Data Mining a Human Digital Twin for Health Assessment and Intervention

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What is a Human Digital Twin?

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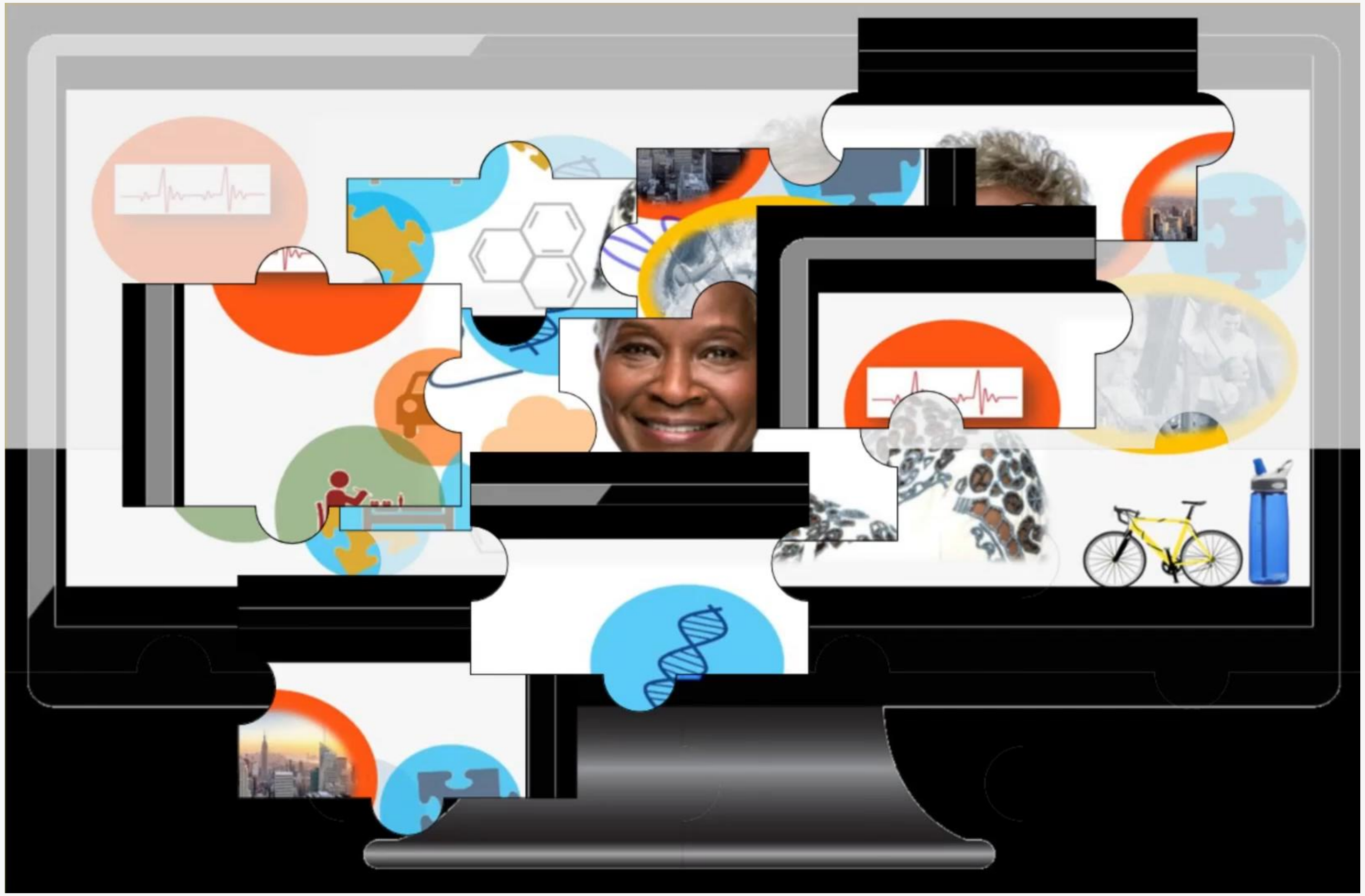
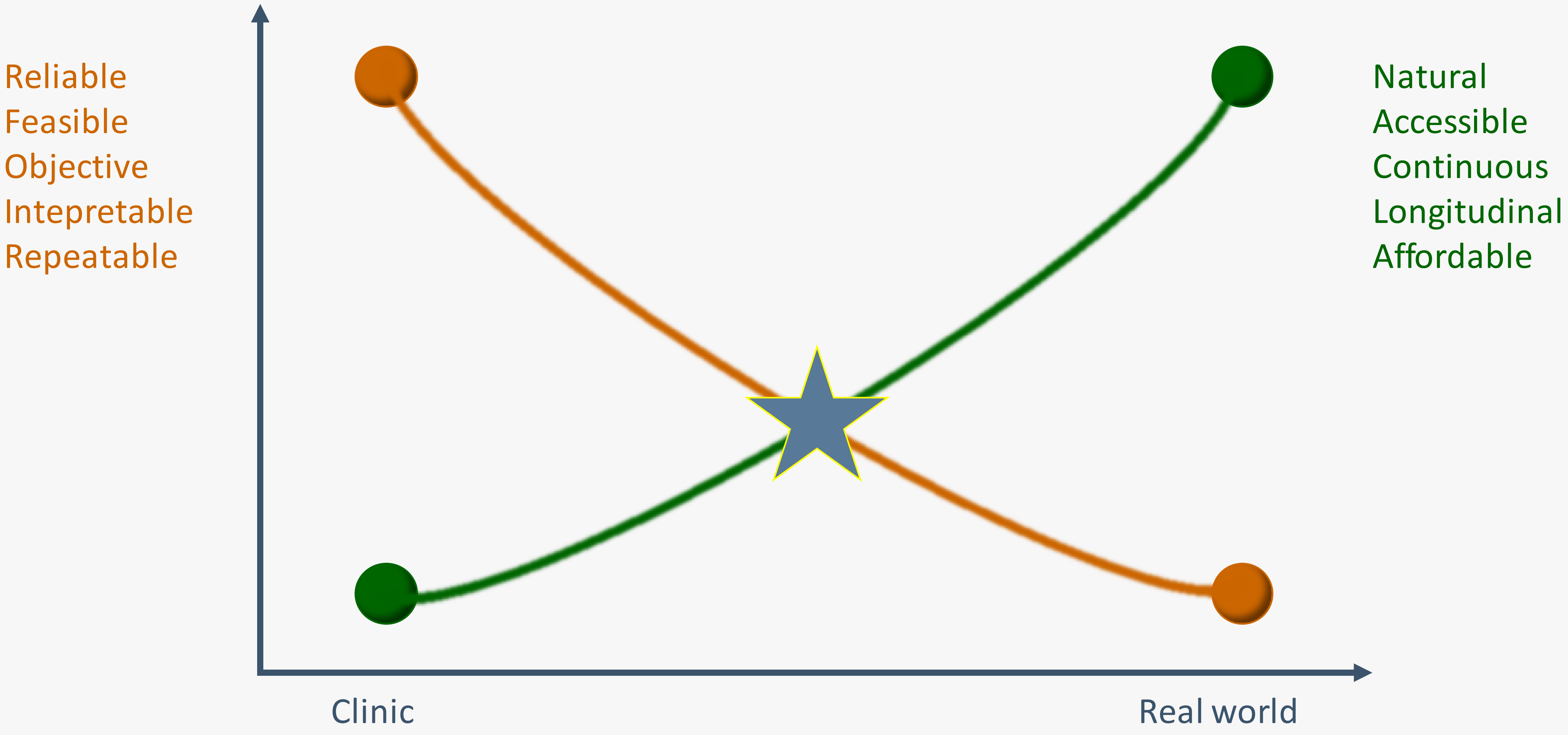
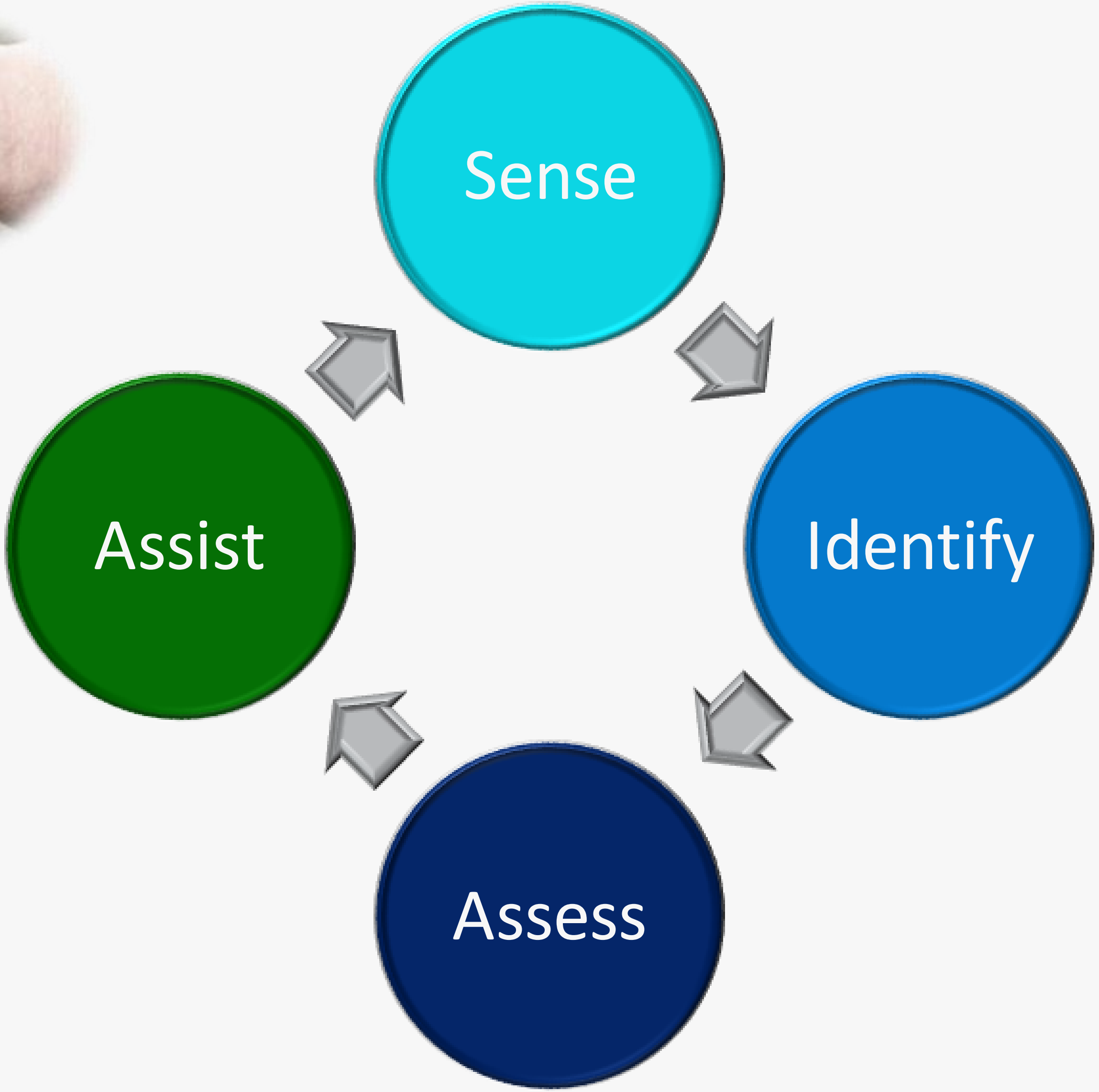
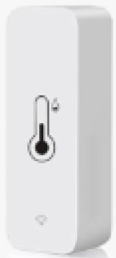


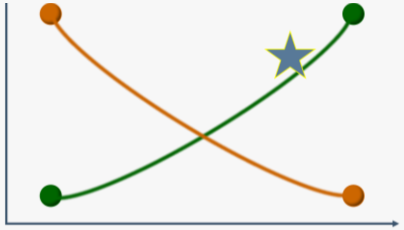
"In-the-wild"



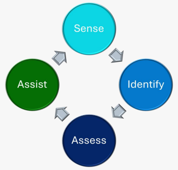
[Ploetz, 2024]


Sense
Identify
Assess
Assist



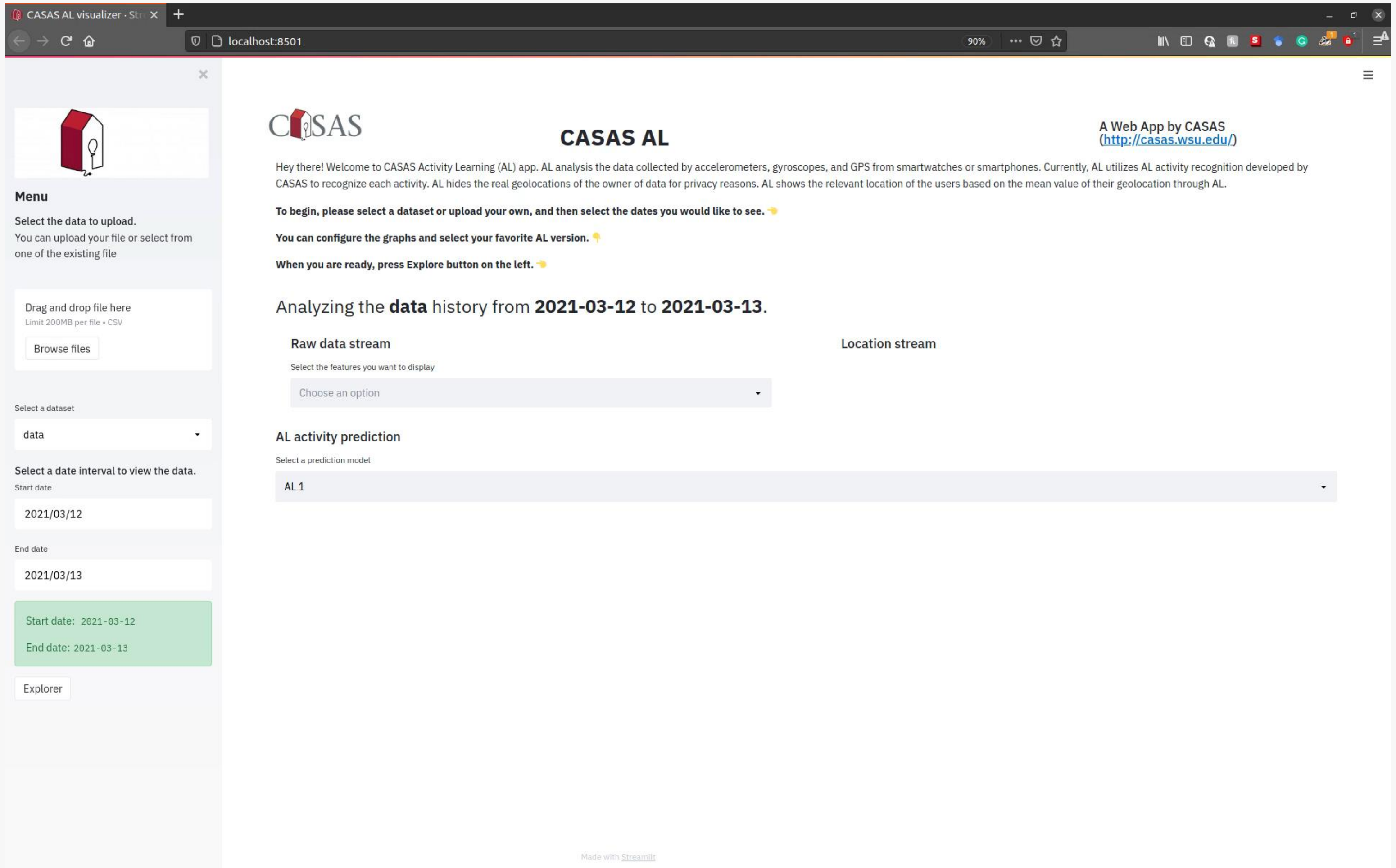


Sense: Smart Home



[IEEE Comp 2013]

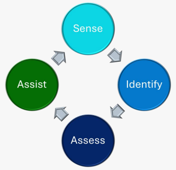
Smartwatch



3d movement, location, EMA, audio/text, n-back

[Neuropsych 2025, Cl Neur 2025]

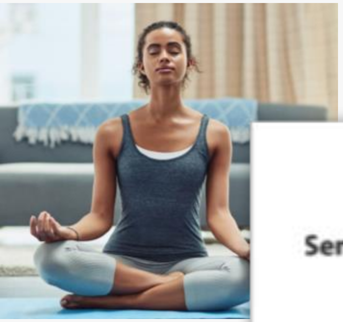
Identify: Behavior Markers

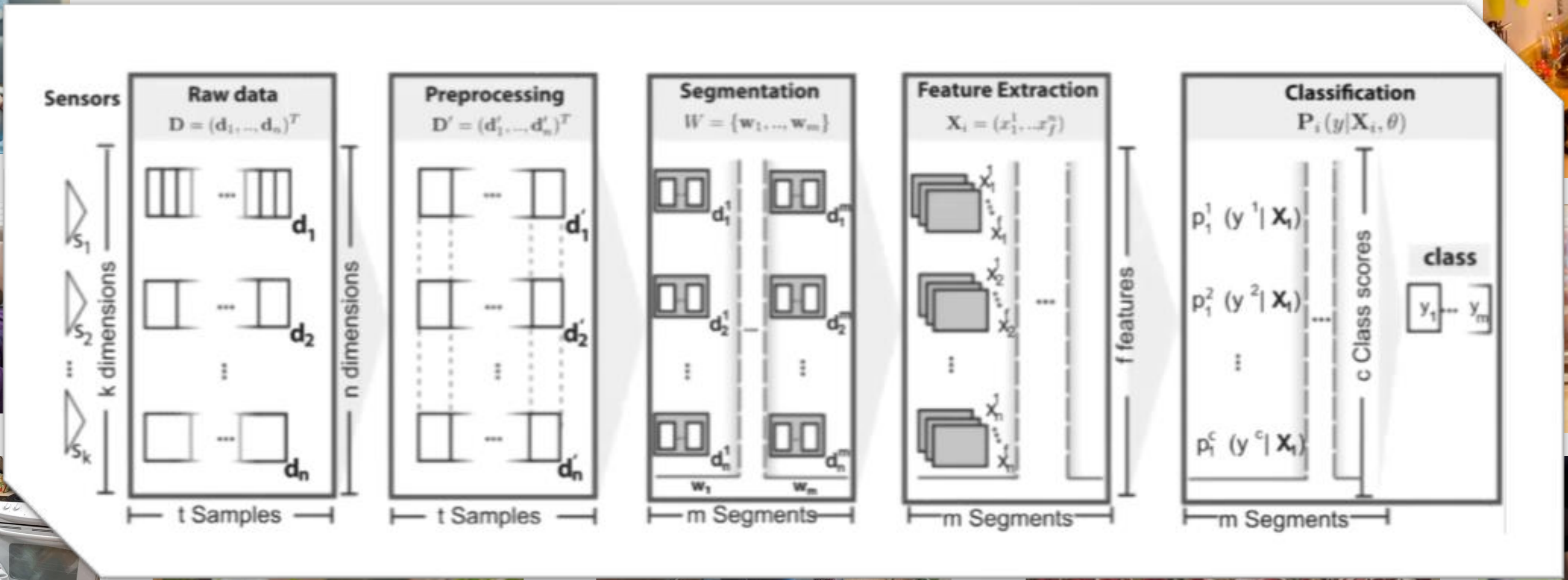


Modality	*Time Period*	*Markers*
home	*day*	number of sensor readings
		number of distinct activities performed
		number of distinct locations visited
		time (seconds) spent on each activity
		time (seconds) spent at each location
		time of day (seconds past midnight) for first occurrence of each activity
		time of day (seconds past midnight) for first visit to each location
	hour	number of sensor readings
		number of distinct activities performed
		number of distinct locations visited
		time spent on each activity
		time spent at each location
	overall	statistics for daily behavior markers: mean, median, standard deviation, max, min, zero/mean crossings, interquartile range, skewness, kurtosis, signal energy
		statistics for hourly behavior markers: mean, median, standard deviation, max, min, zero/mean crossings, interquartile range, skewness, kurtosis, signal energy
		regularity index based on hourly values for number of sensor readings: within weeks, within weekdays, between weeks
		regularity index based on hourly values for number of activities performed: within weeks, within weekdays, between weeks
		regularity index based on hourly values for number of locations visited: within weeks, within weekdays, between weeks
		circadian rhythm: sensor reading count, number of activities, locations visited

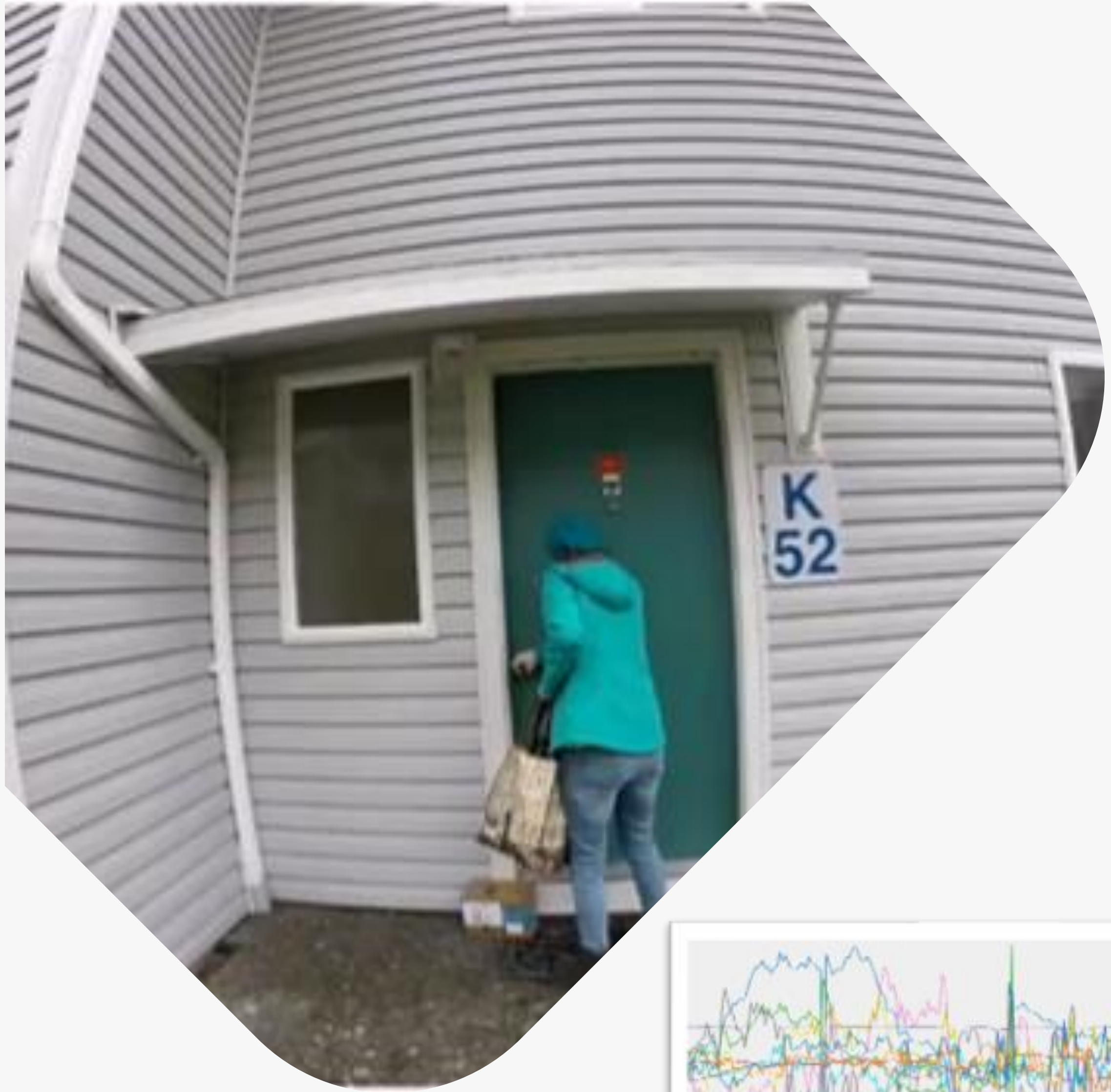
Modality	*Time Period*	*Markers*
watch	*day*	total acceleration
		total rotation
		number of missing readings
		total distance traveled
		time (seconds) spent on each one-class activity and each primary activity
		time spent at each location type
		time of day (seconds past midnight) for first occurrence of each primary activity
		time of day (seconds past midnight) for first visit to each location type
	hour	total acceleration
		total rotation
		number of missing readings
		time spent on each one-class activity
		time spent on each primary activity
		time spent at each location type
	overall	statistics for daily behavior markers: mean, median, standard deviation, max, min, zero/mean crossings, interquartile range, skewness, kurtosis, signal energy
		statistics for hourly behavior markers: mean, median, standard deviation, max, min, zero/mean crossings, interquartile range, skewness, kurtosis, signal energy
		regularity index of total acceleration: within weeks, within weekdays, between weeks
		regularity index of total rotation: within weeks, within weekdays, between weeks
		regularity index of total distance: within weeks, within weekdays, between weeks
		circadian rhythm: total acceleration, total rotation, total distance

Identify: Human Activity Recognition





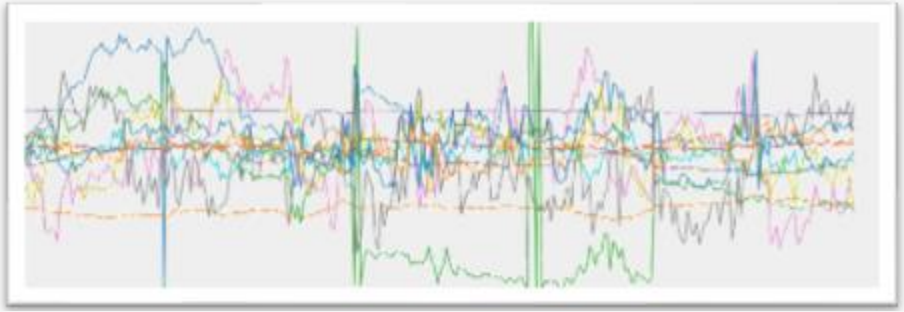
HAR is Challenging!



- Noise
- Activity variations
- Semantic ambiguity
- Crowdsourced ground truth
- Small datasets
- Imbalanced class distributions

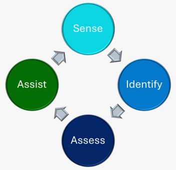
(that makes it fun)

- Reshape the activity space
- Change point detection
- Domain adaptation
- Multi-task (joint) prediction
- Contrastive pretraining



[IEEE Sensors 2025, ACM TIST 2024&2020, KDD 2020, AAAI 2017]

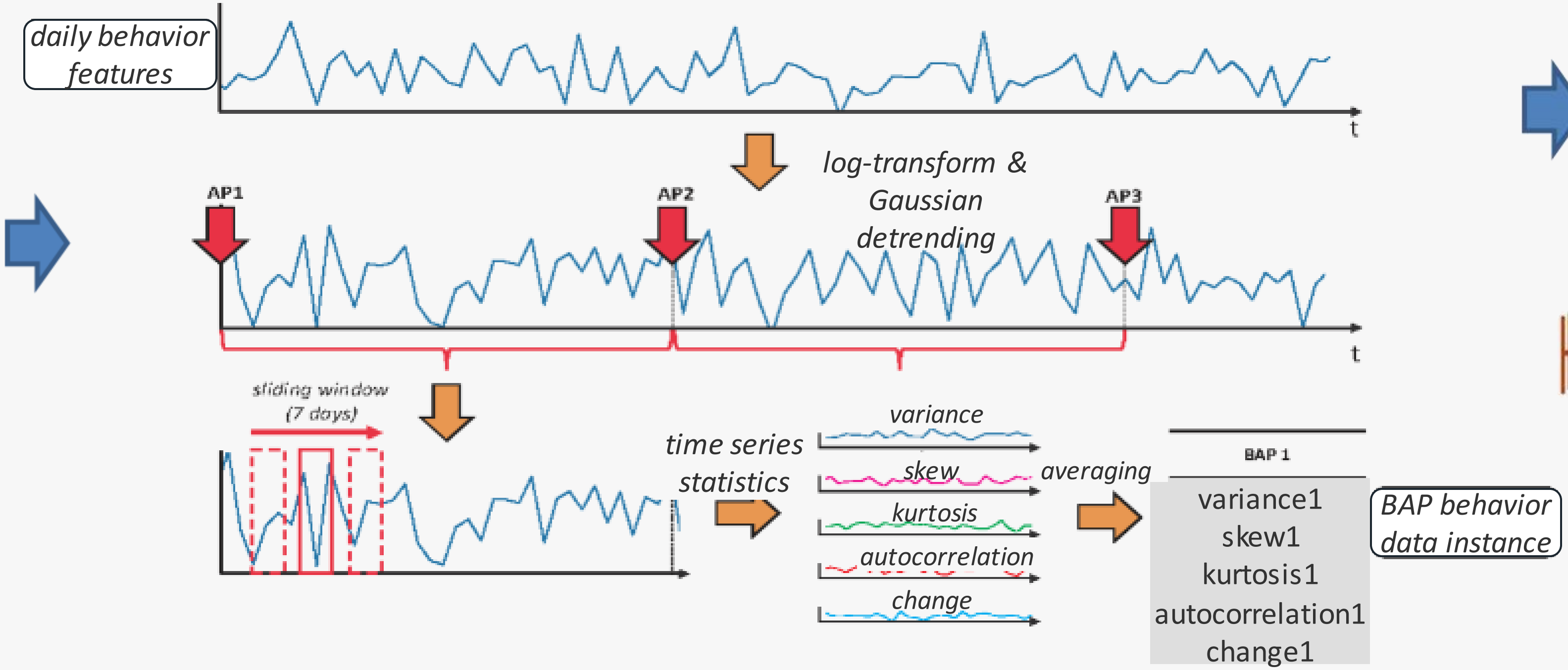
Assess: Predict Measures

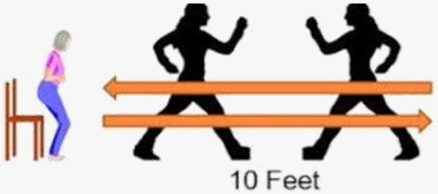


(n=39 older adult subjects, smart home behavior markers)

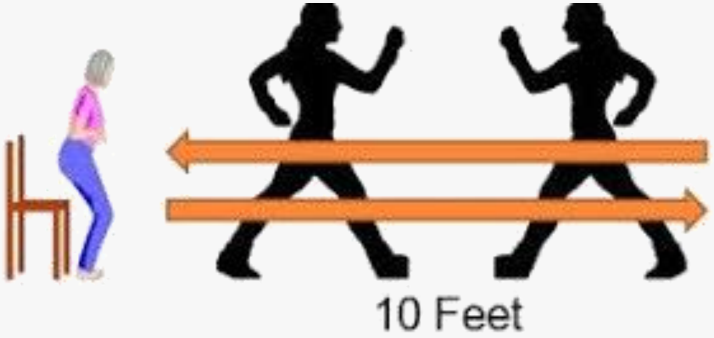
Clinical scores

Multi-year participants





Assess



Repeatable Battery for the Assessment of Neuropsychological Status (RBANS).

Timed Up and Go Test (TUG)

Instrumental Activities of Daily Living – Compensation (IADL-C)

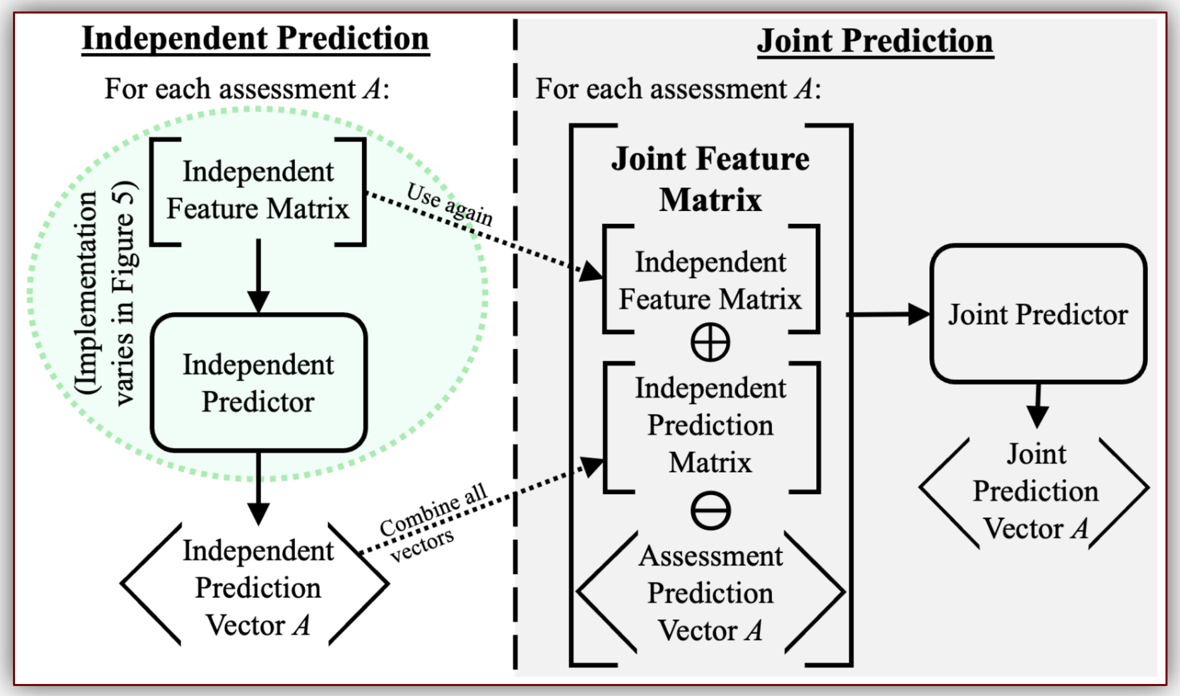
Regression results (Pearson's r)

RBANS	TUG	IADL-C
0.78	0.80	0.61 (IADL-C F4, 0.88)

[JBI 2018, JBI 2016, PMC 2016

Assess: Multi-task Inference

(n=21 healthy older adult subjects)

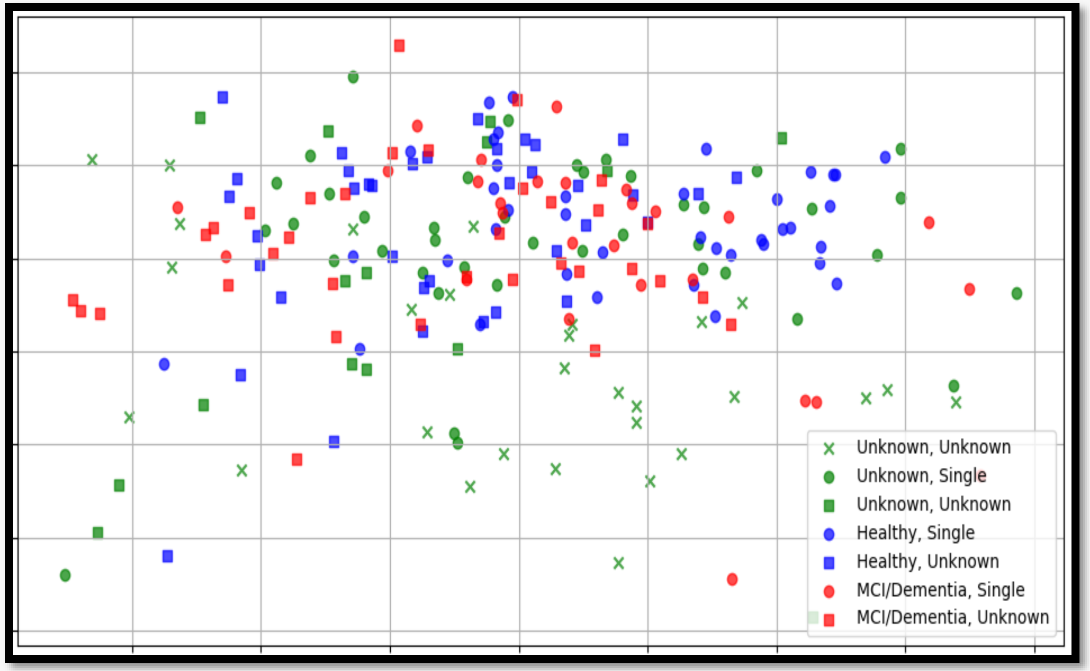


Measure (r)	Behaviorome – Independent	Behaviorome - Joint
WTAR	0.323	**0.879**
RBANS	0.358	**0.962**
TICS	**0.358**	0.188
FAS	0.498	**0.806**
TUG	0.353	**0.492**
DEX	0.617	**0.881**
ADLC	0.303	**0.437**
Average	0.309	**0.621**

[IEEE Access, 2021]

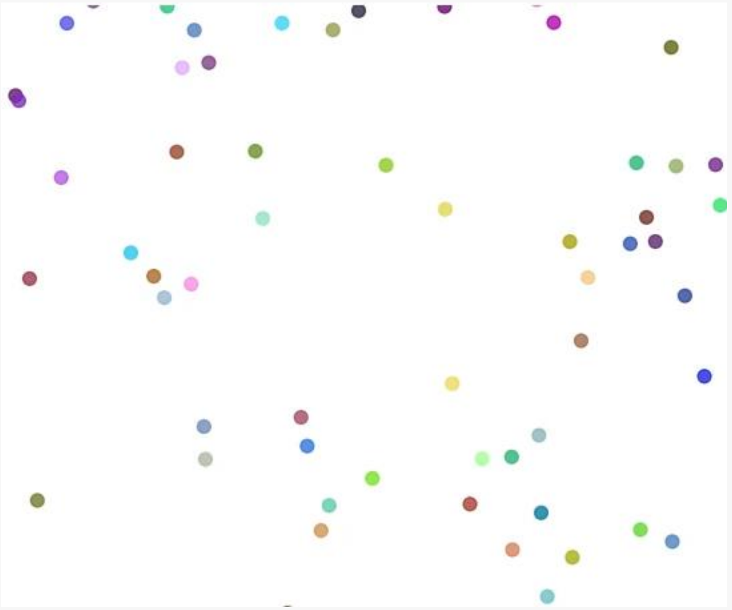
Assess: Predict Cognitive Diagnosis

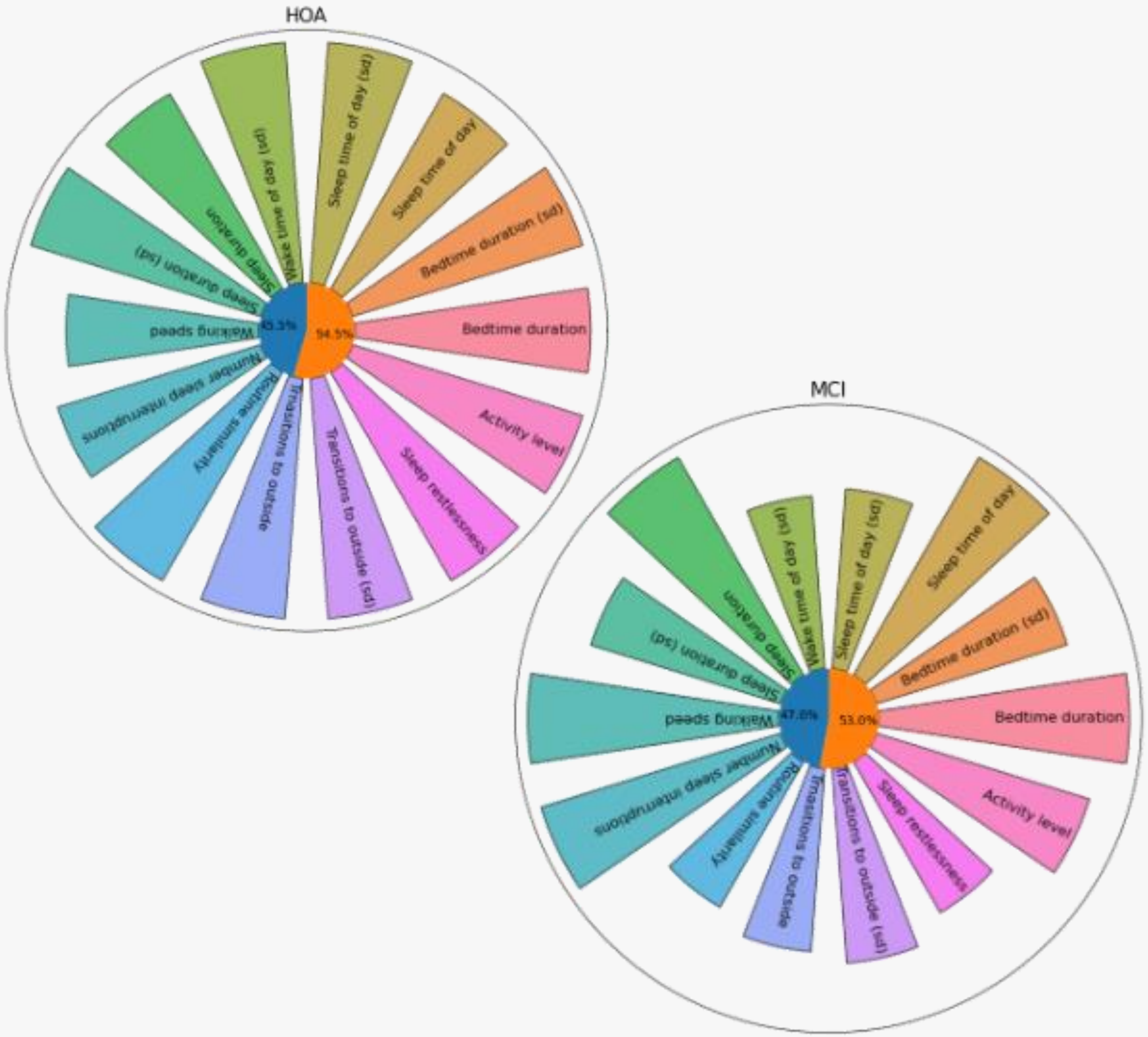
(n=137 labelled, 85 unlabelled smart homes)



Assess: Predict Cognitive Diagnosis

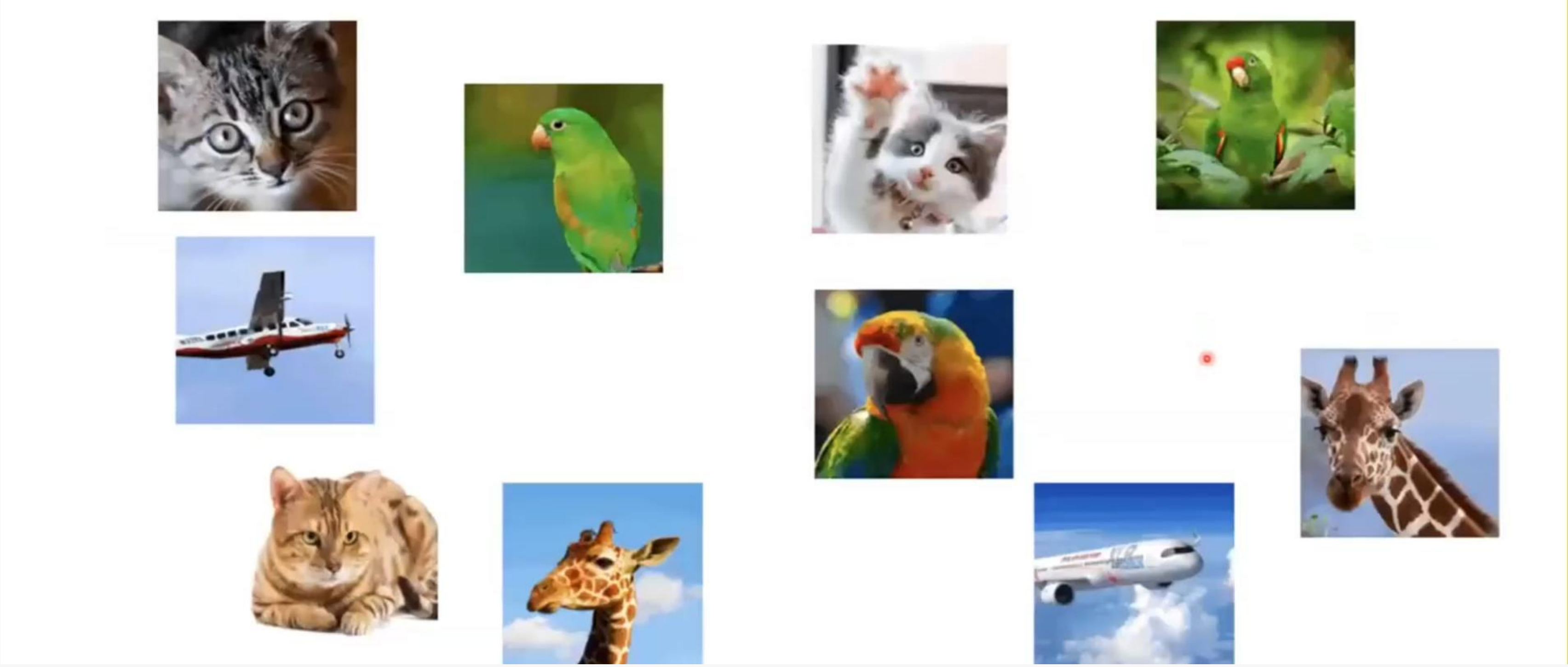
(n=137 labelled, 85 unlabelled smart homes)





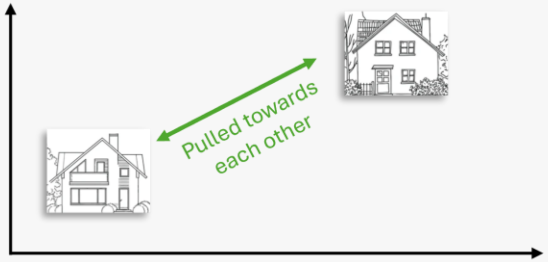
	Accuracy	F1
Decision tree	0.445	0.397
Logistic regression	0.526	0.454

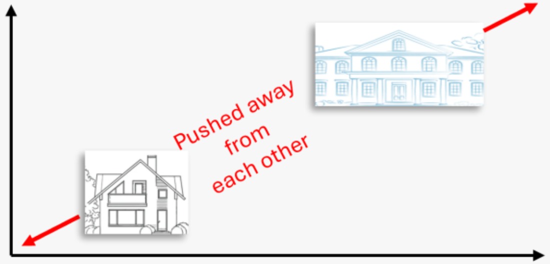
Contrastive Pretraining



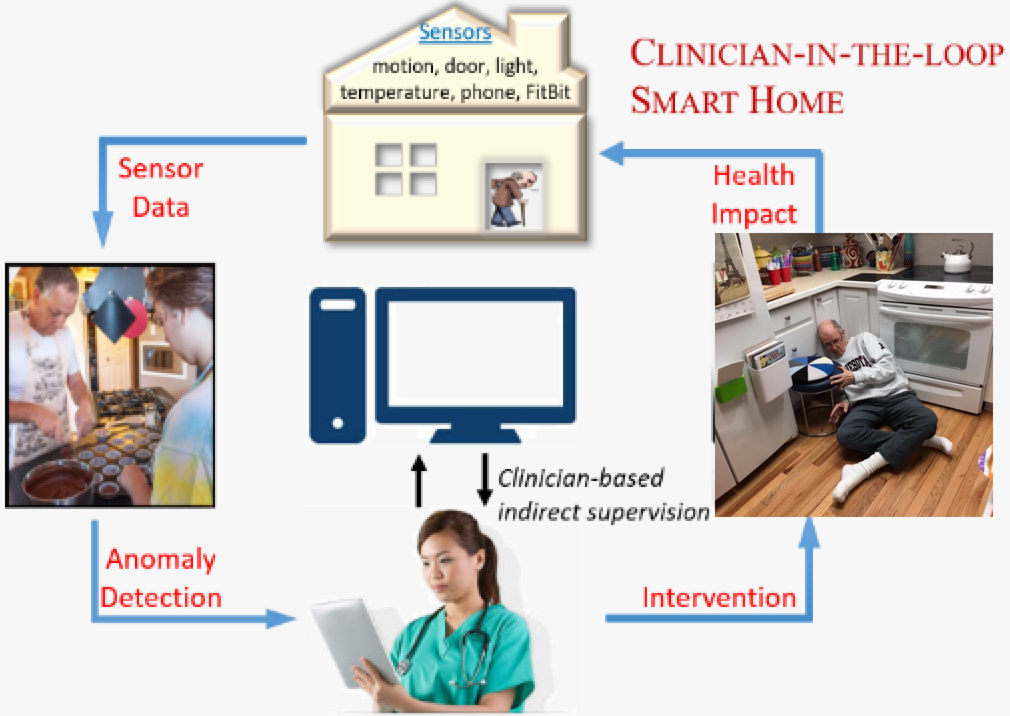
[Salim 2024]

	Accuracy	F1
Decision tree	0.445	0.397
Logistic regression	0.526	0.454
TCN	0.577	0.463
TCN with pretraining	0.854	0.770



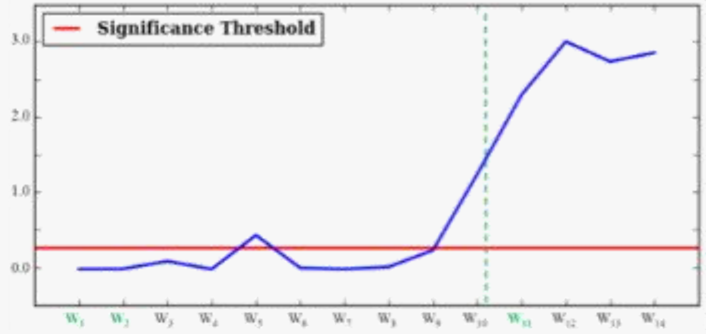


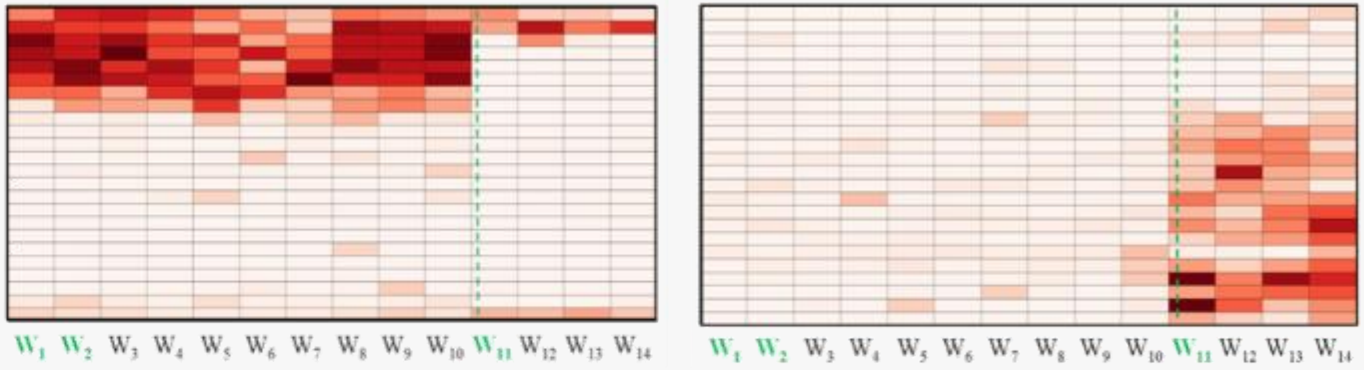
Assess: Detection of condition flareups



[Nursing Studies 2022, ACM TIST 2021, IEEE JBHI 2020]

CIL: Behavior change detection





Sleep

Enter Home

CIL: Clinician-guided anomaly detection

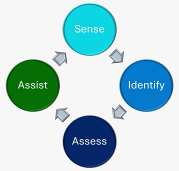
Age	Sex	Health Conditions	Health Events
89	F	Hypoxia	Depression, Weakness
83	M	PD, Sjogren's	Nocturia, Falls
88	F	COPD, oxygen	Depression
75	M	PD	Falls
89	F	CHF	Nocturia

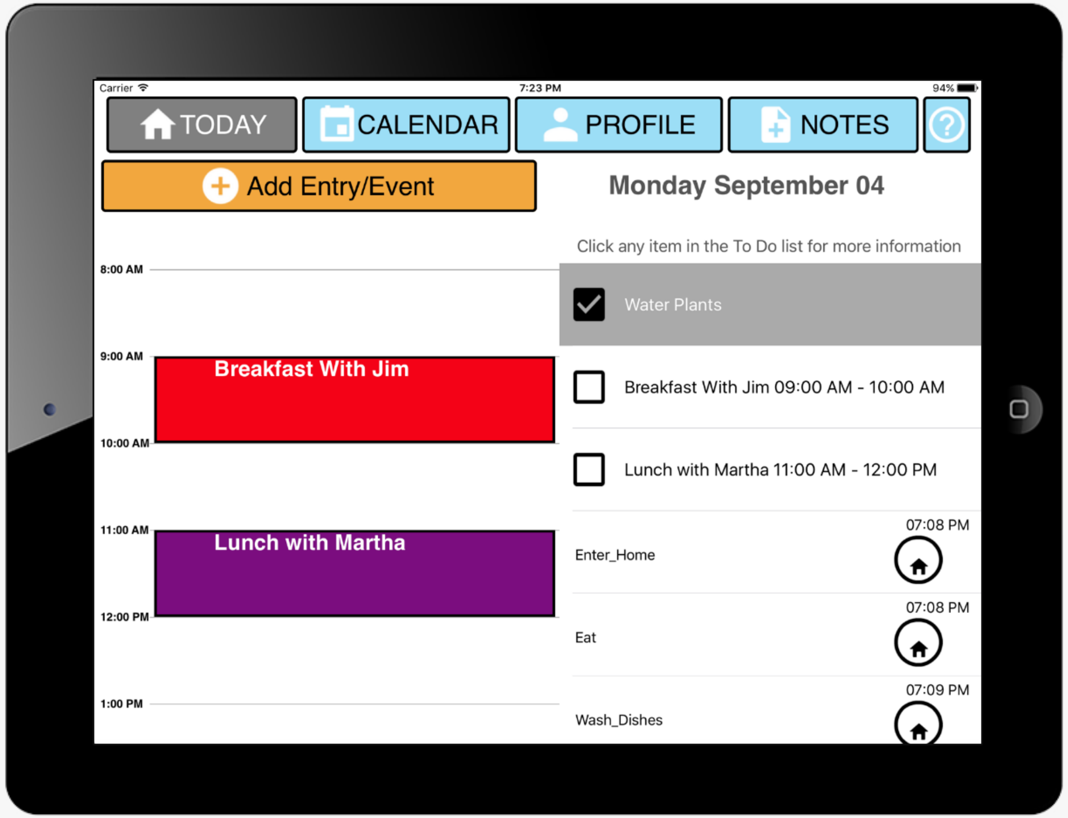
Health event-related sensor readings
0.02% of all data

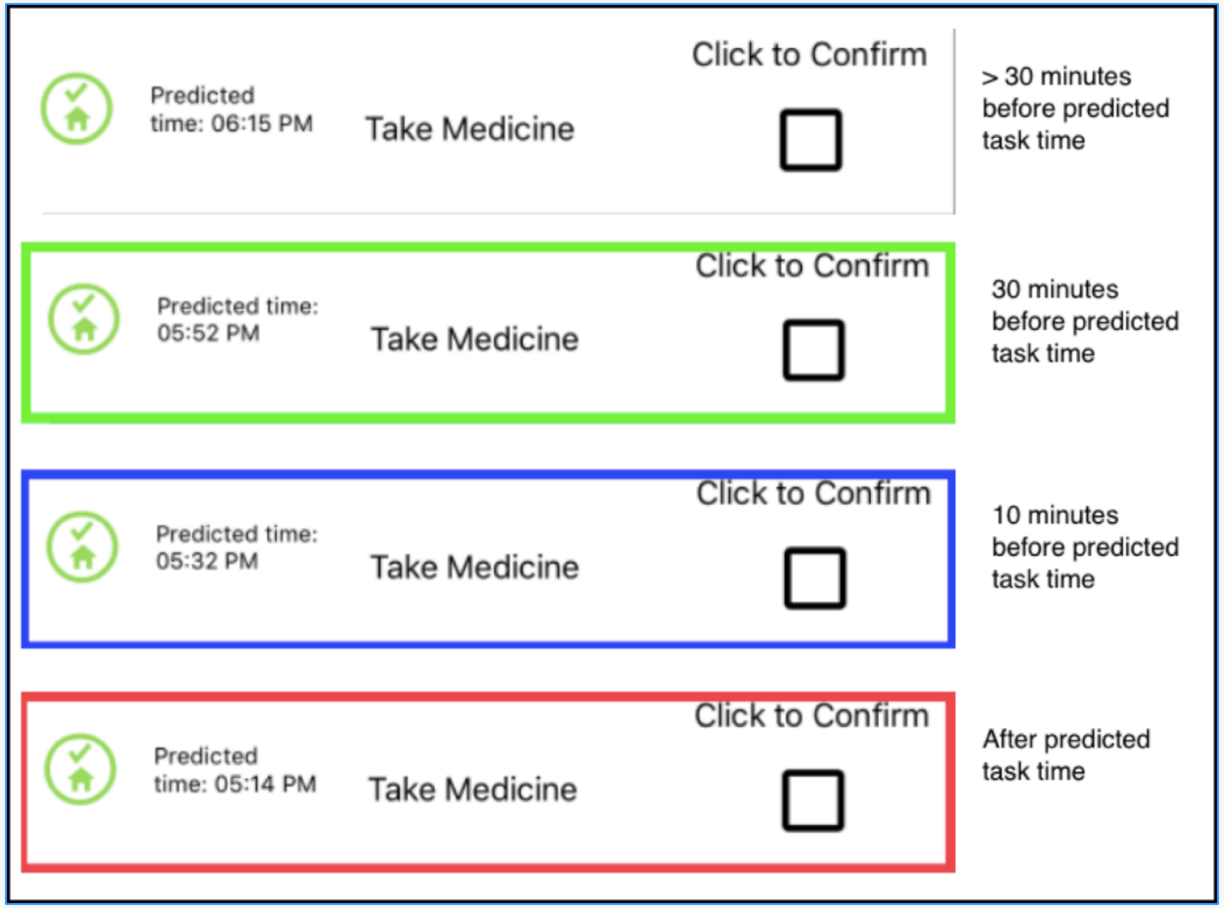
Health event	Indirectly-supervised (CIL)	Unsupervised (iForest)	Supervised (SVM)
Fall, nocturia, depression/sleep, depression/speed, depression/sit, weakness	0.133	0.064	0.047

gmean

Intervene: EMMA

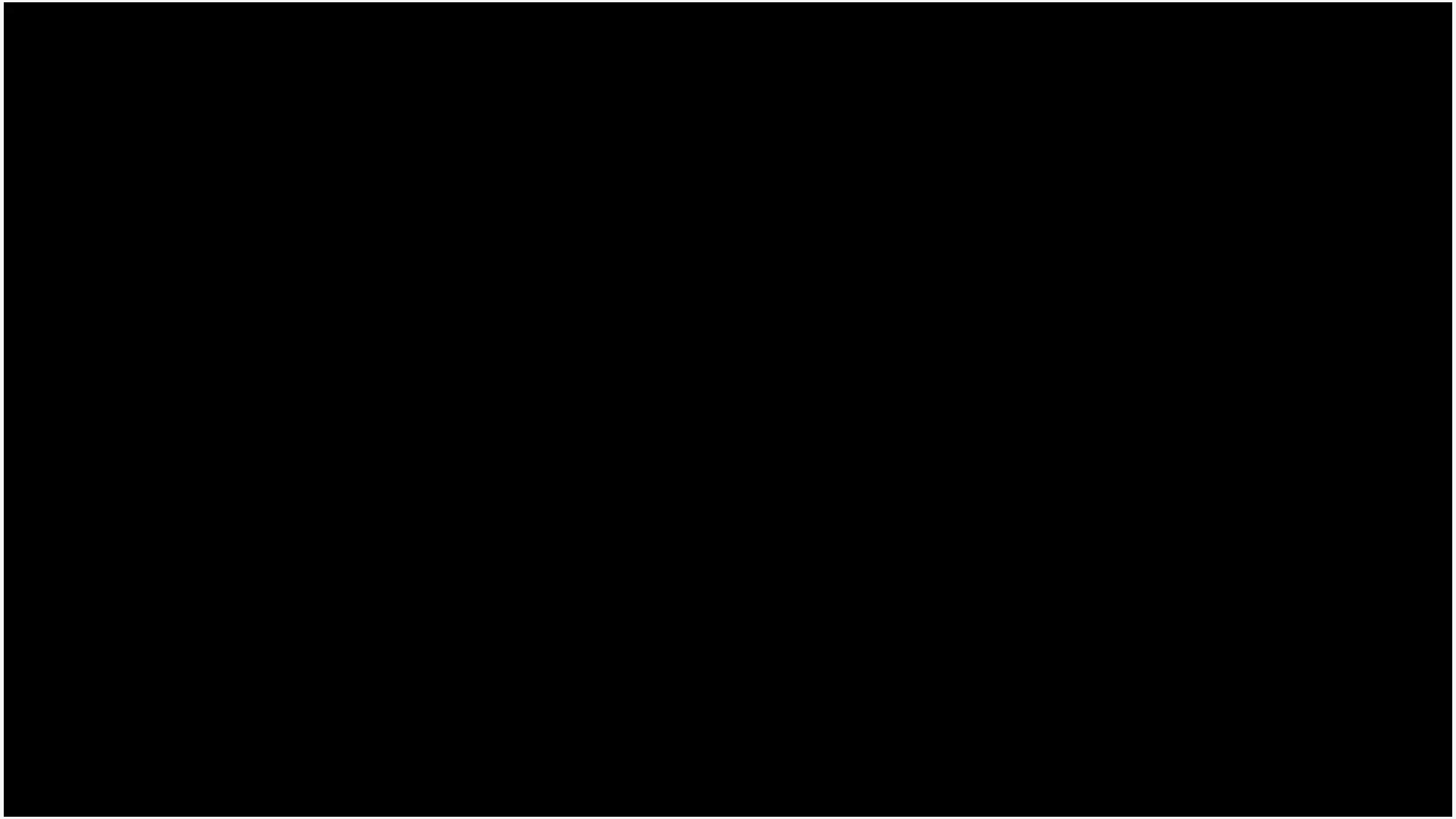






[Dis Rehab 2020, Gerontech 2019]

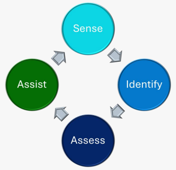
Digital Memory Notebook

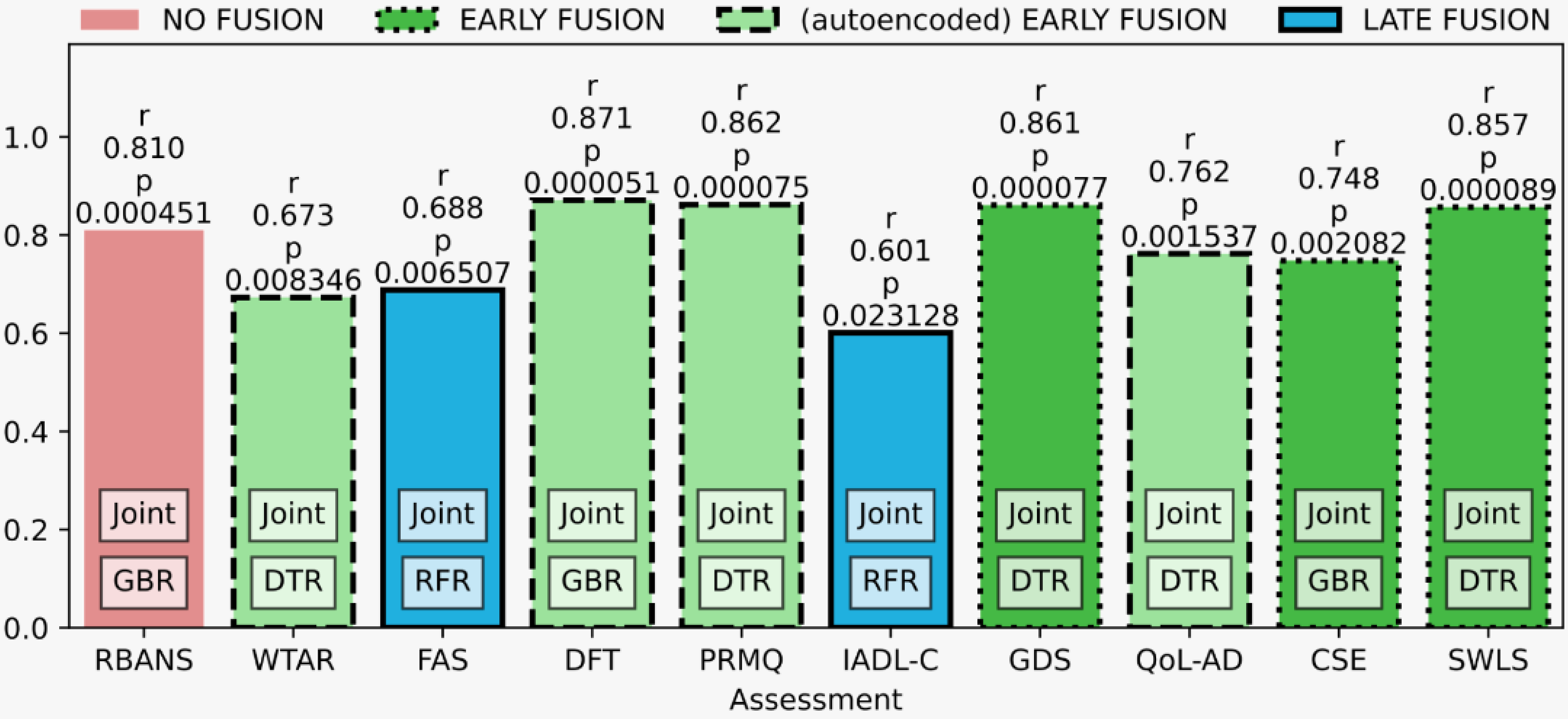


[Alz Disease 2022, Geron 2021]

From Intervene to Assess

(n=14 subjects with amnestic MCI; mean age 74; 10f, 4m)

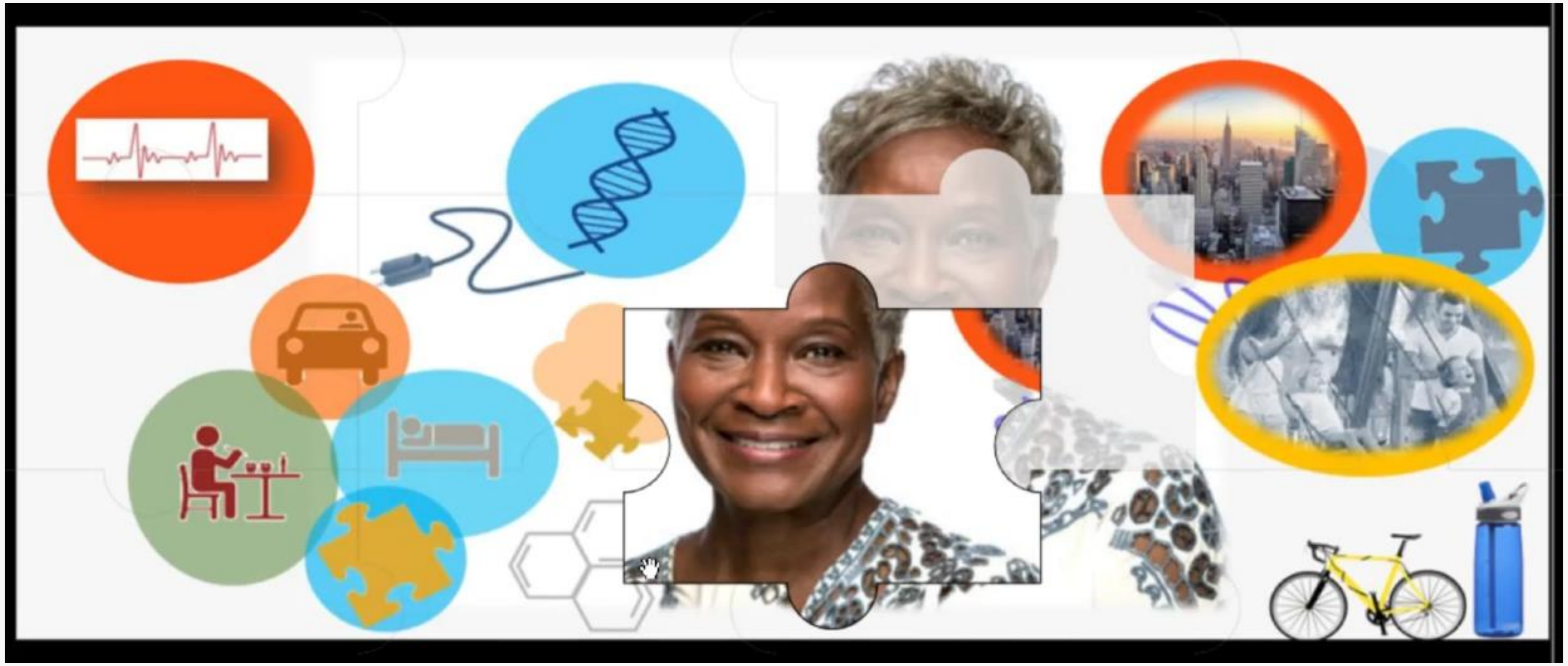


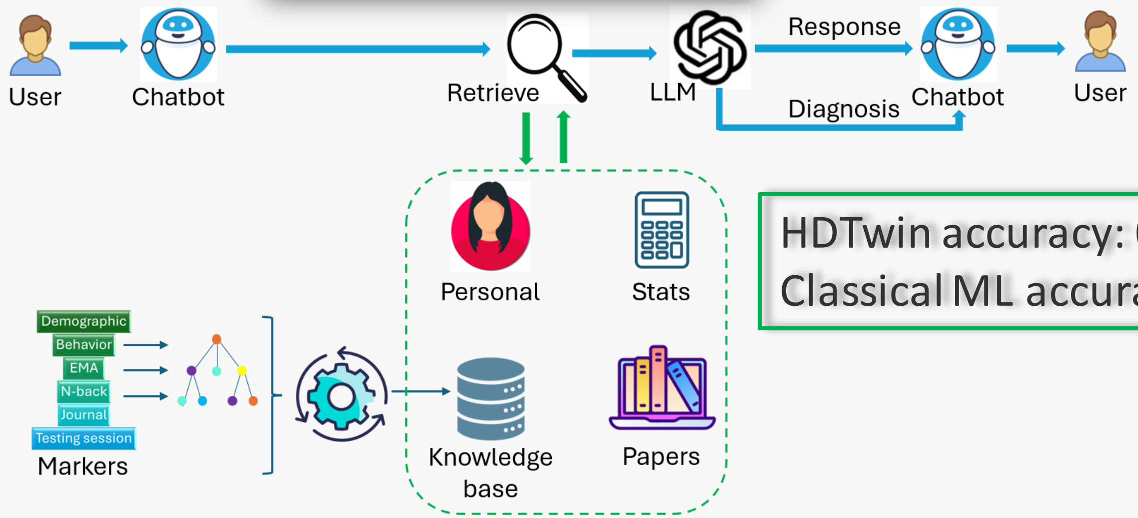


[ACM Health 2022]

LLMs as the Puzzle Glue

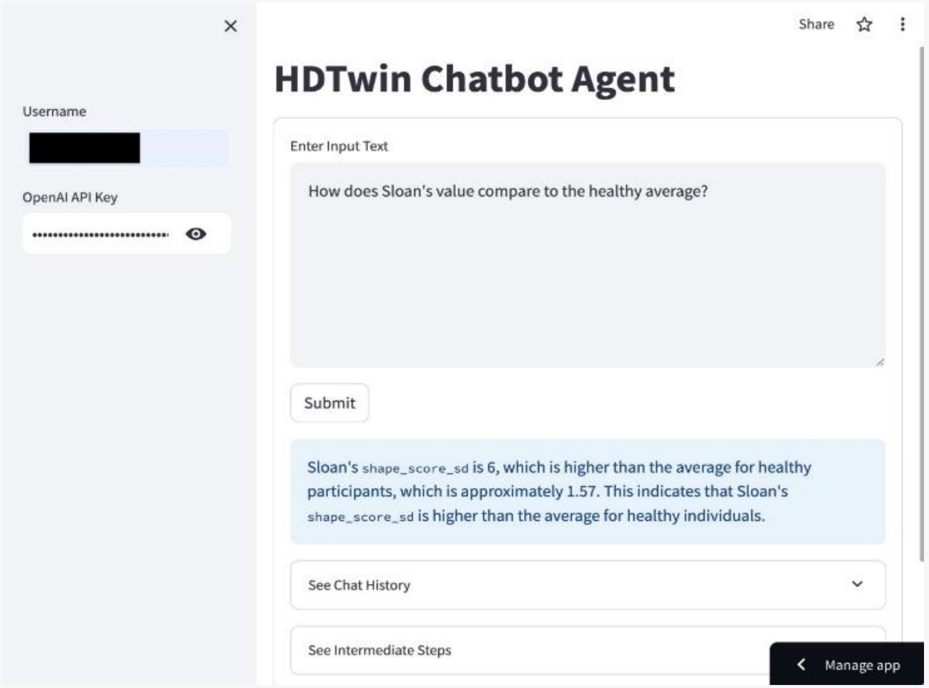
HDTWIN
DIGITAL TWIN



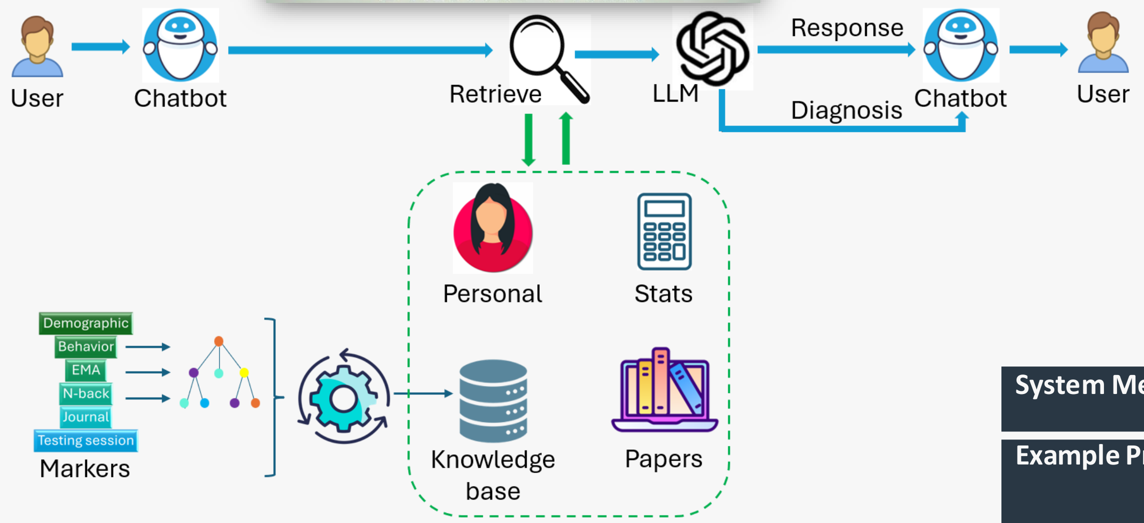


HDTwin accuracy: 0.77
Classical ML accuracy: 0.64

- Demographic markers
- Behavior markers
- EMA markers
- N-back markers
- Speech markers (audio journal)
- Testing session markers (text)
- Prior research (paper abstracts)



[ACM Health 2025, JMIR 2024]



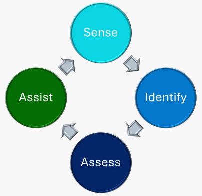
- Demographic markers
- Behavior markers
- EMA markers
- N-back markers
- Speech markers (audio journal)
- Testing session markers (text)
- Prior research (paper abstracts)

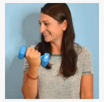
System Message	**You are a knowledgeable health assistant designed to diagnose someone as "healthy" or "mild cognitive impairment" using diagnosis rules and relevant personal information.**
Example Prompt	Diagnose Sloan as healthy or mild cognitive impairment by applying the following rules to Sloan's information. Diagnosis Rules Sloan's Information: shape_learning_rate: 9 shape_score_sd: 6 journal_text: made a list and went to the store and got everything on it and didn't alter from it interview_assessment: Category Fluency (Animals): Participant's Answer: "turkey" Rating: 2 <text removed for brevity> Answer using the format: Diagnosis: ... Explanation: ...
Example Response	Diagnosis: Mild Cognitive Impairment Explanation: Based on the provided information, Sloan's shape_score_sd is 6, which is greater than 2.5, and the shape_learning_rate is 9, indicating a high learning rate. According to Rule #3, when shape_score_sd is greater than 2.5 and shape_learning_rate is higher than 1.5, the individual is more likely to have mild cognitive impairment. Additionally, some of Sloan's interview_assessment ratings are <= 3, such as the ratings for Category Fluency (Animals) and Letter Fluency (F), further supporting the diagnosis of mild cognitive impairment.

HDTwin accuracy: 0.77
Classical ML accuracy: 0.64

Takeaways

- Machine learning empowers digital twins
- Digital twins improve health assessment and intervention
- LLMs can assist with DT creation, ML explanation
- Digital twins can improve traditional methods
- This is hard! Many challenges remain





Thank you

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