IJCCI 2026
AGENTICS ECTA EXPLAINS FCTA NCTA
18th International Joint Conference on Computational Intelligence
Angers, France 28 - 30 October, 2026

Advancing Explainable AI for Mental Health Monitoring

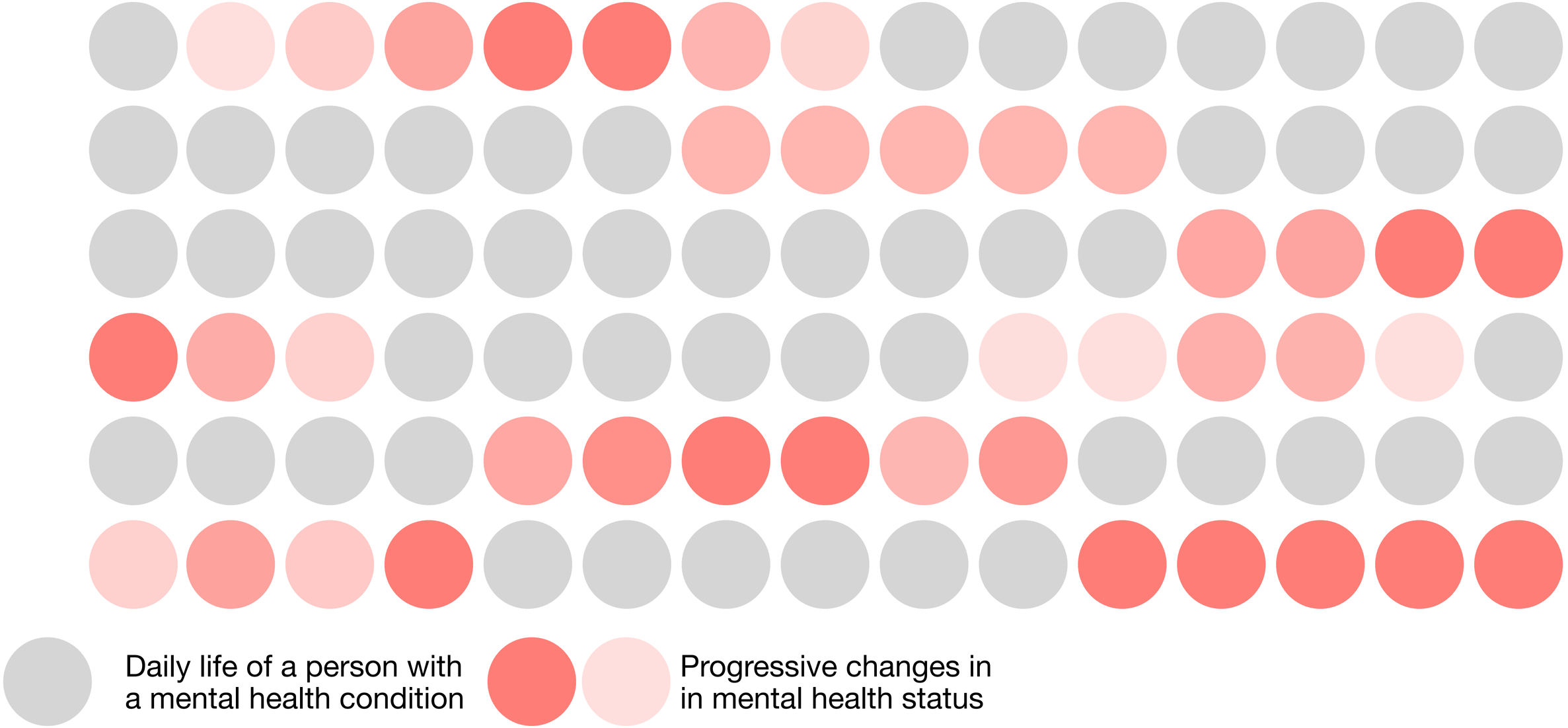
Gabriella Casalino

gabriella.casalino@uniba.it





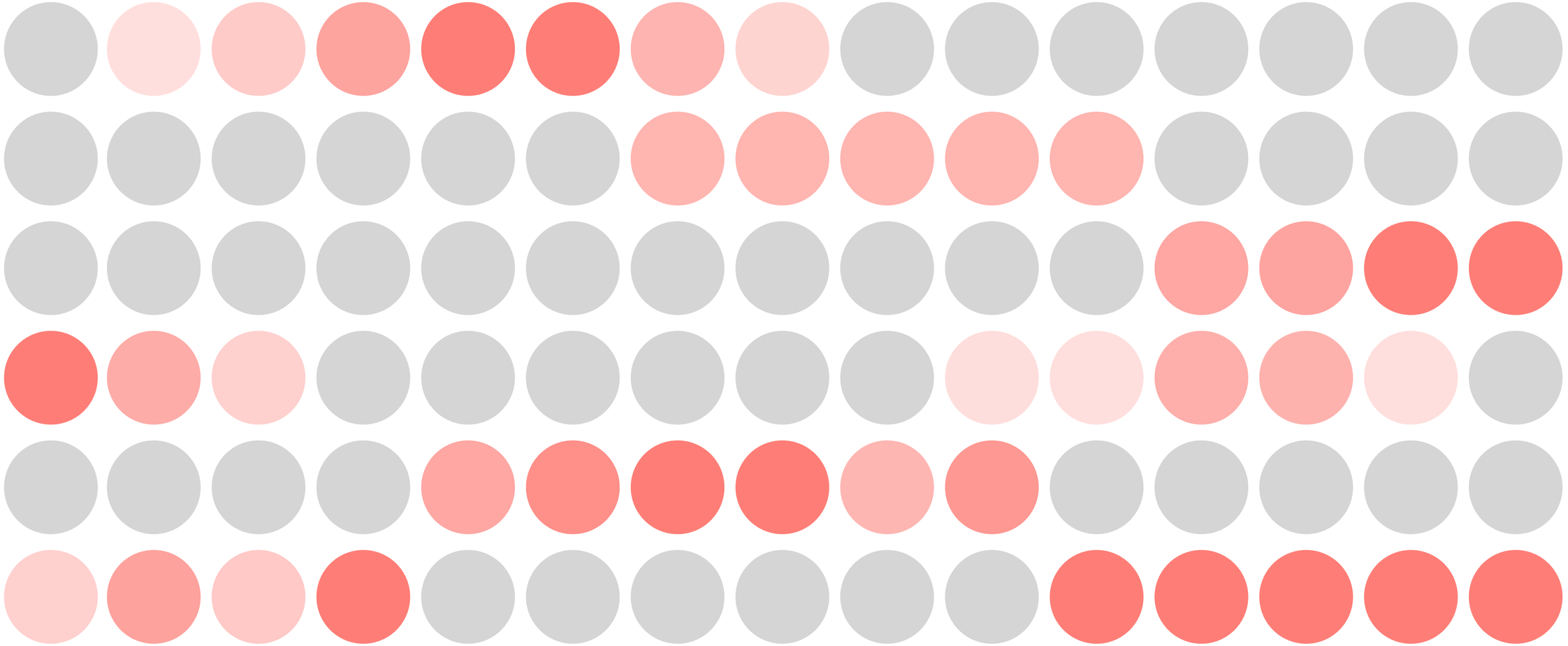
Mental health is not static



Daily life of a person with a mental health condition

Progressive changes in in mental health status

What do clinicians actually see?

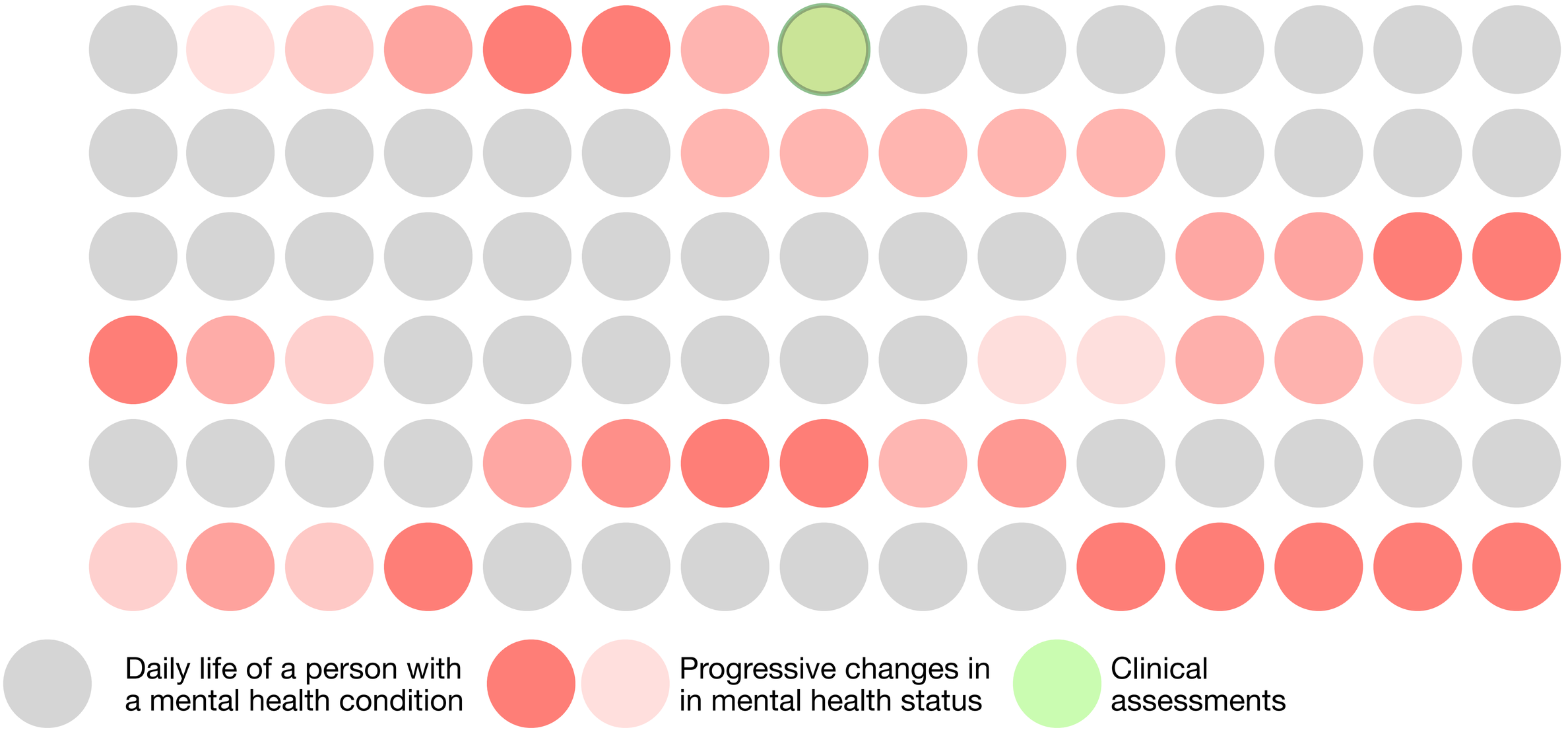


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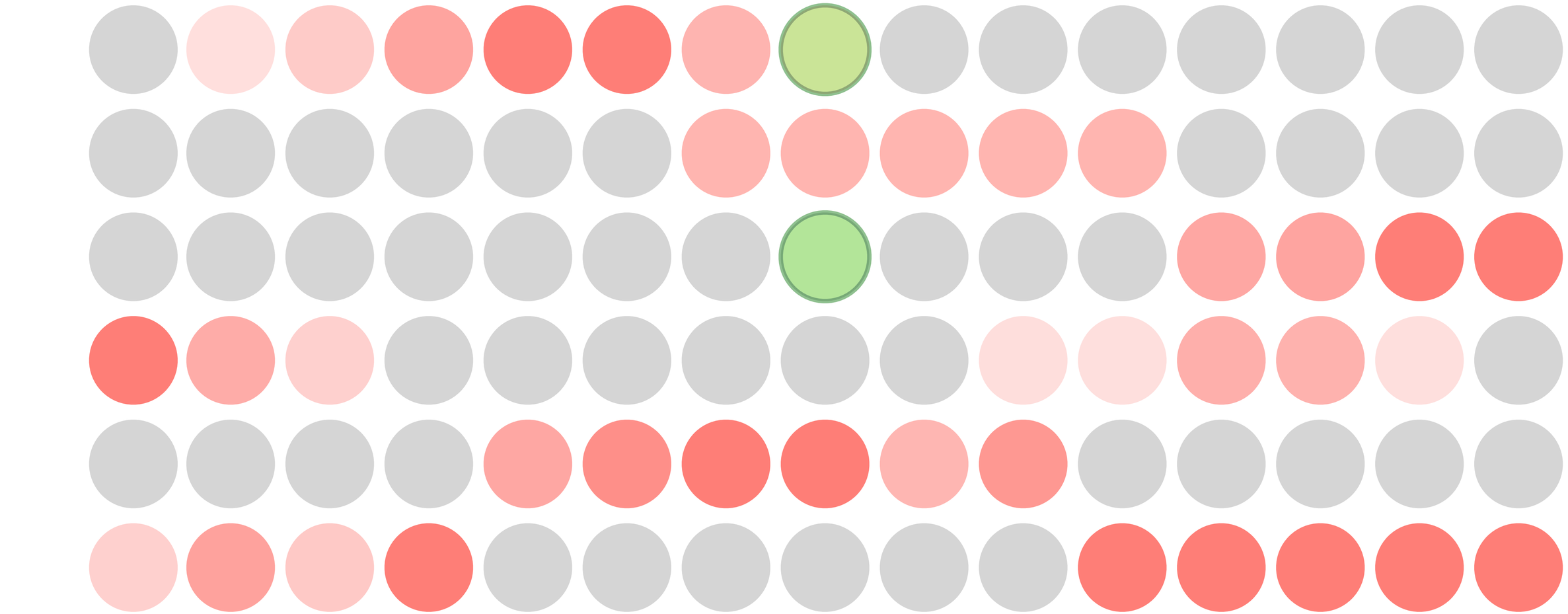
Progressive changes in in mental health status

Clinical assessments

What do clinicians actually see?



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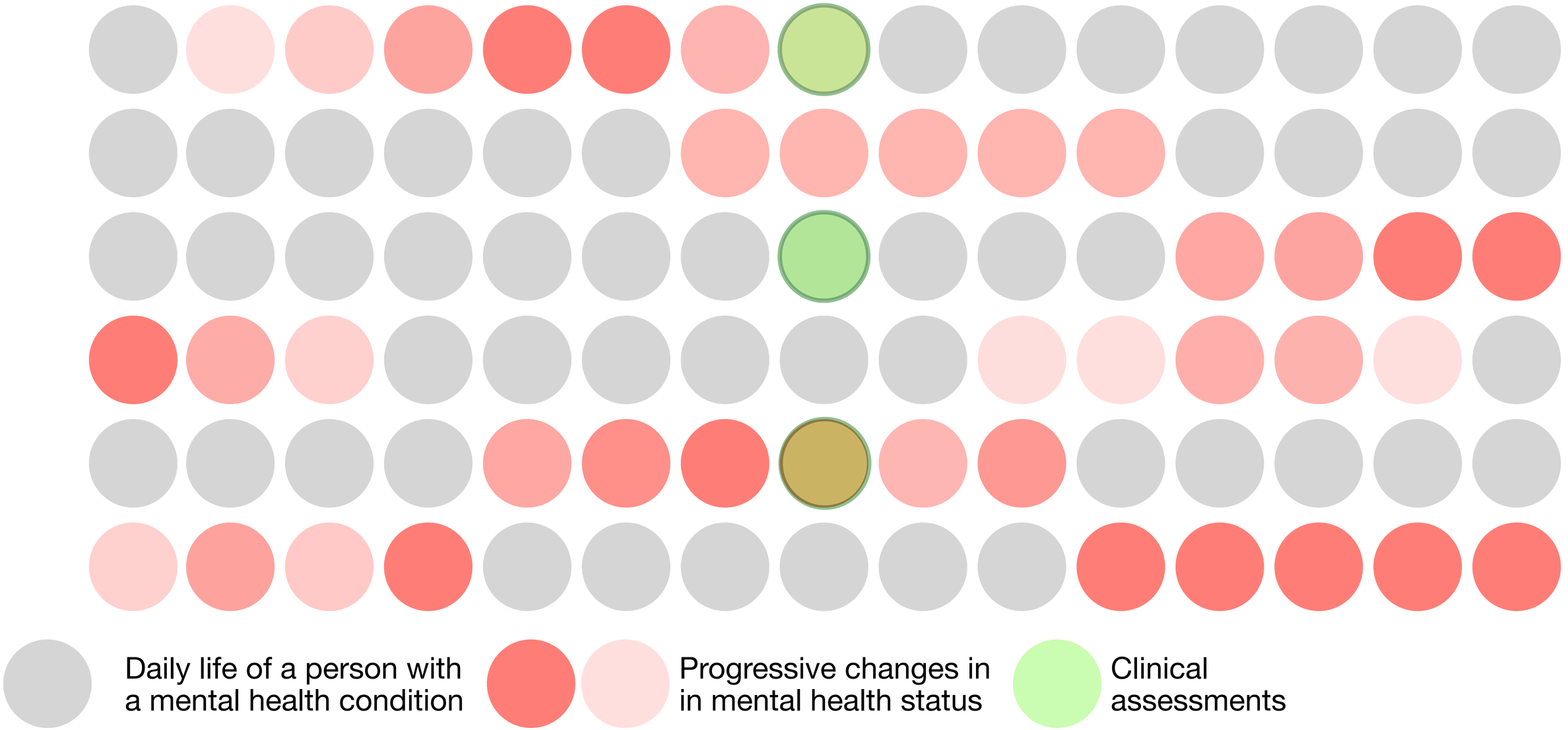


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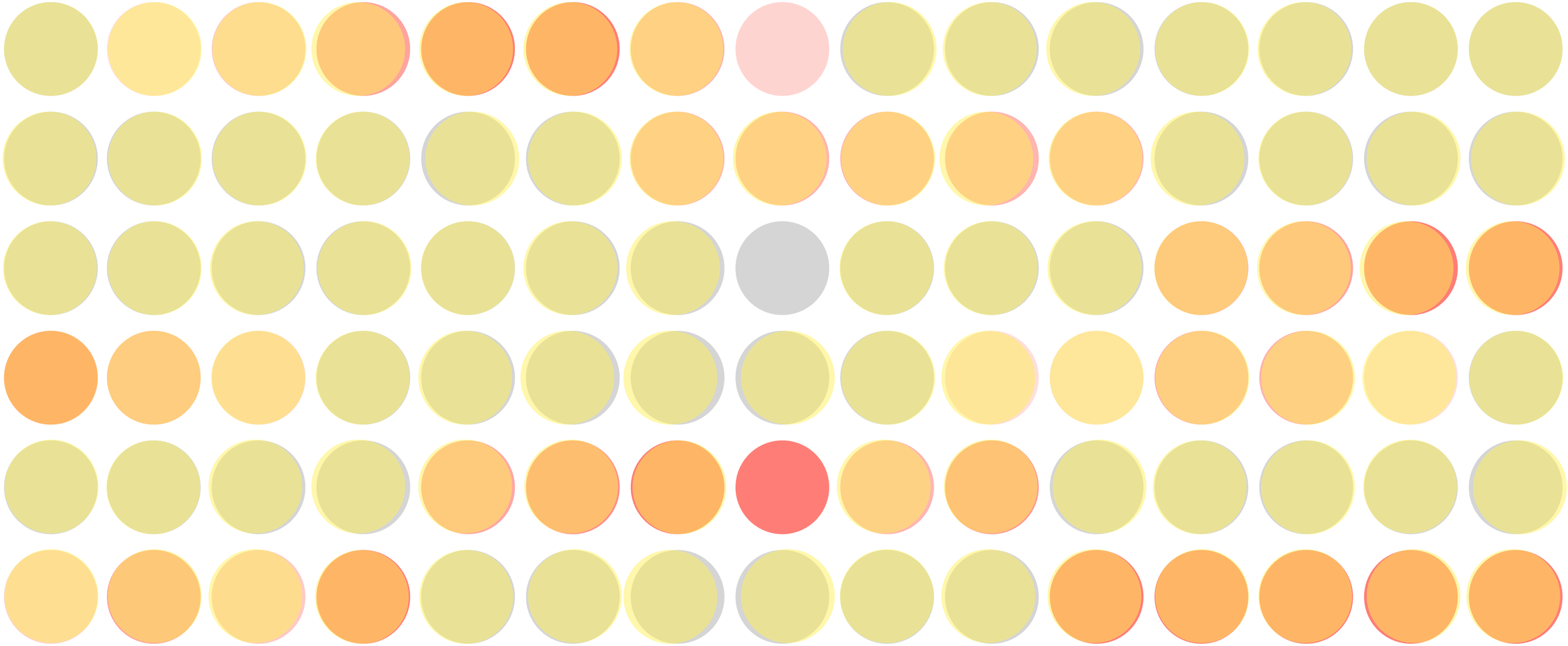
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What do clinicians actually see?



From snapshots to continuous monitoring



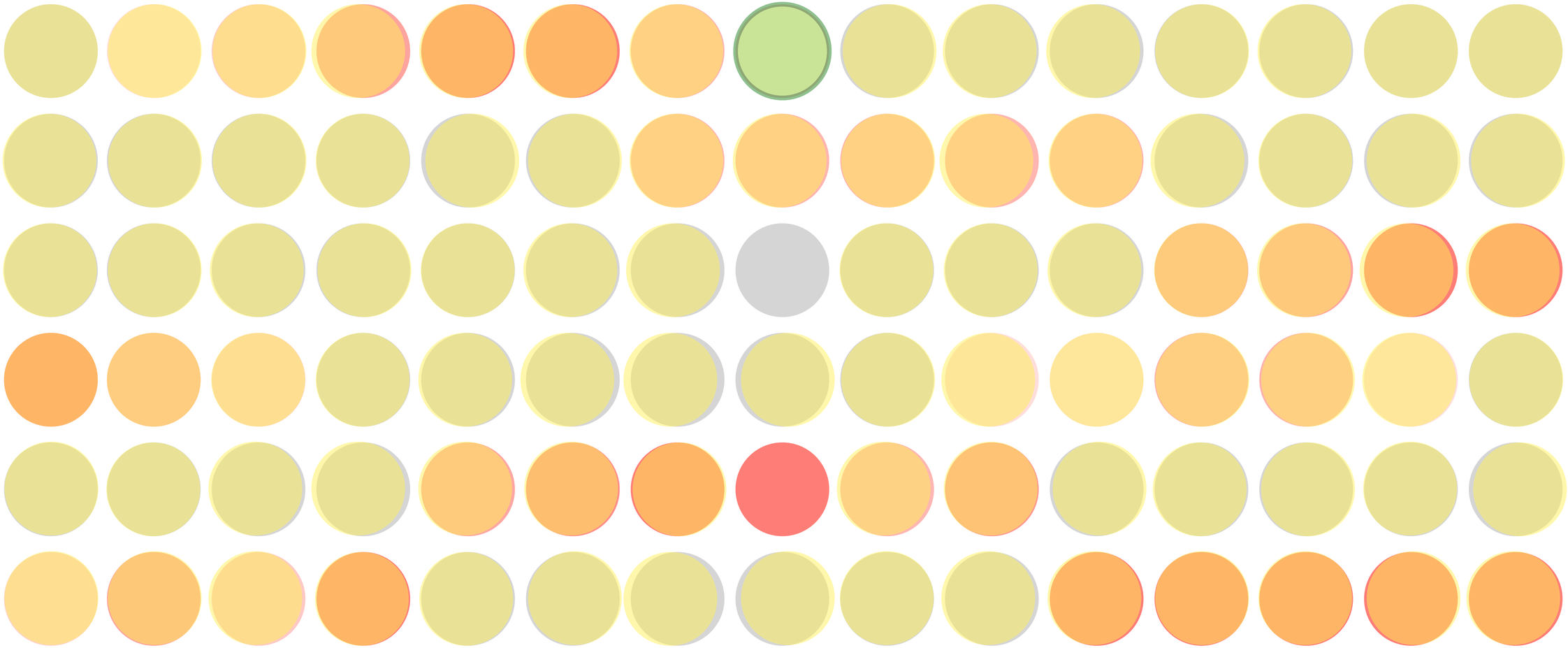
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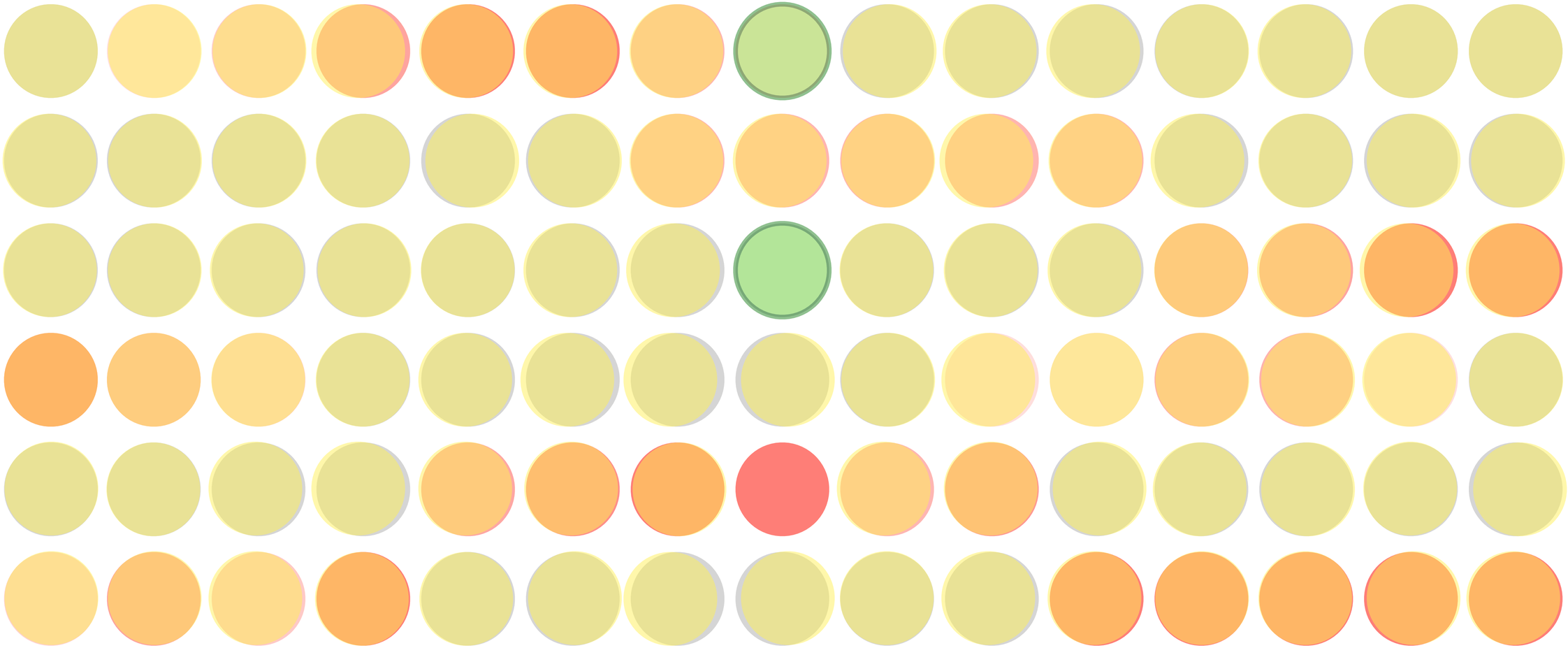
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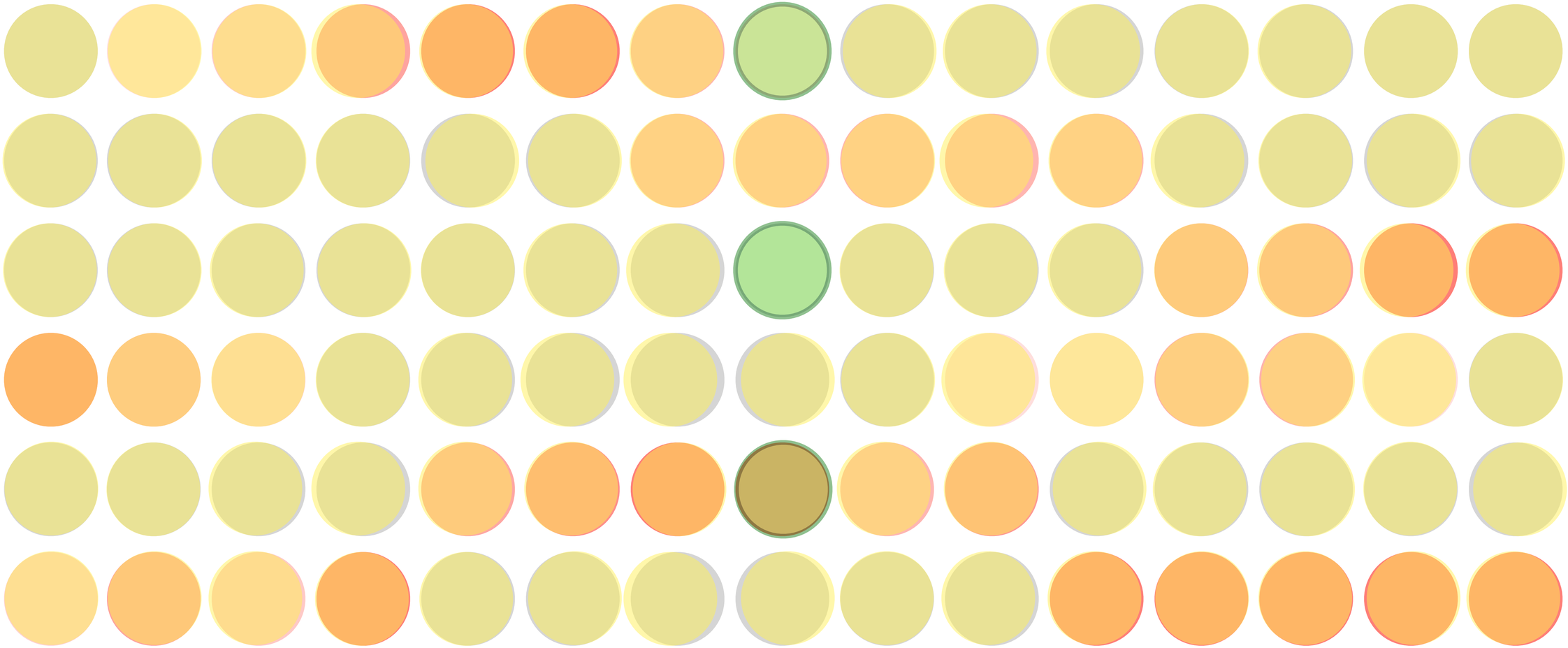
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Daily life of a person with a mental health condition

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Clinical assessments

Daily monitoring

Which signals can help us monitor mental health?



Which signals can help us monitor mental health?

😴 Sleep



Which signals can help us monitor mental health?

😴 Sleep









🚶 Mobility & Activity

Which signals can help us monitor mental health?

😴 Sleep





🚶 Mobility & Activity





⌚ Physiological Signals

Which signals can help us monitor mental health?

😴 Sleep





🚶 Mobility & Activity

📱 Smartphone Usage





⌚ Physiological Signals

Speech as a window into mental health



Speech as a window into mental health

Naturally produced



Speech as a window into mental health

Naturally produced

Non-invasive



Speech as a window into mental health

Naturally produced

Non-invasive



Everyday devices

Speech as a window into mental health

Naturally produced

Non-invasive



Everyday devices

Behavioral and cognitive state

Bipolar Disorder



Mood Changes Can Be Heard in the Voice

"The greater the severity of mania in males, the louder and higher the tone of voice, more clearly, and more sharply they speak, and their conversations are longer"

"The greater the severity of bipolar depression in males, the quieter and less clearly they speak"

Briganti, G., & Lechien, J. R. (2025). Speech and voice quality as digital biomarkers in depression: a systematic review. Journal of Voice.

Kaczmarek-Majer, K., Dominiak, M., Antosik, A. Z., Hryniewicz, O., Kamińska, O., Opara, K., ... & Święcicki, Ł. (2025). Acoustic features from speech as markers of depressive and manic symptoms in bipolar disorder: A prospective study. *Acta Psychiatrica Scandinavica*, *151*(3), 358-374.

Capturing speech in the real world





BIPOLAR

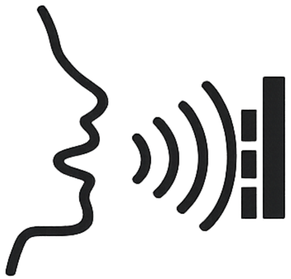
ExplainMe

What information is hidden in speech?

Loudness-related features

Energy

Loudness



Describe the overall strength and perceived intensity of the voice

Spectral-related features

Fftmag spectral flux

Fftmag spectral centroid

Fftmag spectral harmonicity



Describe how the tone and intensity of the voice change over time

Pitch-related features

F0 envelope

F0 final



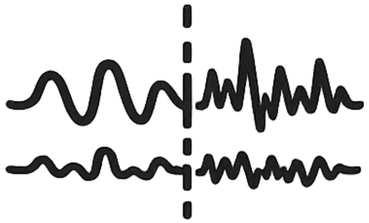
Capture changes in how high or low the voice sounds

Voice-related features

Jitter ddp

Jitter local

Shimmer local

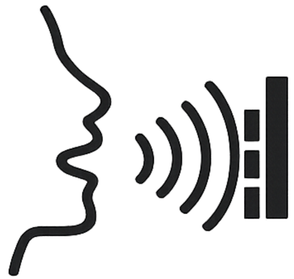


Measure tiny variations in how steady or smooth the voice sounds while speaking

K. Kaczmarek-Majer, G. Casalino, G. Castellano, O. Hryniewicz, M. Dominiak, Explaining Smartphone-based Acoustic Data in Bipolar Disorder: Semi-Supervised Fuzzy Clustering and Relative Linguistic Summaries, Information Sciences, 2021,ISSN 0020-0255, https://doi.org/10.1016/j.ins.2021.12.049

Clinical hypotheses

Loudness-related features



Describe the overall strength and perceived intensity of the voice

Spectral-related features



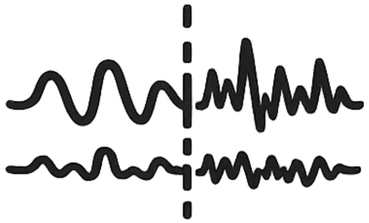
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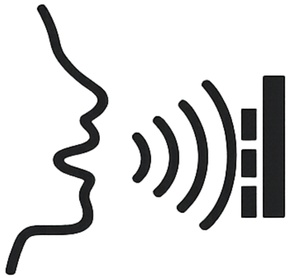
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Patients in affective stated are expected to speak louder compared to euthymia



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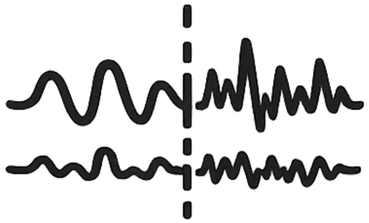
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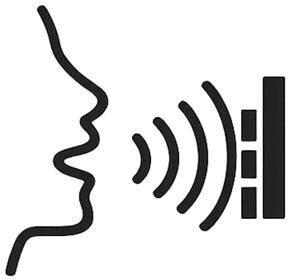
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Patients in the affective state are expected to have lower dynamics of changes in speech signal spectrum



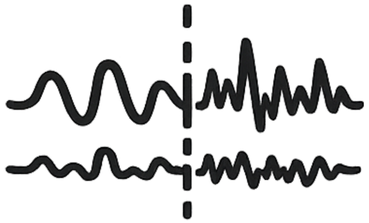
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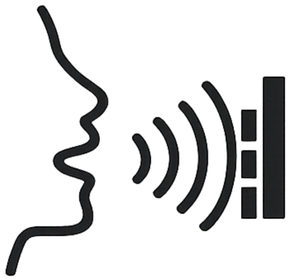
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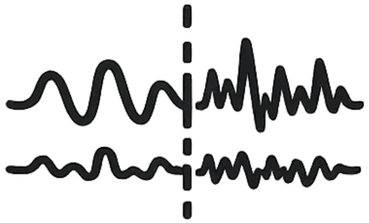
Pitch-related features

Patients in an affective state are expected to speak with a higher or lower tone of voice



Capture changes in how high or low the voice sounds

Voice-related features



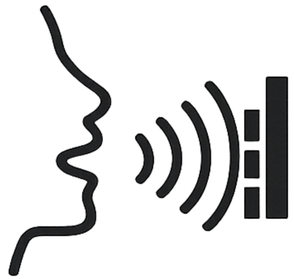
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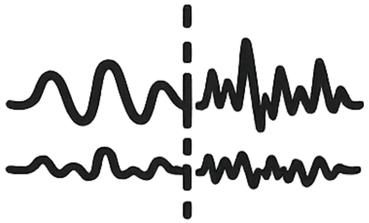
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Voice-related features

Depressive and manic states are associated with distinct patterns of speech production.

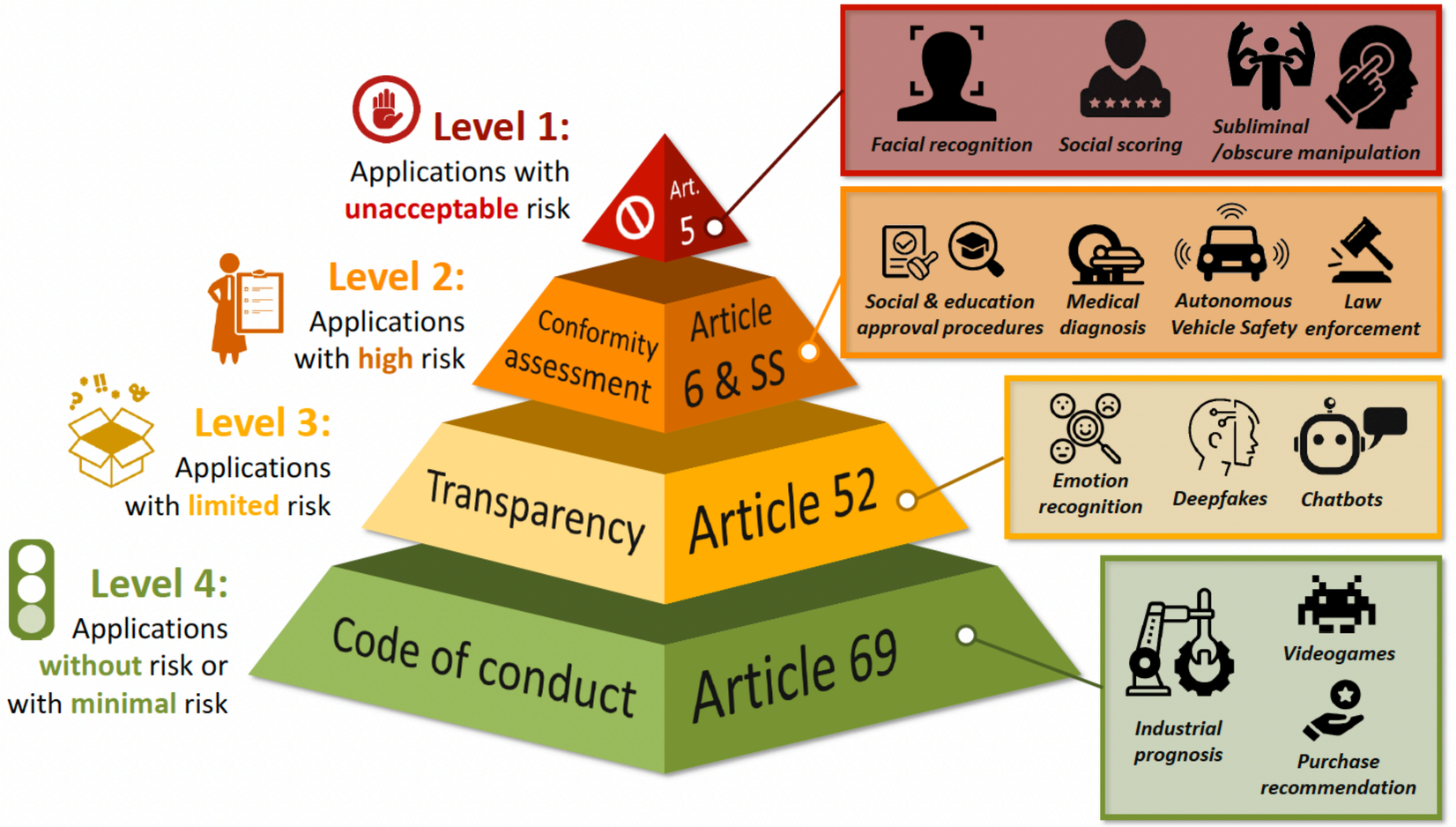


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EU AI ACT

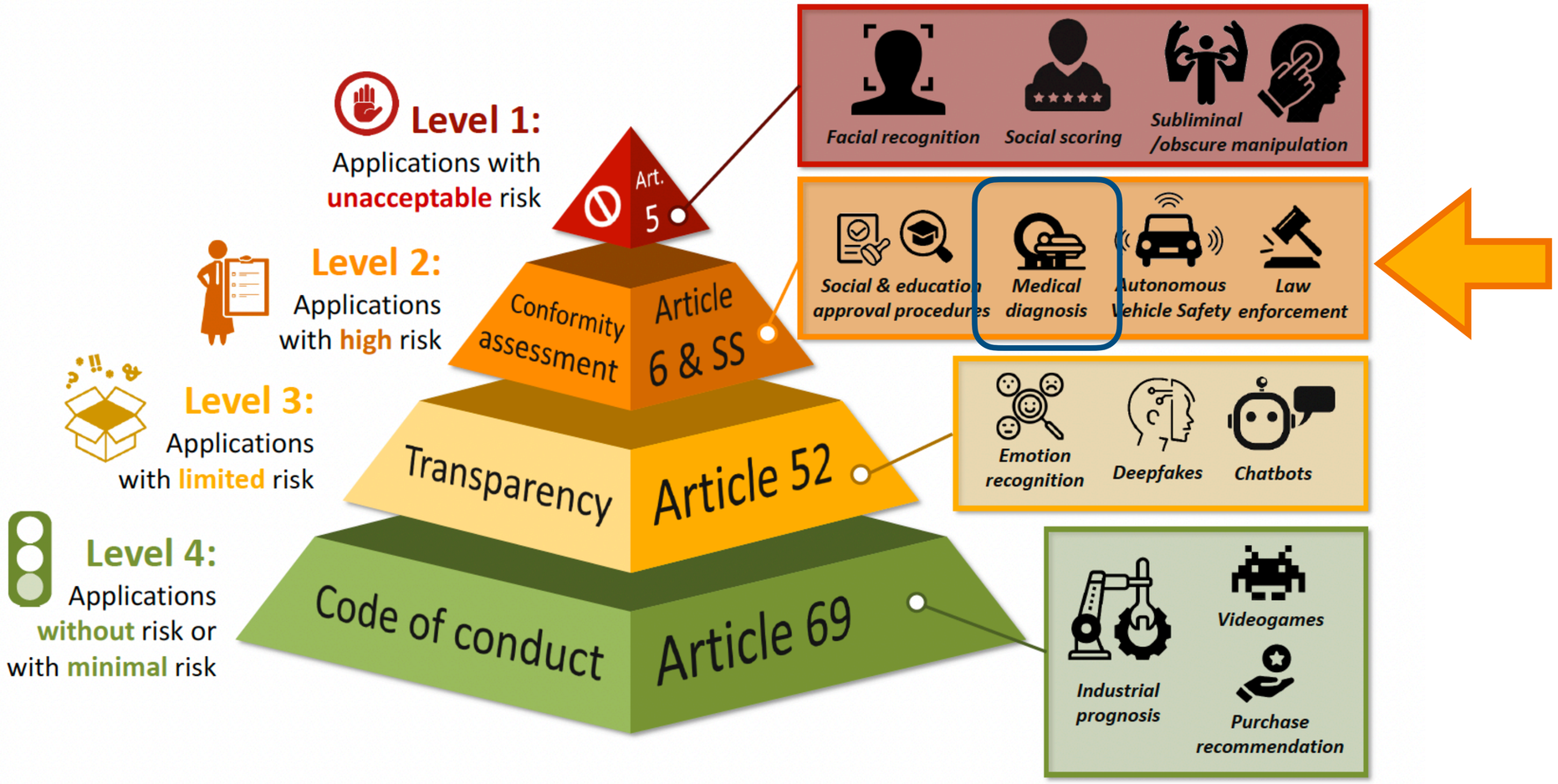
https://www.euractiv.com/section/artificial-intelligence/news/meps-seal-the-deal-on-artificial-intelligence-act/



Díaz-Rodríguez, N., Del Ser, J., Coeckelbergh, M., De Prado, M. L., Herrera-Viedma, E., & Herrera, F. (2023). Connecting the dots in trustworthy Artificial Intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation. Information Fusion, 99, 101896.

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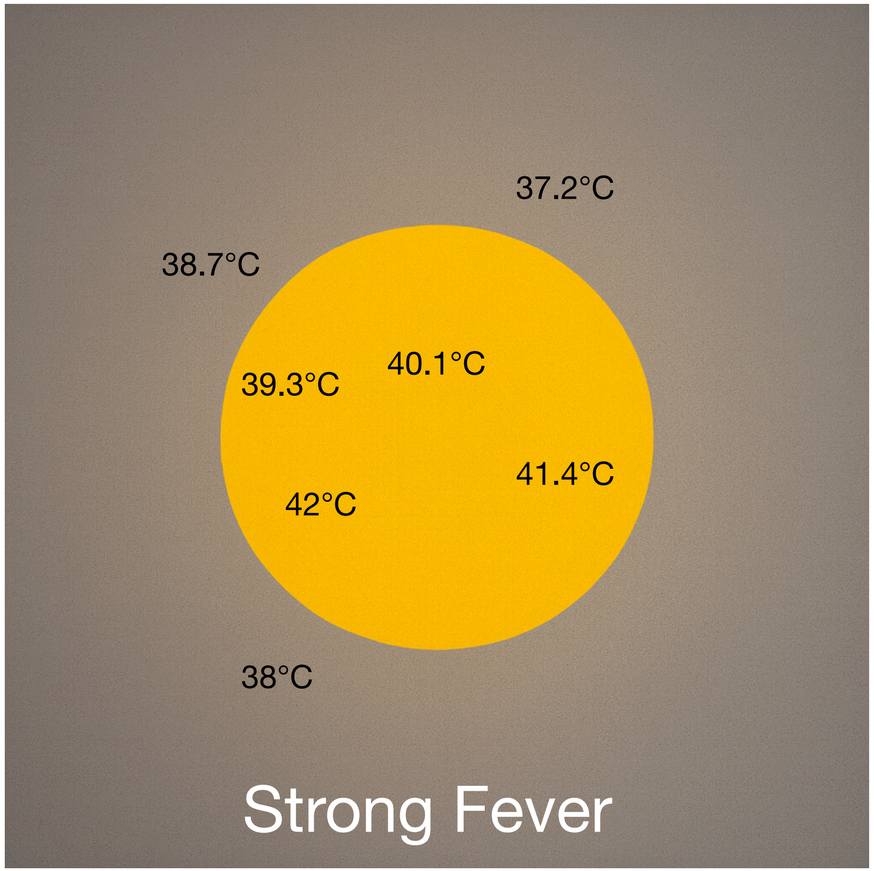
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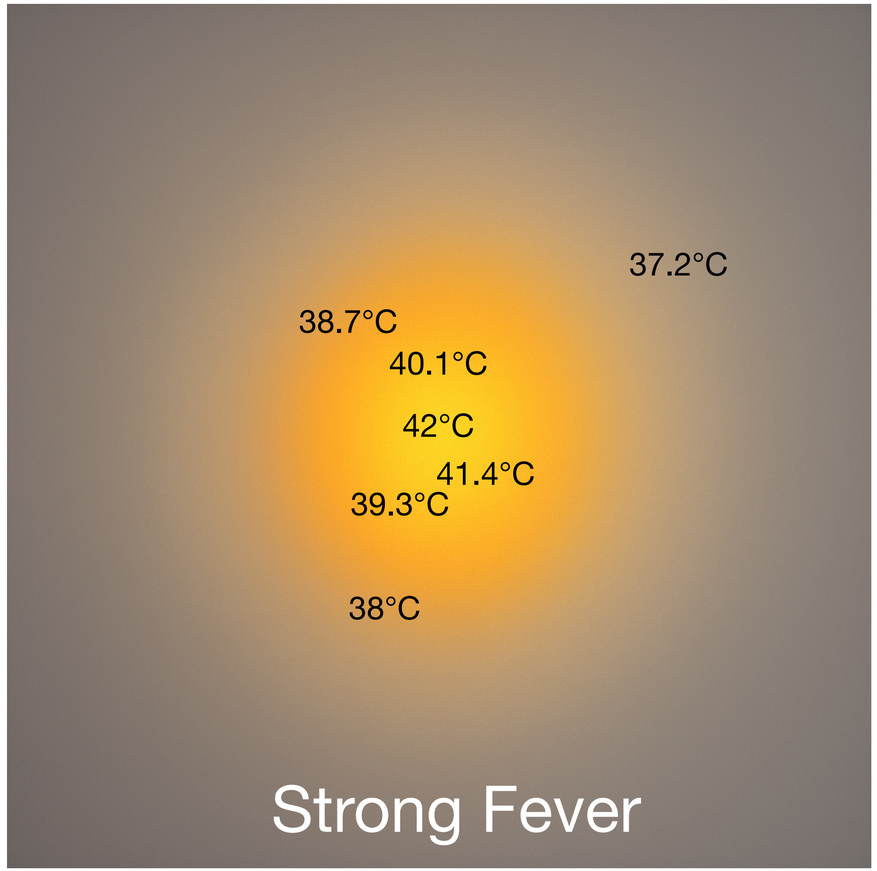
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Fuzzy Set Theory

Conventional Boolean Set Theory



Fuzzy Set Theory



Zadeh, L. A. (2008). Is there a need for fuzzy logic?. *Information sciences*, *178*(13), 2751-2779.

Can AI transform speech into clinically meaningful insights?

Key Research Challenges

Key Research Challenges

Learning under limited clinical supervision

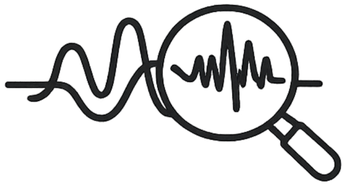


Key Research Challenges

Learning under limited clinical supervision



Making acoustic biomarkers explainable to clinicians

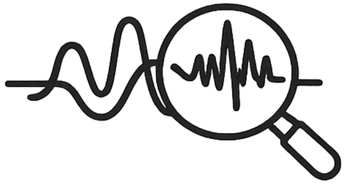


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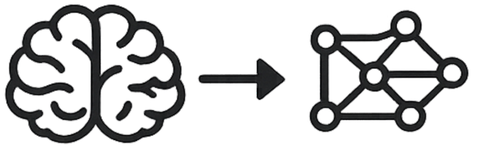
Learning under limited clinical supervision



Making acoustic biomarkers explainable to clinicians



Bringing clinical knowledge into AI models

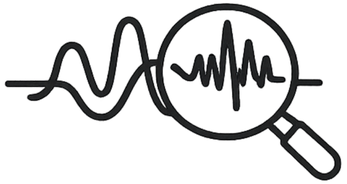


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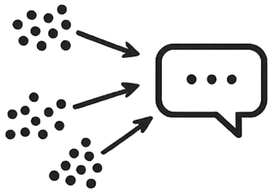
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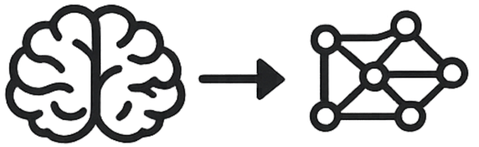
Making acoustic biomarkers explainable to clinicians



Understanding and communicating latent patterns

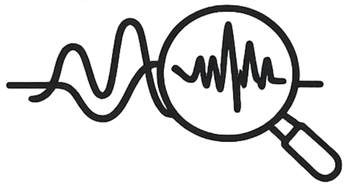


Bringing clinical knowledge into AI models



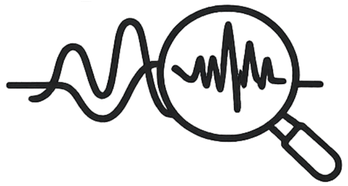
Learning from Limited Supervision and Explaining Acoustic Biomarkers





Learning from Limited Supervision and Explaining Acoustic Biomarkers





How can we transform evolving and partially labeled data into meaningful and explainable insights?

DISSFCM

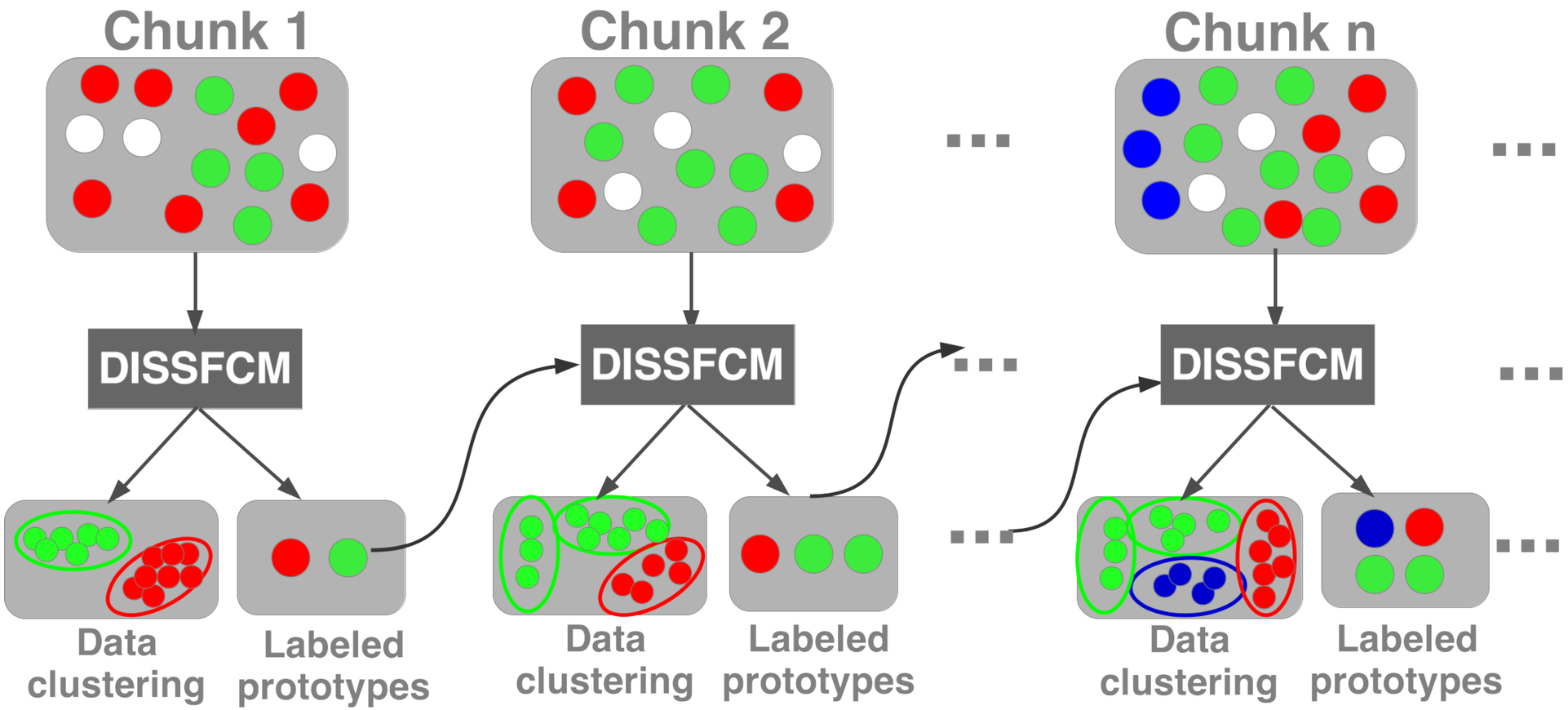
- **DISSFCM:** Dynamic Incremental Semi-Supervised Fuzzy C-Means
- a method for evolving data classification that
  - Operates **incrementally** on subsequent non-overlapping chunks
  - Dynamically **adapts the number of clusters and classes** (via splitting mechanism)
  - Processes **partially labeled data**
- Based on SSFCM - Semi-Supervised FCM (Pedrycz and Waletzky, 1997)

Supervised component

$$J = \sum_{k=1}^{K}\sum_{j=1}^{N_t} u_{jk}^m d_{jk}^2 + \alpha \sum_{k=1}^{K}\sum_{j=1}^{N_t} (u_{jk} - b_j f_{jk})^m d_{jk}^2$$

G. Casalino, G. Castellano, C. Mencar, (2019) Data stream classification by dynamic incremental semi-supervised fuzzy clustering, in International Journal on Artificial Intelligence Tools (IJAIT), ISSN 02182130, Vol. 28, No. 8 (2019) 1960009, World Scientific Publishing Company, DOI: 10.1142/S0218213019600091

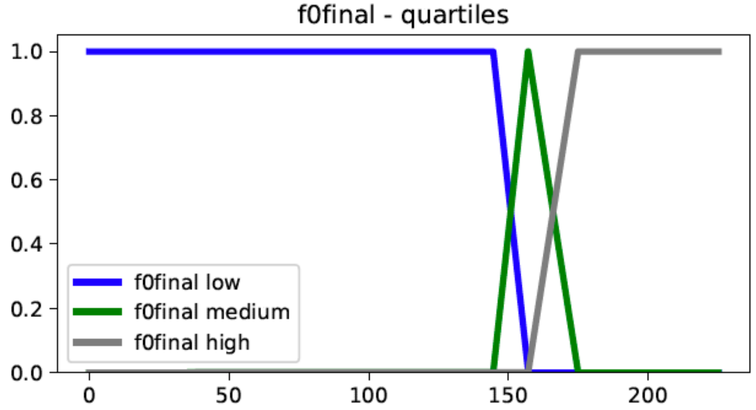
DISSFCM


Chunk 1
Chunk 2
Chunk n
DISSFCM
DISSFCM
DISSFCM
Data clustering
Labeled prototypes
Data clustering
Labeled prototypes
Data clustering
Labeled prototypes

Linguistic summaries with fuzzy clustering (LS-FC)

“Most calls in the state of mania have low spectrum compared to the state of euthymia”

1. Fuzzification of acoustic features using clusters prototypes learned by DISSFCM



2. Granulation of the acoustic features

- Pitch
- Spectrum
- Loudness
- Quality of voice

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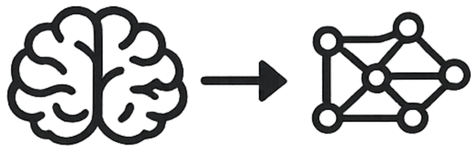
3. Derivation of the Linguistic Summaries

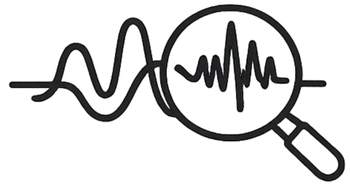
Relative LS based on short protoform	*T*
Most calls in the state of mania have low spectrum compared to the state of euthymia.	1.0
Most calls in the state of mania have low quality compared to the state of euthymia.	1.0
Most calls in the state of hypomania have low spectrum compared to the state of euthymia.	1.0
Most calls in the state of hypomania have low loudness compared to the state of euthymia.	1.0
Most calls in the state of hypomania have low qualty compared to the state of euthymia.	1.0
Relative LS based on extended protoform - HYPOMANIA	*T*
Most calls with low loudness in hypomania have low spectrum compared to the state of euthymia.	1.0
Most calls with low loudness in hypomania have low quality compared to the state of euthymia.	1.0
Most calls with high loudness in hypomania have high spectrum compared to the state of euthymia.	1.0
Most calls with high loudness in hypomania have high quality compared to the state of euthymia.	1.0
Most calls with low pitch in hypomania have low spectrum compared to the state of euthymia.	1.0
Most calls with low pitch in hypomania have low loudness compared to the state of euthymia.	1.0
Most calls with low pitch in hypomania have low quality compared to the state of euthymia.	1.0
Most calls with low spectrum in hypomania have low loudness compared to the state of euthymia.	1.0
Most calls with low spectrum in hypomania have low quality compared to the state of euthymia.	1.0
Most calls with high spectrum in hypomania have high loudness compared to the state of euthymia.	1.0
Most calls with high spectrum in hypomania have high quality compared to the state of euthymia.	1.0
Most calls with low quality in hypomania have low loudness compared to the state of euthymia.	1.0
Most calls with low quality in hypomania have low spectrum compared to the state of euthymia.	1.0
Most calls with high quality in hypomania have high loudness compared to the state of euthymia.	1.0
Most calls with high quality in hypomania have high spectrum compared to the state of euthymia.	1.0

Relative LS based on extended protoform - MANIA	*T*
Most calls with low loudness in mania have low spectrum compared to the state of euthymia.	1.0
Most calls with low loudness in mania have low pitch compared to the state of euthymia.	0.6
Most calls with low loudness in mania have low quality compared to the state of euthymia.	1.0
Most calls with high loudness in mania have low spectrum compared to the state of euthymia.	1.0
Most calls with low pitch in mania have low spectrum compared to the state of euthymia.	1.0
Most calls with low pitch in mania have low loudness compared to the state of euthymia.	1.0
Most calls with low pitch in mania have low quality compared to the state of euthymia.	1.0
Most calls with low spectrum in mania have low pitch compared to the state of euthymia.	0.7
Most calls with low spectrum in mania have low loudness compared to the state of euthymia.	1.0
Most calls with low spectrum in mania have low quality compared to the state of euthymia.	1.0
Most calls with medium spectrum in mania have high loudness compared to the state of euthymia.	0.8
Most calls with medium spectrum in mania have low quality compared to the state of euthymia.	0.6
Most calls with high spectrum in mania have high loudness compared to the state of euthymia.	1.0
Most calls with low quality in mania have low loudness compared to the state of euthymia.	1.0
Most calls with low quality in mania have low spectrum compared to the state of euthymia.	1.0
Most calls with high quality in mania have high loudness compared to the state of euthymia.	1.0
Most calls with high quality in mania have high spectrum compared to the state of euthymia.	1.0

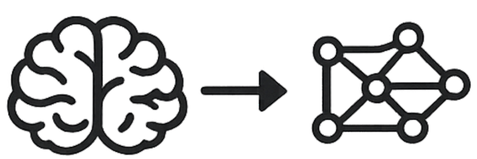
K. Kaczmarek-Majer, G. Casalino, G. Castellano, O. Hryniewicz, M. Dominiak, Explaining Smartphone-based Acoustic Data in Bipolar Disorder: Semi-Supervised Fuzzy Clustering and Relative Linguistic Summaries, Information Sciences, 2021,ISSN 0020-0255, https://doi.org/10.1016/j.ins.2021.12.049

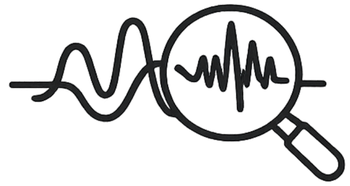
Clinically-Informed Explainable AI





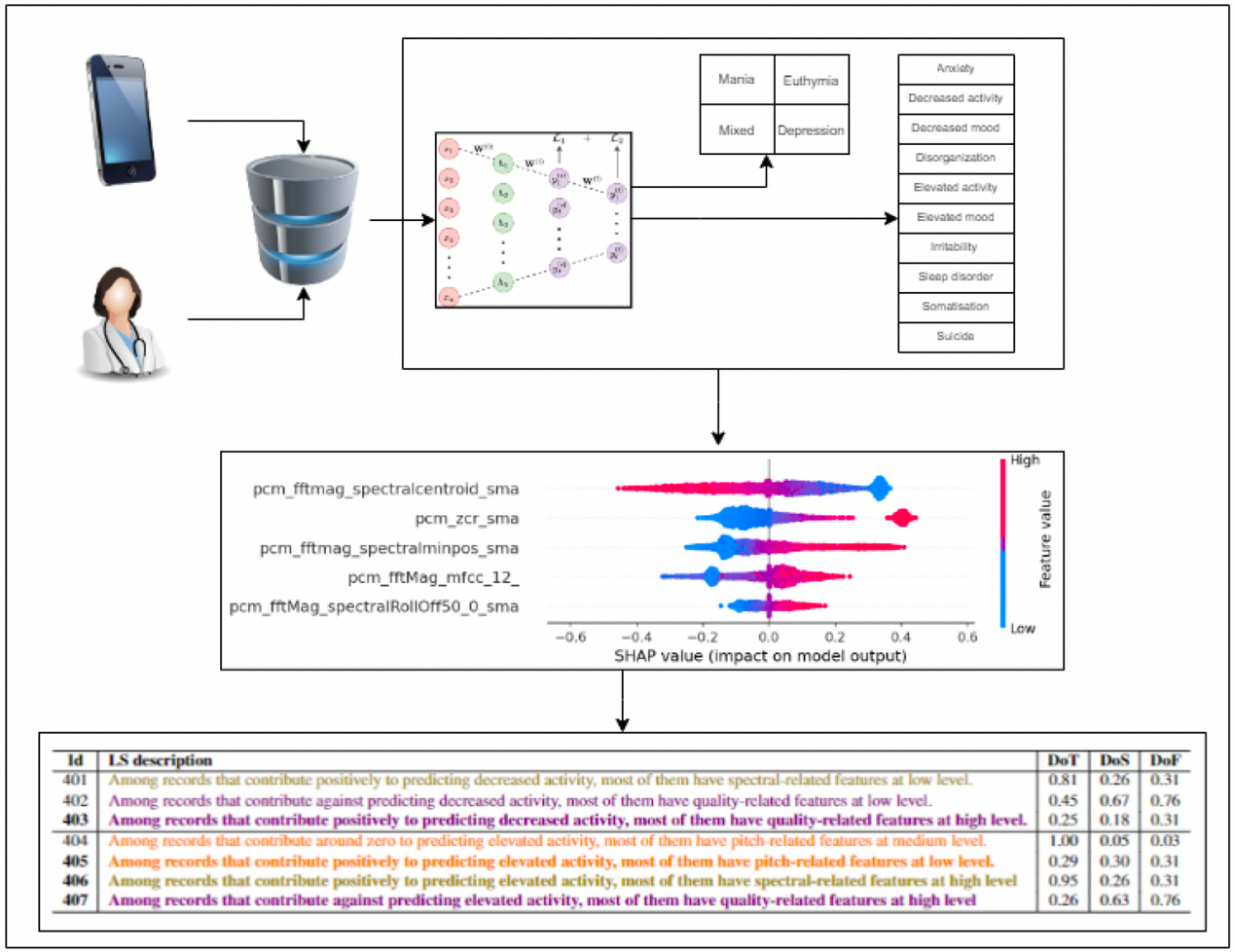
Clinically-Informed Explainable AI





Can clinical knowledge improve AI reasoning?

PLENARY: Explaining black-box models in natural language through fuzzy linguistic summaries



Id	LS description	DoT	DoS	DoF
401	Among records that contribute positively to predicting decreased activity, most of them have spectral-related features at low level.	0.81	0.26	0.31
402	Among records that contribute against predicting decreased activity, most of them have quality-related features at low level.	0.45	0.67	0.76
403	Among records that contribute positively to predicting decreased activity, most of them have quality-related features at high level.	0.25	0.18	0.31
404	Among records that contribute around zero to predicting elevated activity, most of them have pitch-related features at medium level.	1.00	0.05	0.03
405	Among records that contribute positively to predicting elevated activity, most of them have pitch-related features at low level.	0.29	0.30	0.31
406	Among records that contribute positively to predicting elevated activity, most of them have spectral-related features at high level	0.95	0.26	0.31
407	Among records that contribute against predicting elevated activity, most of them have quality-related features at high level	0.26	0.63	0.76

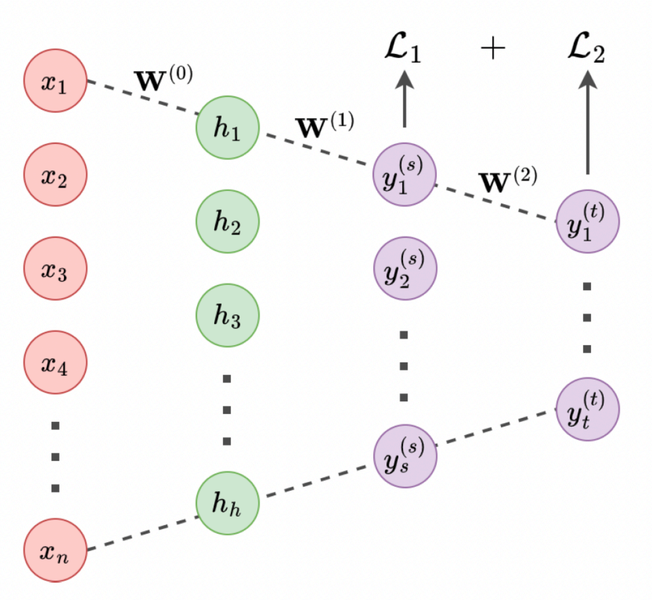
Katarzyna Kaczmarek-Majer, Gabriella Casalino, Giovanna Castellano, Monika Dominiak, Olgierd Hryniewicz, Olga Kamińska, Gennaro Vessio, Natalia Díaz-Rodríguez, PLENARY: Explaining black-box models in natural language through fuzzy linguistic summaries, Information Sciences, Volume 614, 2022, Pages 374-399

PLENARY

STEP1: Creation of a Multi-output sequential and compositional MLP

Symptoms

Anxiety	Elevated mood
Decreased activity	Irritability
Decreased mood	Sleep disorder
Disorganization	Somatisation
Elevated Activity	Suicide



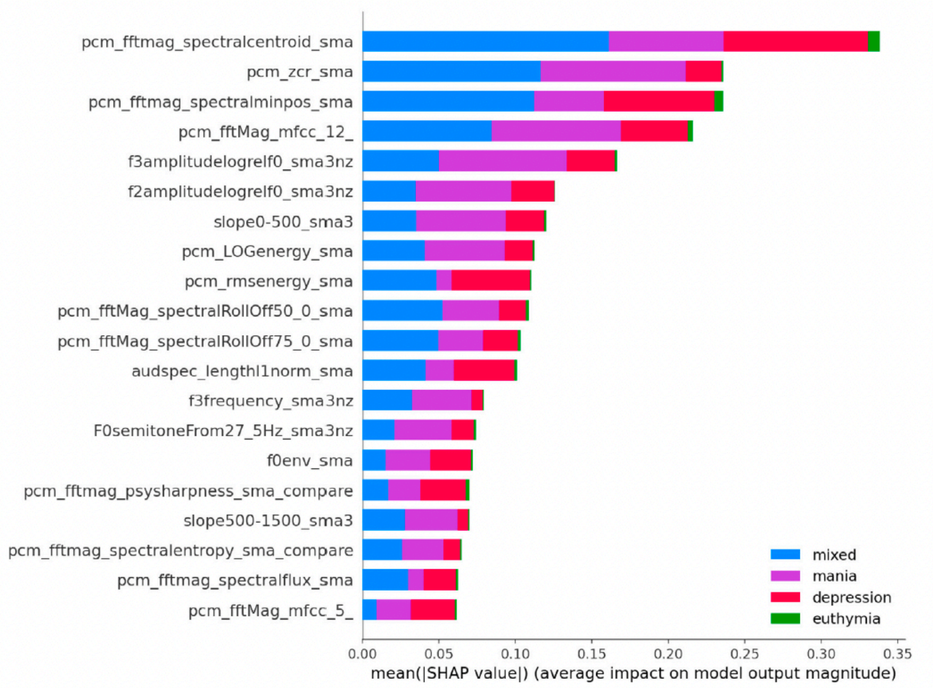
Patient's mood

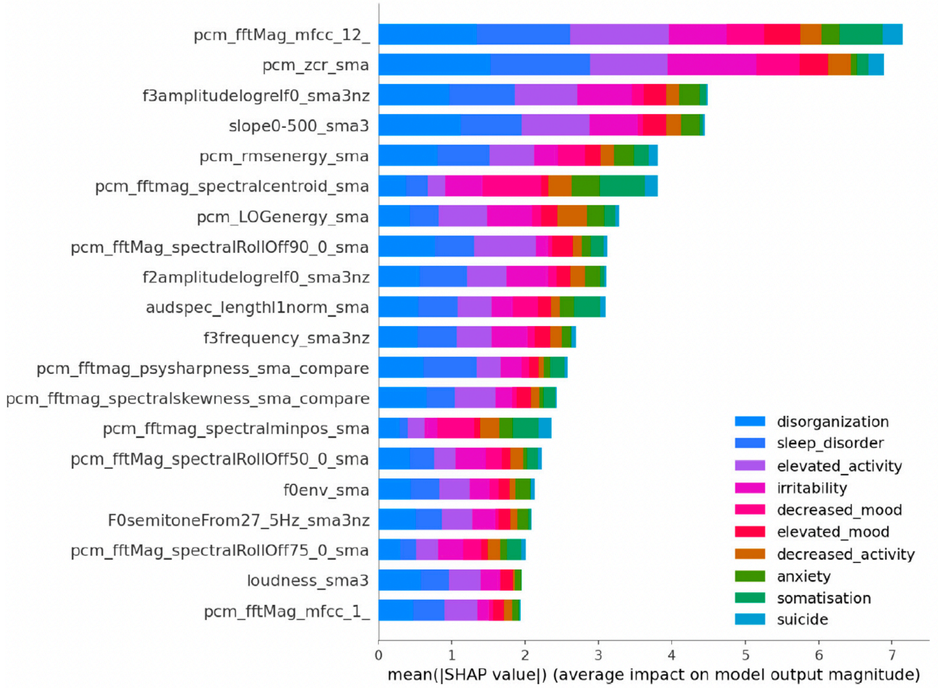
Euthymia	Mania
Depression	Mixed state

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PLENARY

STEP2: Shap Explanations

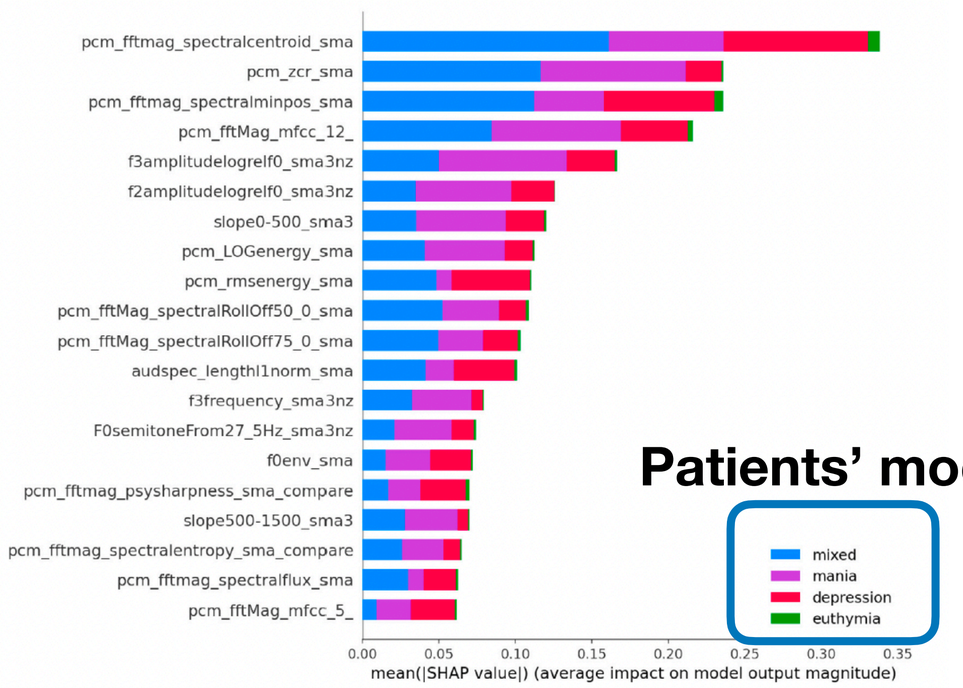


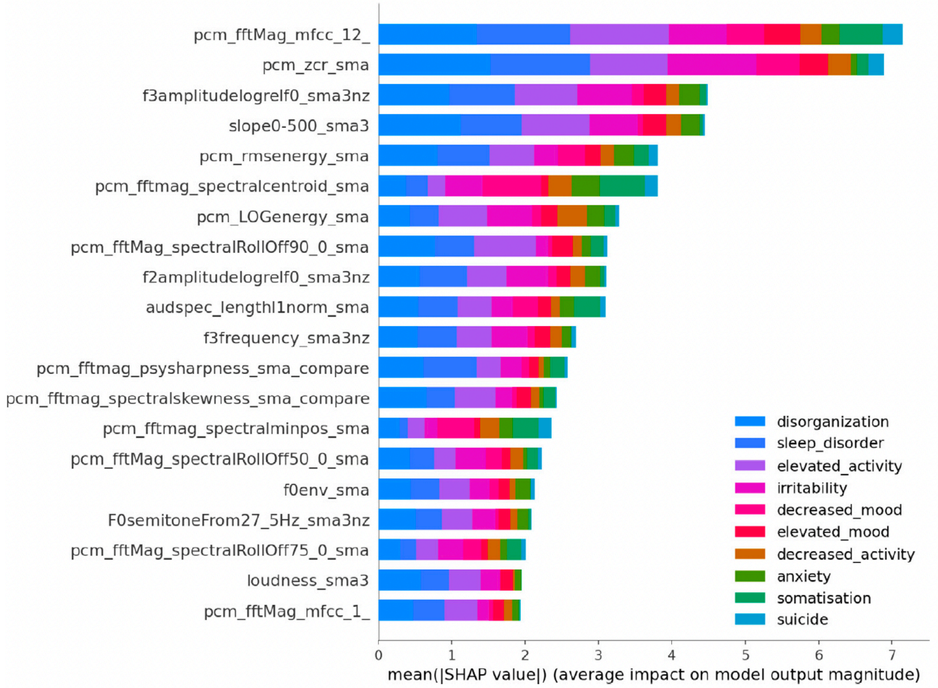


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PLENARY

STEP2: Shap Explanations

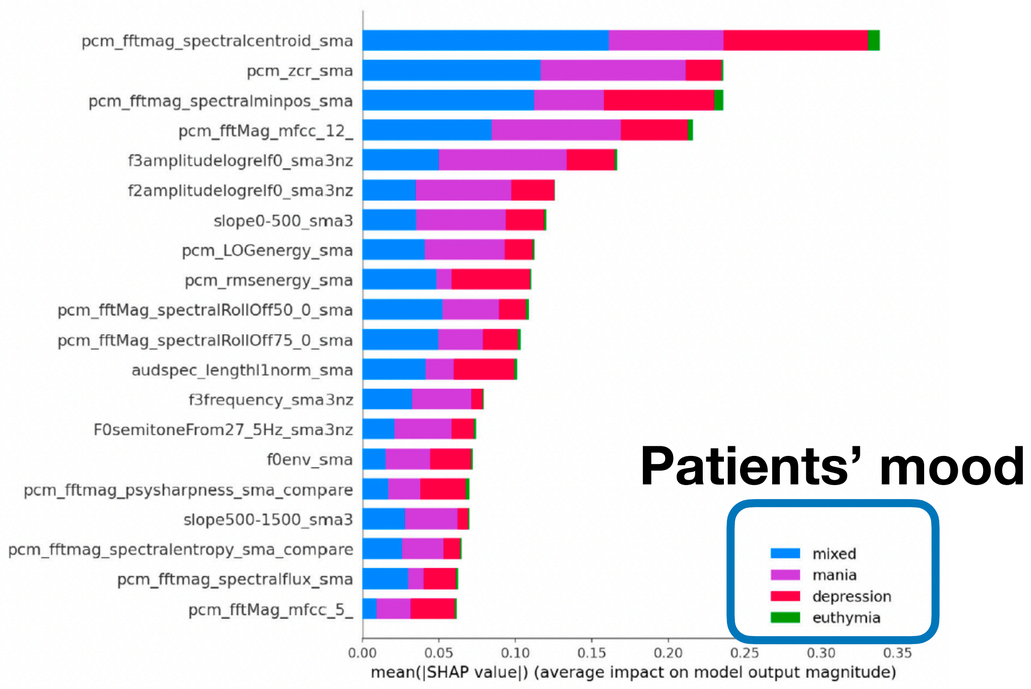


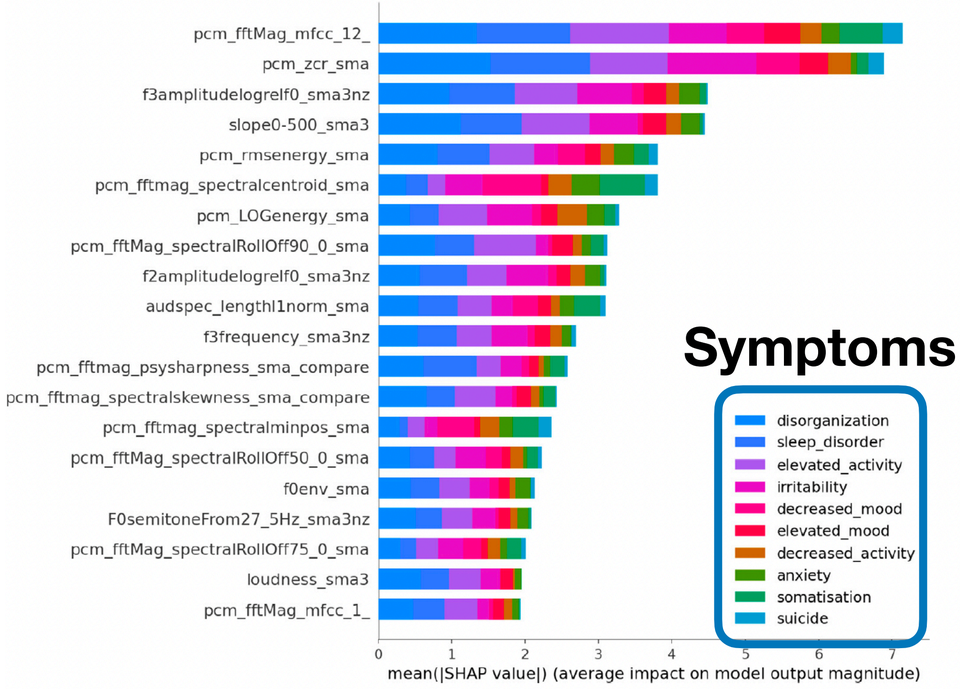


Katarzyna Kaczmarek-Majer, Gabriella Casalino, Giovanna Castellano, Monika Dominiak, Olgierd Hryniewicz, Olga Kamińska, Gennaro Vessio, Natalia Díaz-Rodríguez, PLENARY: Explaining black-box models in natural language through fuzzy linguistic summaries, Information Sciences, Volume 614, 2022, Pages 374-399

PLENARY

STEP2: Shap Explanations





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PLENARY

STEP3: Linguistic Summaries

Qualifier (“contribute xxx to predicting yyy ”)

$$\mathcal{LS} = LS(Q, R, P) = Among\ R\ objects\ from\ O,\ Q\ have\ P$$

Quantifier (“most recordings”)

Summariser (“high level of the Shapley values”)

Table 6

Evaluation of linguistic summaries from PLENARY for the prediction of BD classes with the sequential and compositional MLP model. Degree of truth, degree of support, degree of focus, and expert-based degree of usefulness are applied as criteria. Post-processing criteria: $DoT > 0.1$ and $DoF > 0.05$. Summaries that contribute positively to predicting a class are presented in bold. The font colors of the LS description indicate the high-level semantic groups of acoustic features. LS related to: the energy-related features are marked in black; the spectral-related features are marked in olive; the pitch-related features in orange; and the quality-related features are marked in purple.

Id	LS description	DoT	DoS	DoF	DoU
001	Among records that contribute around zero to predicting euthymia, most of them have energy-related features at low level.	0.58	0.17	0.06	1
002	**Among records that contribute positively to predicting euthymia, most of them have energy-related features at low level.**	0.24	0.17	0.21	5
003	Among records that contribute against predicting euthymia, most of them have spectral-related features at high level.	0.19	0.54	0.63	2
004	Among records that contribute around zero to predicting euthymia, most of them have spectral-related features at low level.	0.53	0.17	0.06	1
005	**Among records that contribute positively to predicting euthymia, most of them have spectral-related features at low level.**	1.00	0.30	0.21	4
006	Among records that contribute against predicting euthymia, most of them have quality-related features at high level.	0.26	0.70	0.63	3
007	**Among records that contribute positively to predicting euthymia, most of them have quality-related features at low level.**	0.23	0.19	0.21	4
101	Among records that contribute around zero to predicting depression, most of them have energy-related features at high level.	0.12	0.17	0.06	1
102	**Among records that contribute positively to predicting depression, most of them have spectral-related features at high level.**	1.00	0.29	0.31	5
103	Among records that contribute against predicting depression, most of them have quality-related features at low level.	0.51	0.61	0.76	4
104	**Among records that contribute positively to predicting depression, most of them have quality-related features at low level.**	1.00	0.18	0.31	5
201	Among records that contribute against predicting mania, most of them have energy-related features at low level.	0.33	0.68	0.73	4
202	Among records that contribute around zero to predicting mania, most of them have energy-related features at low level.	1.00	0.19	0.03	1
203	Among records that contribute against predicting mania, most of them have pitch-related features at low level.	0.25	0.45	0.73	4
204	Among records that contribute around zero to predicting mania, most of them have pitch-related features at low level.	1.00	0.05	0.03	1
205	**Among records that contribute positively to predicting mania, most of them have pitch-related features at high level.**	0.59	0.39	0.44	5
206	**Among records that contribute positively to predicting mania, most of them have spectral-related features at low level.**	1.00	0.27	0.44	5
301	**Among records that contribute positively to predicting mixed state, most of them have energy-related features at high level.**	0.11	0.16	0.31	5
302	**Among records that contribute positively to predicting mixed state, most of them have pitch-related features at low level.**	0.45	0.34	0.31	5
303	Among records that contribute against predicting mixed state, most of them have spectral-related features at low level.	0.11	0.50	0.63	3
304	**Among records that contribute positively to predicting mixed state, most of them have spectral-related features at high level.**	1.00	0.27	0.31	5
305	Among records that contribute against predicting mixed state, most of them have quality-related features at low level.	0.75	0.66	0.63	3

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PLENARY

STEP4: Evaluation of the explanations

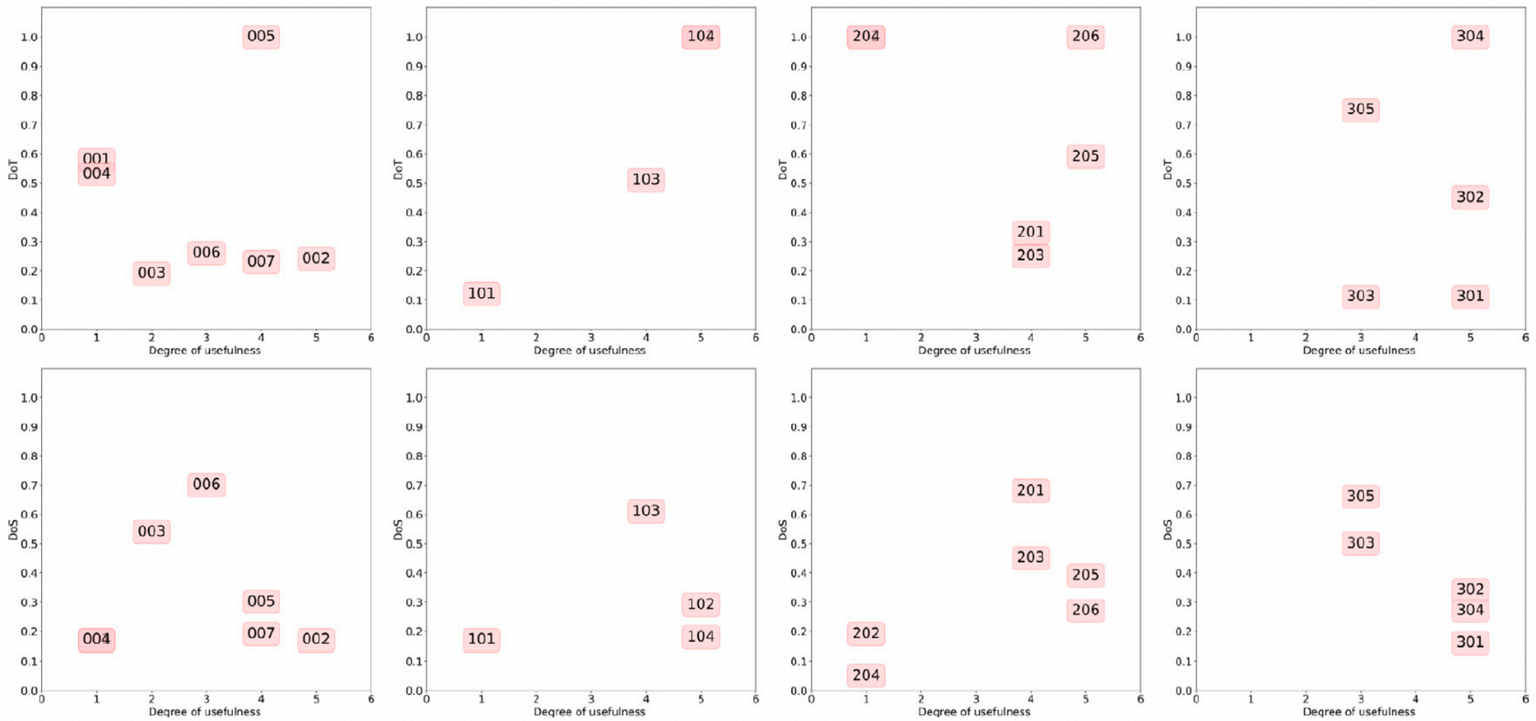
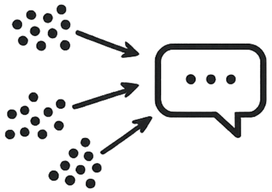
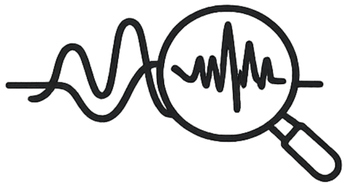


Fig. 9. Top row from left to right: degree of usefulness and degree of truth for linguistic summaries on euthymia, depression, mania, and mixed state from the sequential and compositional MLP model. Bottom row: degree of usefulness and degree of support for linguistic summaries for prediction of euthymia, depression, mania, and mixed state. The descriptions of the Ids are provided in Table 6.

Katarzyna Kaczmarek-Majer, Gabriella Casalino, Giovanna Castellano, Monika Dominiak, Olgierd Hryniewicz, Olga Kamińska, Gennaro Vessio, Natalia Díaz-Rodríguez, PLENARY: Explaining black-box models in natural language through fuzzy linguistic summaries, Information Sciences, Volume 614, 2022, Pages 374-399

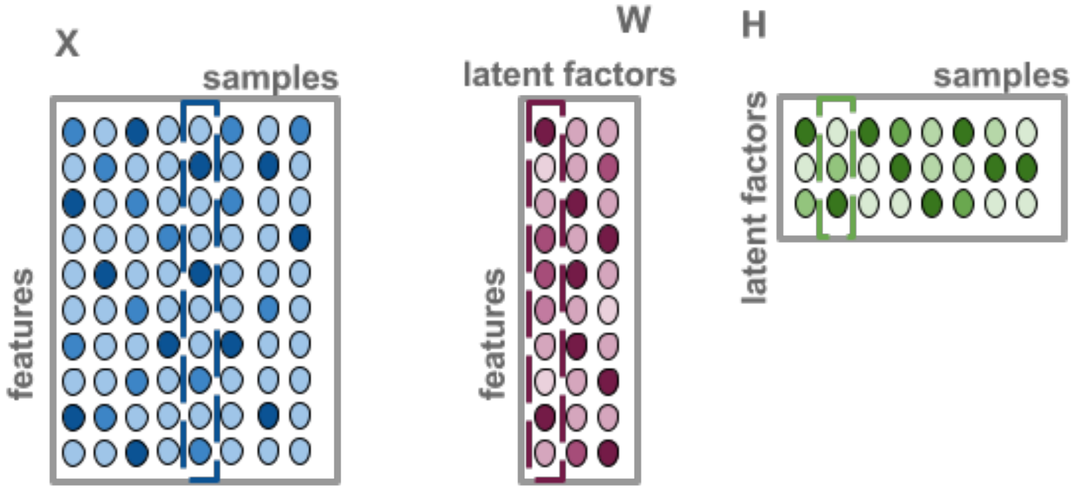
Understanding and Communicating Latent Patterns





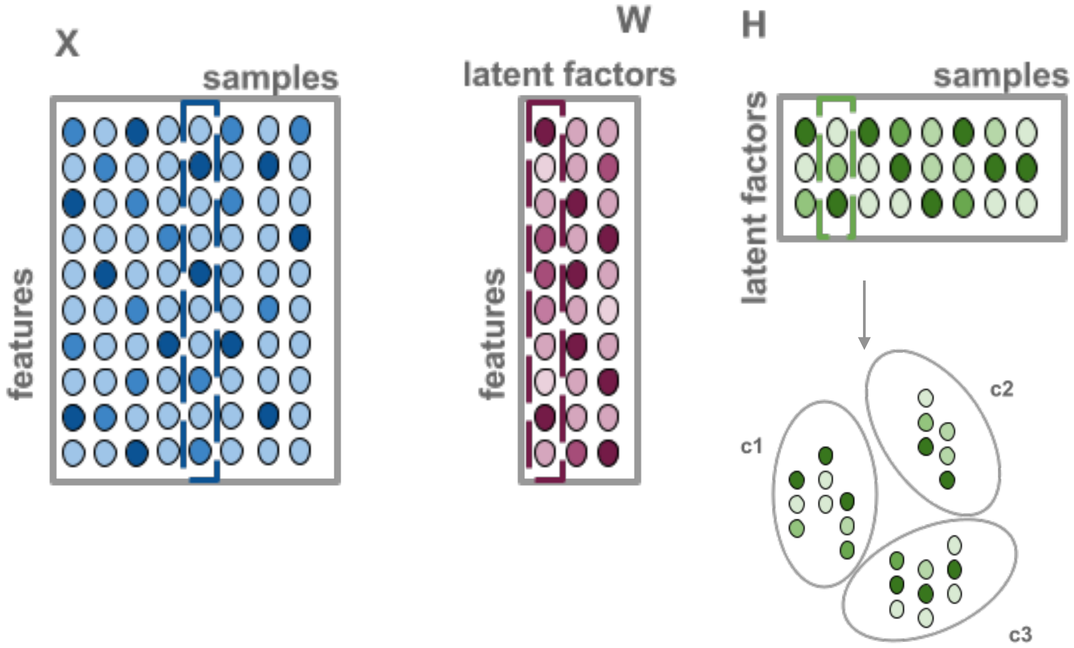
Can we uncover hidden patterns in speech data and communicate them to clinicians?

Background – Non-Negative Matrix Factorization



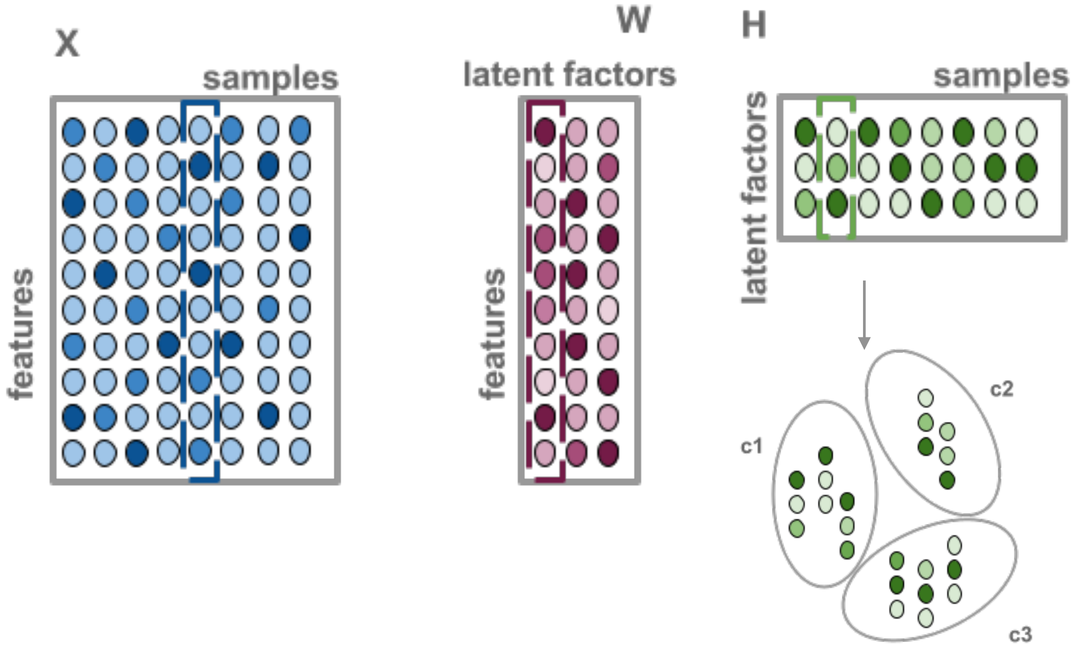
$$\mathbf{X}_{*j} \approx \mathbf{W}_{*1} h_{1j} + \mathbf{W}_{*2} h_{2j} + \ldots + \mathbf{W}_{*k} h_{kj}$$

Background – Non-Negative Matrix Factorization



$$\mathbf{X}_{*j} \approx \mathbf{W}_{*1} h_{1j} + \mathbf{W}_{*2} h_{2j} + \ldots + \mathbf{W}_{*k} h_{kj}$$

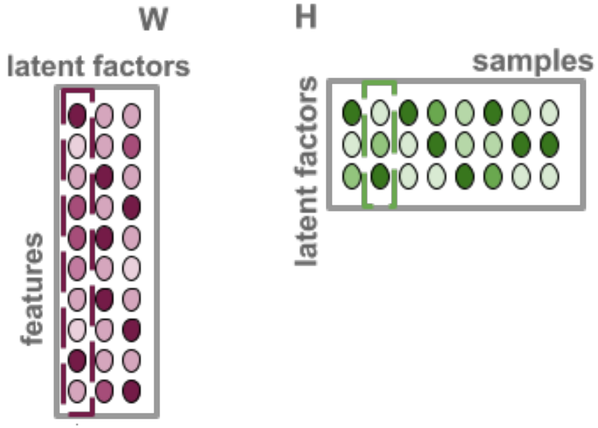
Background – Non-Negative Matrix Factorization



$$\mathbf{x}_{*j} \approx \mathbf{w}_{*1} h_{1j} + \mathbf{w}_{*2} h_{2j} + \ldots + \mathbf{w}_{*k} h_{kj}$$

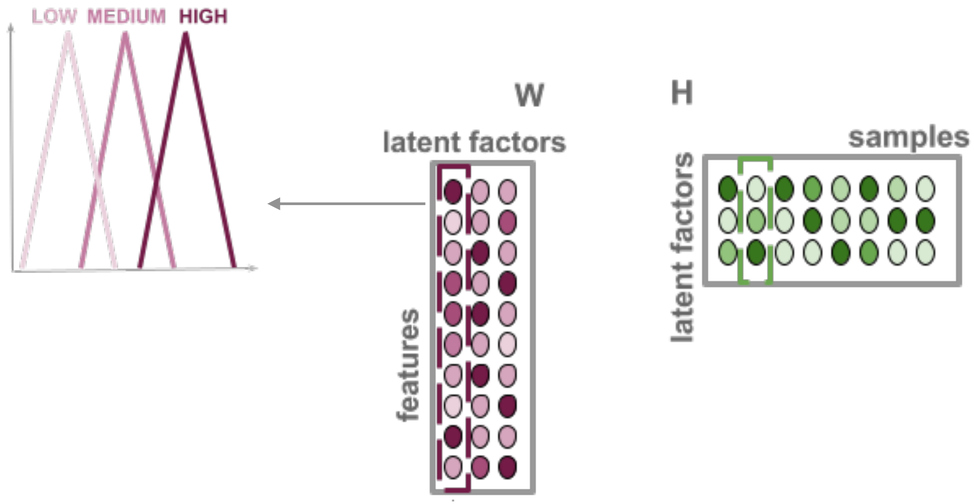
Still, domain experts may struggle to interpret the raw values

From Numerical Representations to Linguistic Concepts



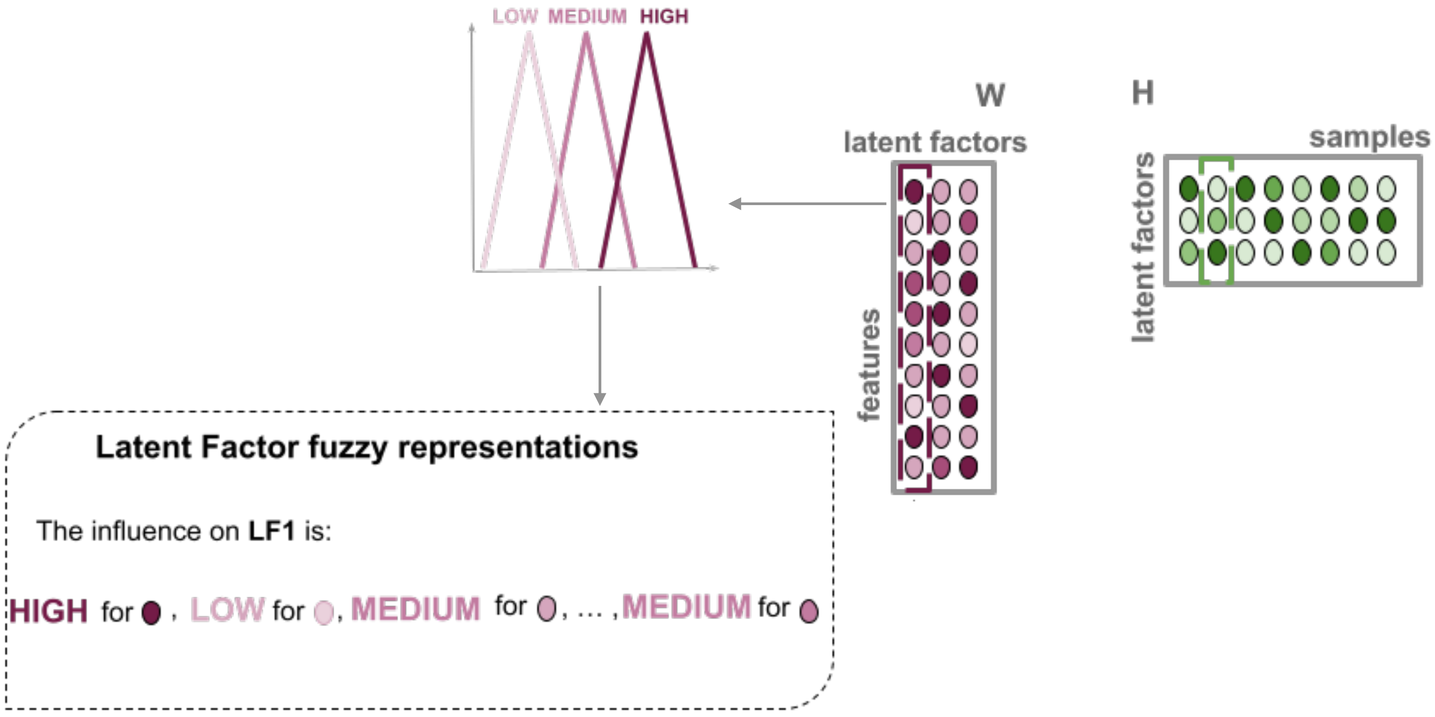
Casalino, G., Castellano, G., Kaczmarek-Majer, K., & Zaza, G. (2025). Enhancing Non-Negative Matrix Factorization Interpretability with Fuzzy Representations. In 2025 IEEE International Conference on Fuzzy Systems (FUZZ) (pp. 1-6). IEEE.

From Numerical Representations to Linguistic Concepts



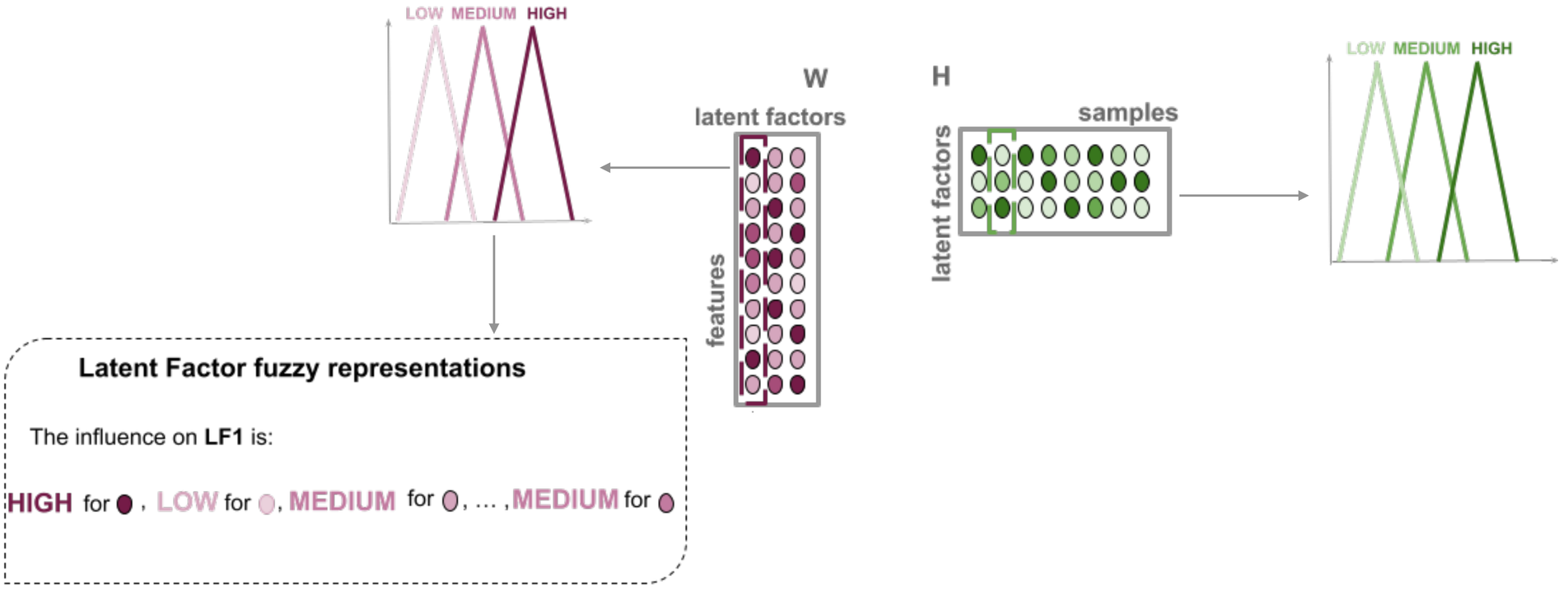
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From Numerical Representations to Linguistic Concepts



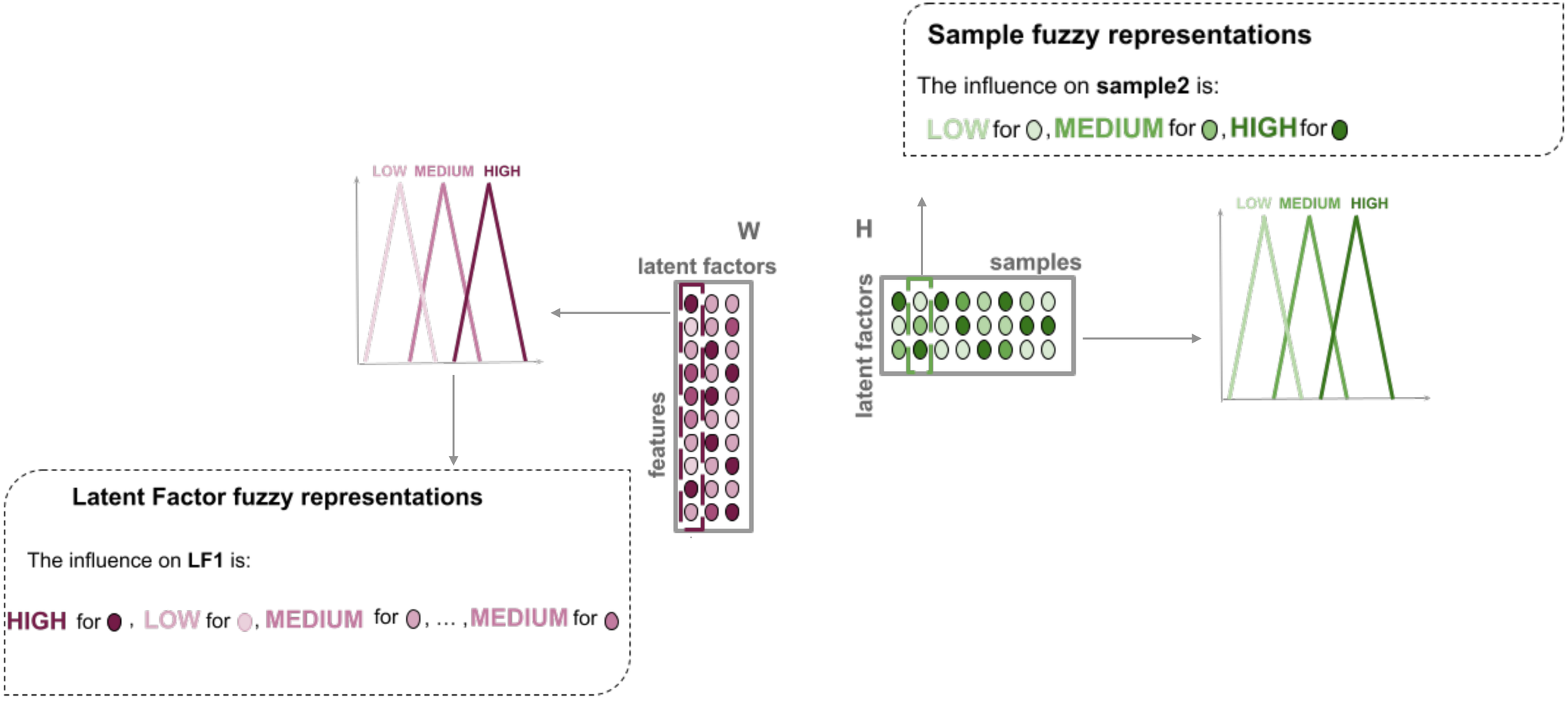
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From Numerical Representations to Linguistic Concepts



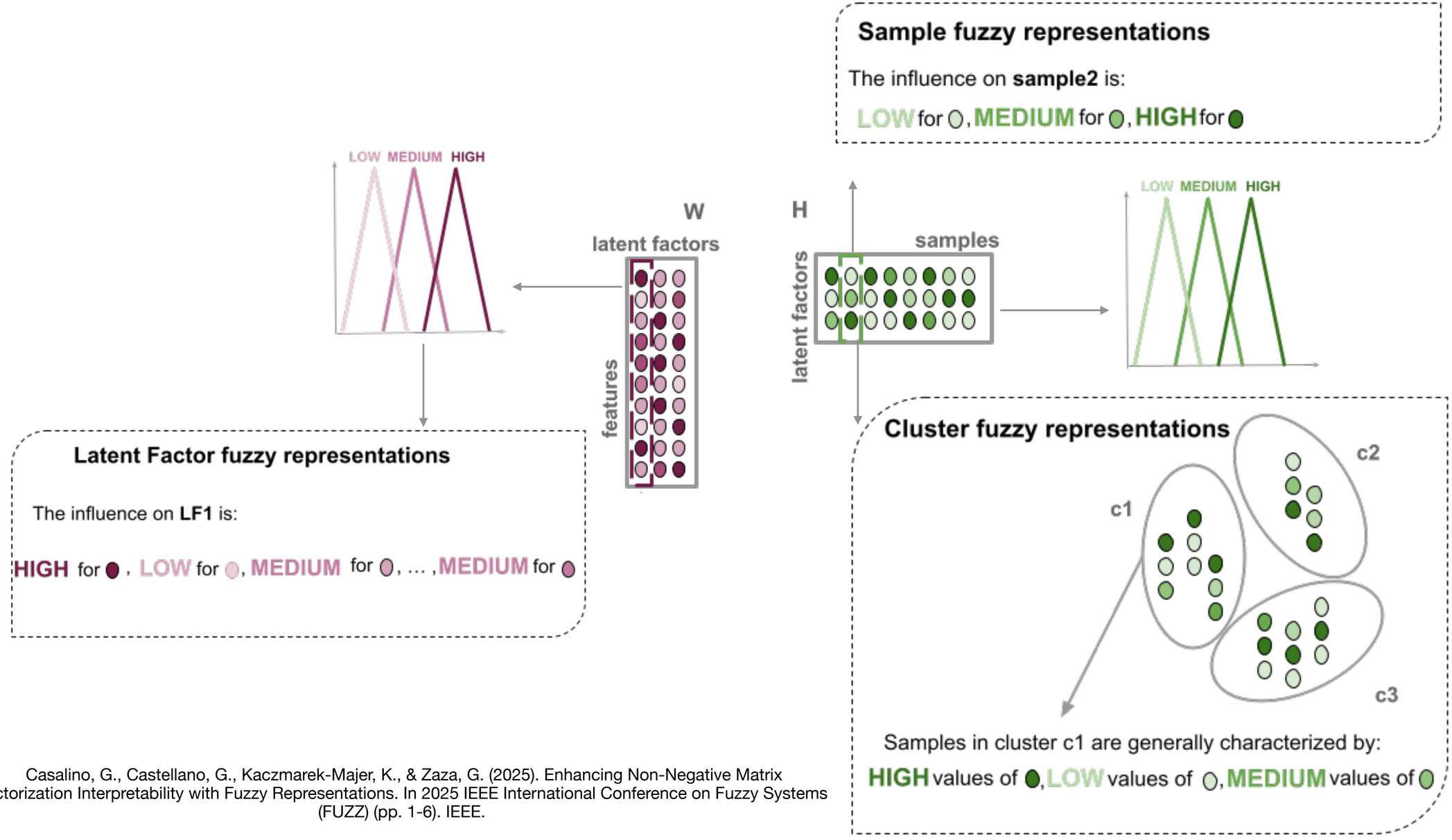
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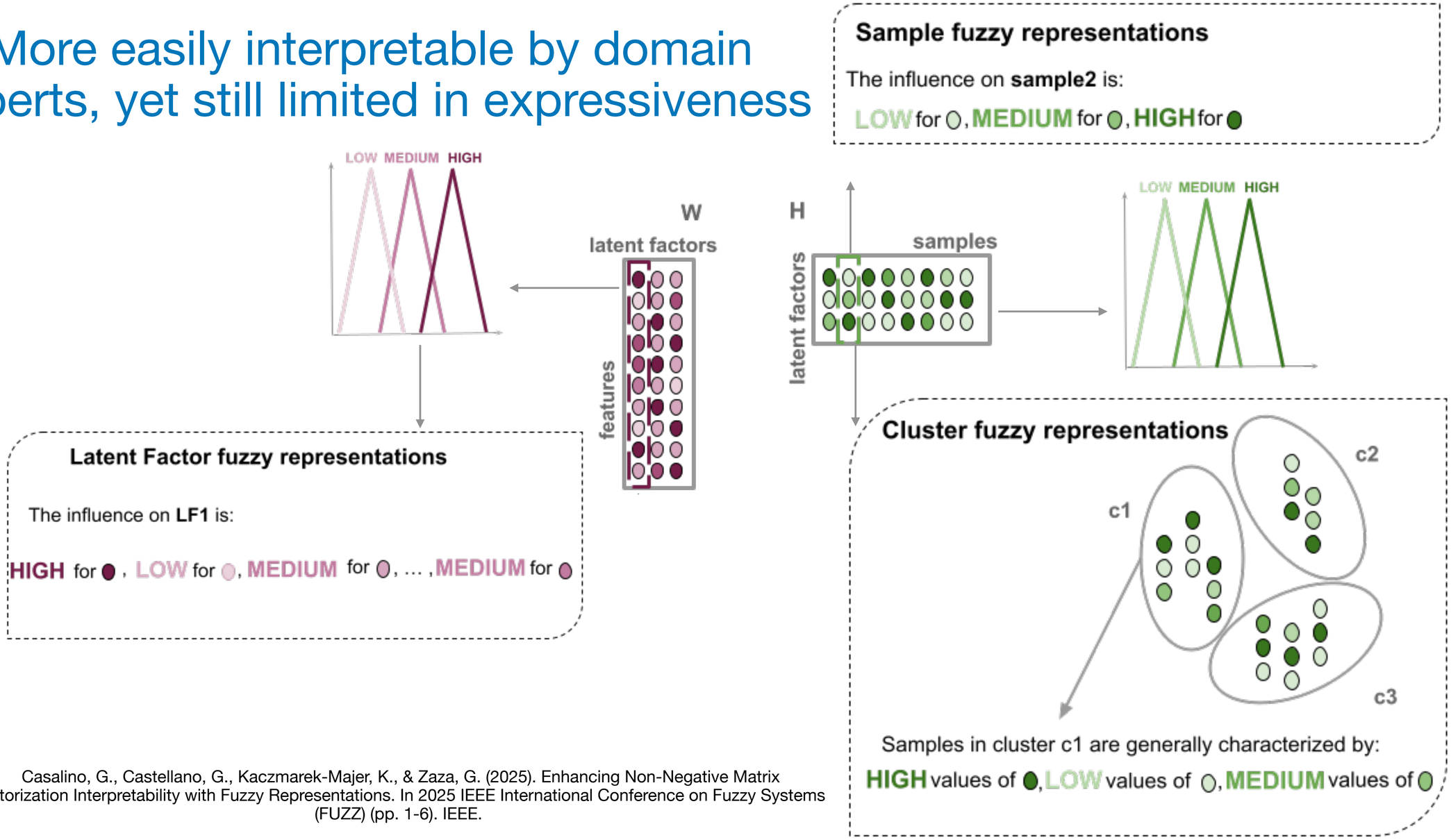
From Numerical Representations to Linguistic Concepts



Casalino, G., Castellano, G., Kaczmarek-Majer, K., & Zaza, G. (2025). Enhancing Non-Negative Matrix Factorization Interpretability with Fuzzy Representations. In 2025 IEEE International Conference on Fuzzy Systems (FUZZ) (pp. 1-6). IEEE.

From Numerical Representations to Linguistic Concepts

More easily interpretable by domain experts, yet still limited in expressiveness



Casalino, G., Castellano, G., Kaczmarek-Majer, K., & Zaza, G. (2025). Enhancing Non-Negative Matrix Factorization Interpretability with Fuzzy Representations. In 2025 IEEE International Conference on Fuzzy Systems (FUZZ) (pp. 1-6). IEEE.

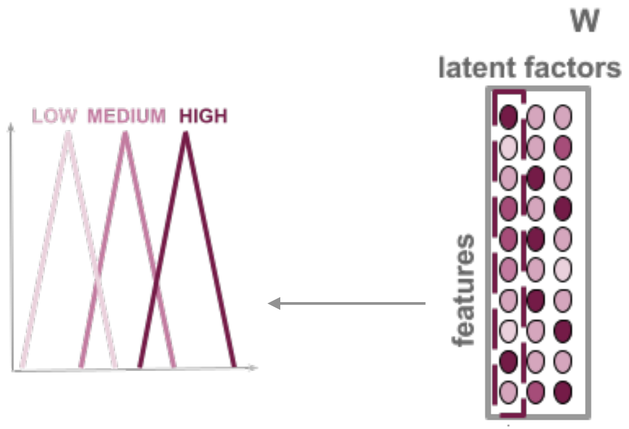
Explaning the semantics of latent factors

The influence on **LF1** is:

High *for* ***f0 envelope****,*
High *for* ***f0 final****,*
High *for* ***spectral centroid****,*
Low for jitter ddp,
Low for jitter local,
Low for loudness,
Low for spectral flux,
Low for fftmag spectral harmonicity,
Low for shimmer local,
Low for energy.

The influence on **LF2** is:

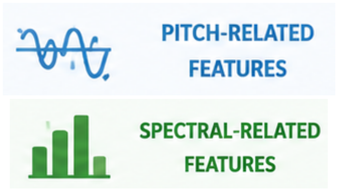
High *for* ***jitter ddp****,*
High *for* ***jitter local****,*
High *for* ***loudness****,*
High *for* ***spectral flux****,*
High *for* ***fftmag spectral harmonicity****,*
High *for* ***shimmer local****,*
High *for* ***energy****,*
Low for f0 envelope,
Low for f0 final,
Low for spectral centroid.



Explaning the semantics of latent factors

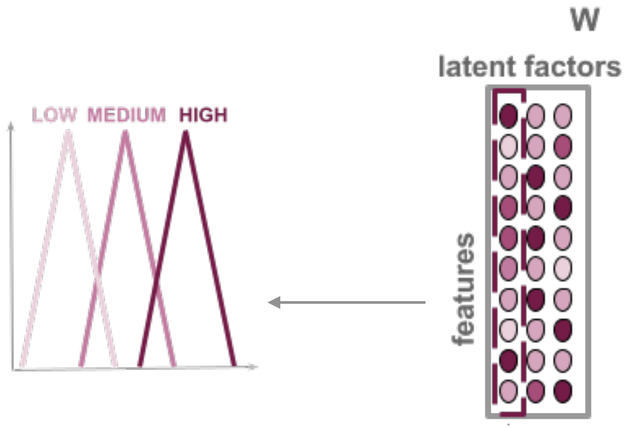
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High *for* ***spectral centroid****,*
Low for jitter ddp,
Low for jitter local,
Low for loudness,
Low for spectral flux,
Low for fftmag spectral harmonicity,
Low for shimmer local,
Low for energy.



The influence on **LF2** is:

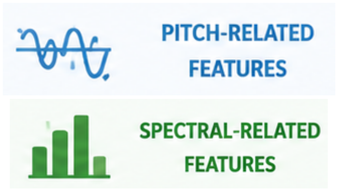
High *for* ***jitter ddp****,*
High *for* ***jitter local****,*
High *for* ***loudness****,*
High *for* ***spectral flux****,*
High *for* ***fftmag spectral harmonicity****,*
High *for* ***shimmer local****,*
High *for* ***energy****,*
Low for f0 envelope,
Low for f0 final,
Low for spectral centroid.



Explaning the semantics of latent factors

The influence on **LF1** is:

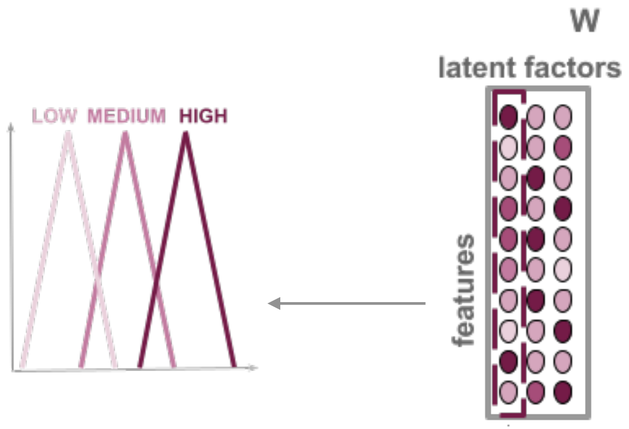
High *for* ***f0 envelope***,
High *for* ***f0 final***,
High *for* ***spectral centroid***,
Low for jitter ddp,
Low for jitter local,
Low for loudness,
Low for spectral flux,
Low for fftmag spectral harmonicity,
Low for shimmer local,
Low for energy.



The influence on **LF2** is:

High *for* ***jitter ddp***,
High *for* ***jitter local***,
High *for* ***loudness***,
High *for* ***spectral flux***,
High *for* ***fftmag spectral harmonicity***,
High *for* ***shimmer local***,
High *for* ***energy***,
Low for f0 envelope,
Low for f0 final,
Low for spectral centroid.

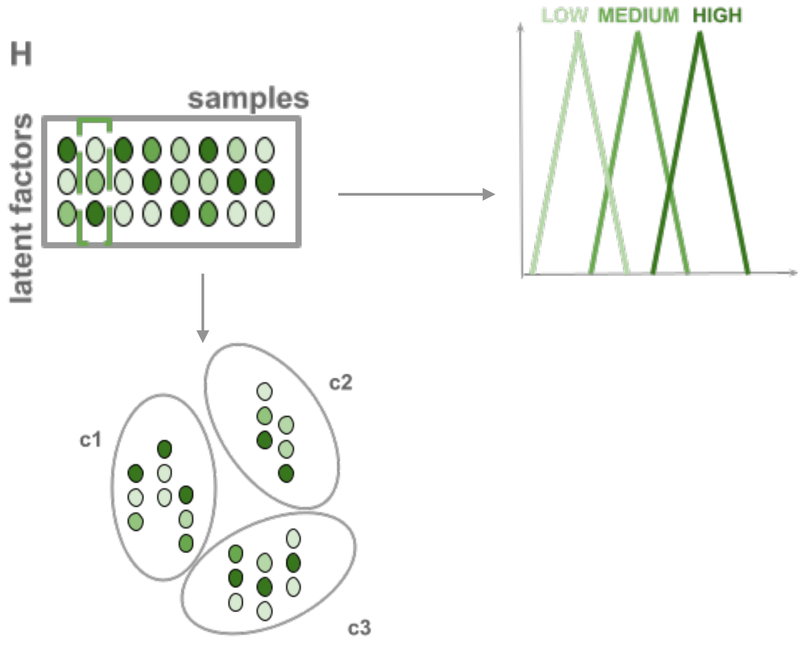




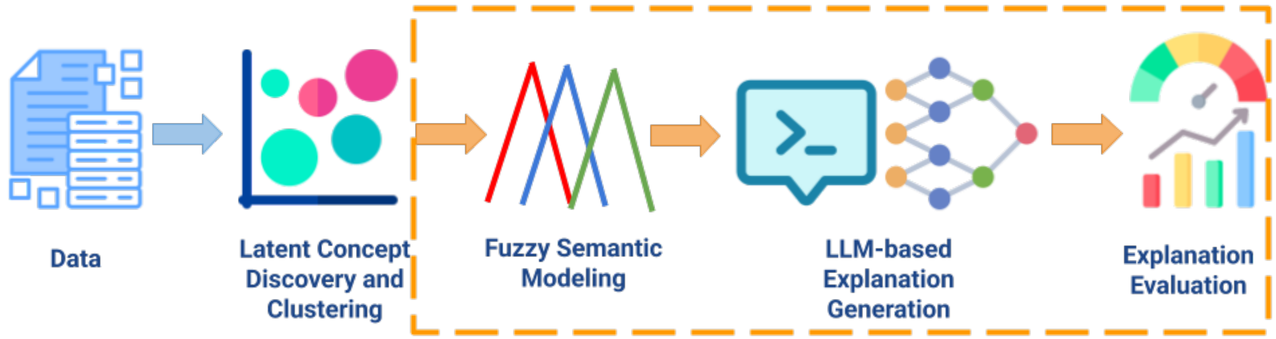
Fuzzy cluster representations

Samples in **cluster** $\mathbf{c^{(1)}}$ are generally characterized by High values of *LF1* AND Low values of *LF2*

Samples in **cluster** $\mathbf{c^{(2)}}$ are generally characterized by Medium values of *LF1* AND Medium values of *LF2*



From Linguistic Concepts to Natural-Language Explanations



Grounded explanations

- Latent factors described through linguistic concepts
- Semantic relations with original features preserved

Multi-level explanations

- Cluster-level explanations
- Sample-level explanations

LLM-guided generation

- Structured prompting
- Human-readable narratives
- Evaluation of models and prompts

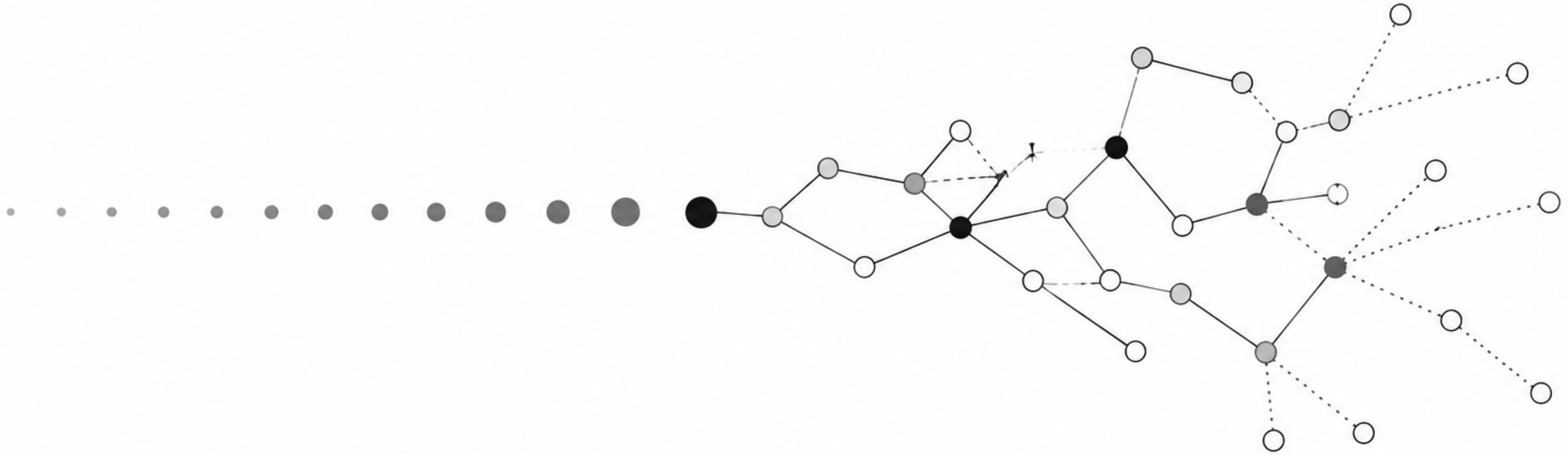
G. Casalino, G. Castellano, K. Kaczmarek-Majer, G. Narracci, V. Nitti, F. Pagliaro, A.G. Valerio, G. Zaza, (i2026), A Human-Centered Explainability Framework for Latent Clustering Based on NMF, Fuzzy Logic, and LLMs. In 2026 IEEE International Conference on Fuzzy Systems (FUZZ) (pp. 1-6). IEEE.

Example of Generated Explanation

P6 - Meta features + context

Cluster Overview	In analyzing the cluster characterized by low values of Latent Factor 1 (LF1) and high values of Latent Factor 2 (LF2), we gain insight into specific vocal patterns associated with patients diagnosed with bipolar disorder. These latent factors, extracted through Non-negative Matrix Factorization (NMF) analysis of acoustic features, offer a way to understand the complex interplay between vocal characteristics and affective states.
LF1 Interpretation	LF1, which is low in this cluster, appears to be inversely related to voice quality and stability. It is significantly influenced by low jitter and shimmer values, indicating a more regular and stable vocal signal. Additionally, LF1 is associated with lower energy and loudness, suggesting softer speech, and a lower spectral centroid, which implies a less dynamic or varied spectral shape. The high influence of f0 envelope and f0 final on LF1 suggests a more controlled fundamental frequency. These characteristics map primarily to the voice quality-related and loudness-related features.
LF2 Interpretation	On the other hand, LF2, which is high in this cluster, suggests a different profile. It is associated with high jitter and shimmer, indicating more variability and instability in the vocal signal. High values of LF2 also correspond to higher loudness and energy, suggesting a more intense vocal output. Furthermore, LF2's strong connection to high spectral flux and harmonicity, alongside lower spectral centroid, points towards a more dynamic and possibly more emotionally charged speech pattern. These characteristics align more closely with spectral-related and loudness-related features.
Link to Bipolar Mood States	When we consider the clinical manifestations of bipolar disorder, fluctuations in affective states such as mania or depression can significantly impact speech patterns. The vocal patterns described by LF1 and LF2 offer a window into these affective states. For instance, heightened vocal excitement or variability (as suggested by high LF2) could be indicative of manic episodes, characterized by elevated mood and increased activity. Conversely, more subdued and stable vocal characteristics (as suggested by low LF1) might reflect depressive episodes, marked by reduced emotional expression and activity.

To Be Continued...



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