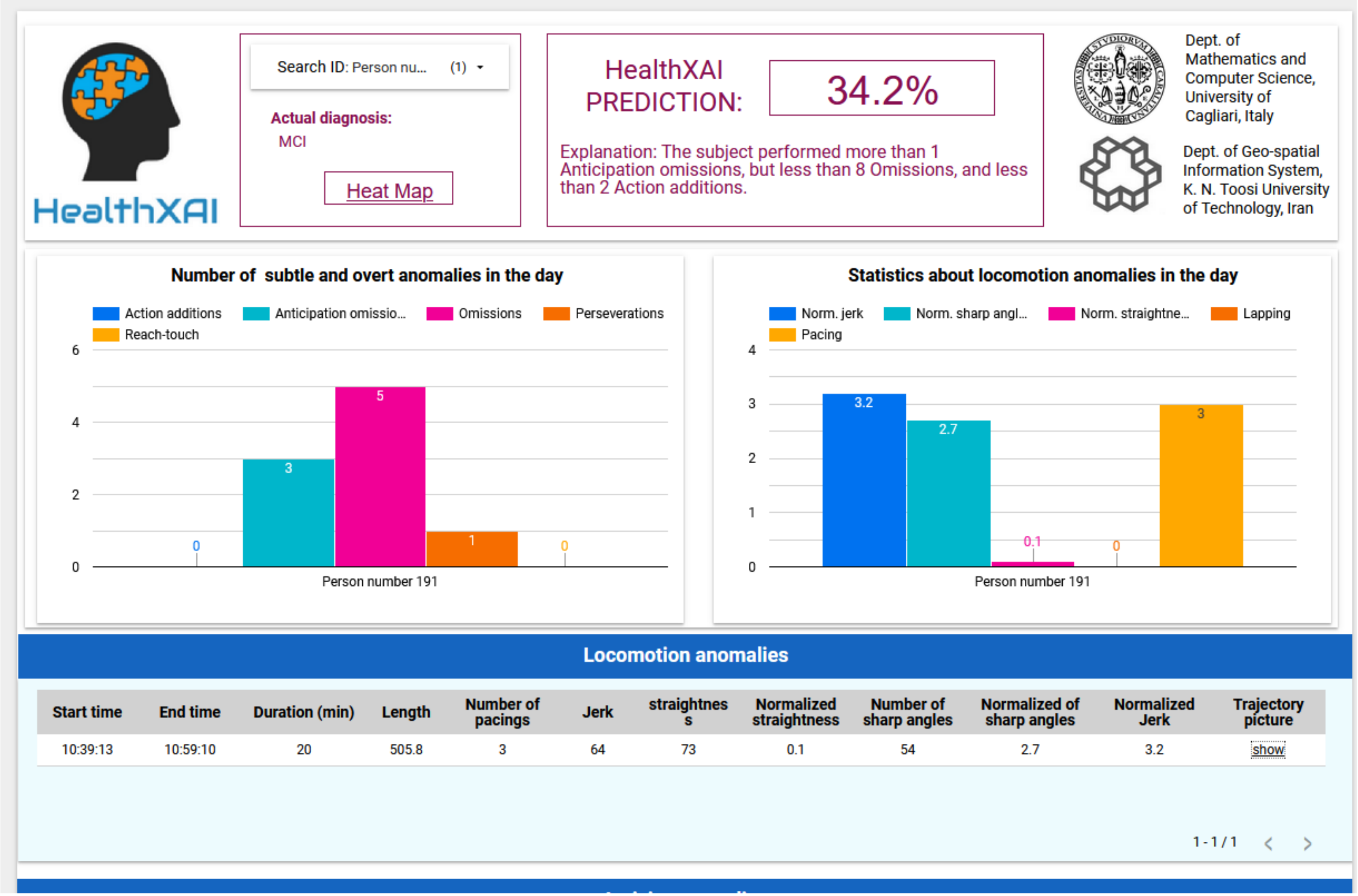
Suppose that the current individual, during the activity 'cooking', performed one perseveration but no other anomaly

"The predicted anomaly level of the activity is 2.3. This is considered a mild anomaly level. Explanation: the individual did less than 3 omissions, but at least one perseveration, and no reach-touch inefficiency"

HEALTHXAI SYSTEM

Dashboard

https://bit.ly/HealthXAI



HEALTHXAI
User study with clinicians
September 2020

✓8 neurologists from hospitals and healthcare facilities in Tehran
(5 males, 3 females, age 36 through 48)

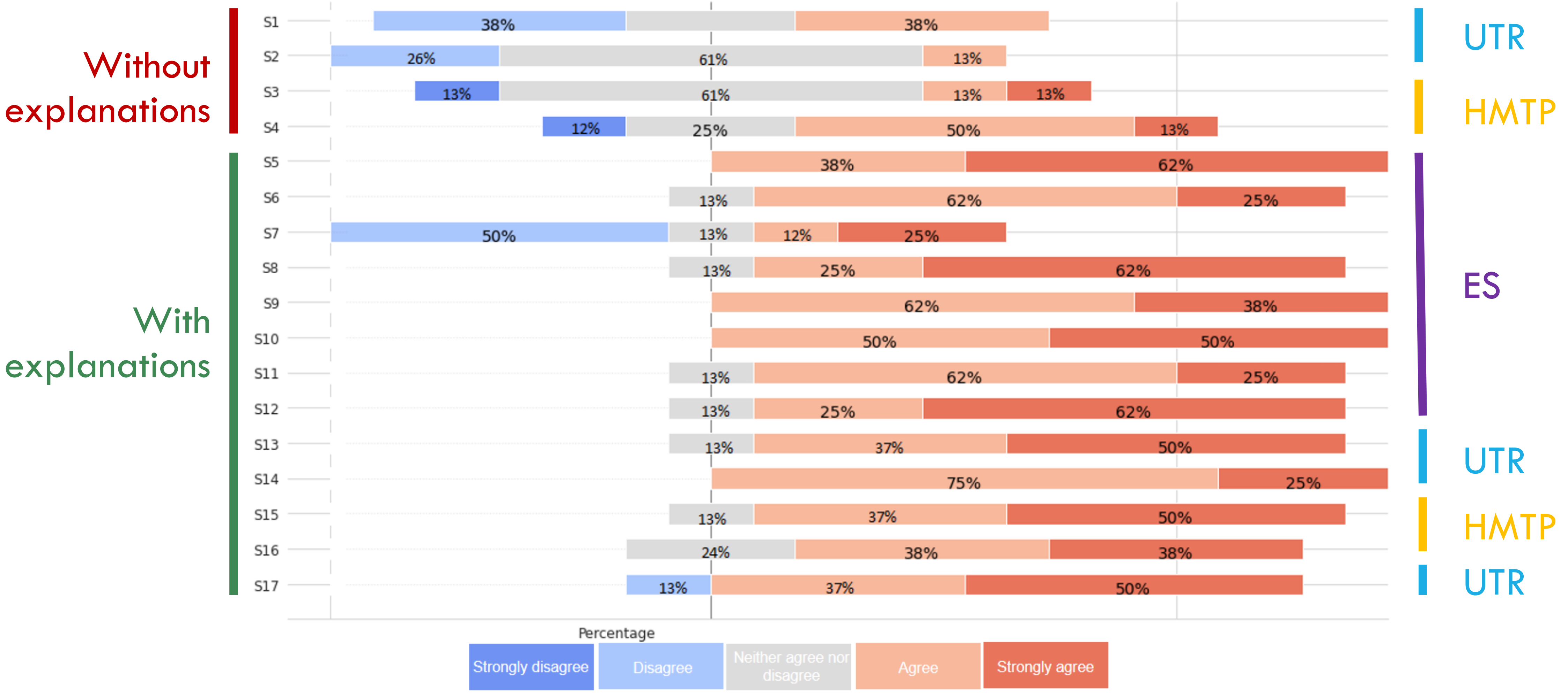
Assessment of:

✓Human-machine task performance (HMTP): "*whether end-users feel that the use of the xAI tool would help them in being more successful in their tasks*"

✓Explanation satisfaction (ES): "*end-user satisfaction and understanding of machine explanations*"

✓User trust and reliance (UTR)

HEALTHXAI Results of the user study



XAI IN PERVASIVE HEALTHCARE

Open challenges

- ✓ Compliance to legal requirements
- ✓ Highest accuracy may be incompatible with Explainability and Verifiability
- ✓ Avoid “black boxes”
- ✓ Respect privacy
- ✓ Build trust from the medical side

XAI IN PERVASIVE HEALTHCARE

Research directions

- ✓Provide effective ML algorithms with explanation capabilities
  - ✓e.g., by SHAP, or Local Interpretable Model-Agnostic Explanations (LIME)
- ✓Use a top-down approach
- ✓User-friendly multimodal interfaces, NLP …
- ✓Keep stakeholders in the loop
  - ✓Clinicians, patients, regulators …

THANKS!

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