Natural language processing for subjectivity analysis in personal narratives

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LISN LABORATOIRE INTERDISCIPLINAIRE DES SCIENCES DU NUMÉRIQUE

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We first address the *content* by classifying elements of personal narratives. Then, we study the *form* through the concept of style

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My research models are publicly hosted on Hugging Face and were trained using the Jean Zay supercomputer

Definition of objectives using cognitive science

G. Cortal and C. Bonard. Improving Language Models for Emotion Analysis: Insights from Cognitive Science. *CMCL @ ACL 2024*.

Psychological theories and emotion annotation schemes

[add refs to klinger, etc.]

Psychological theories	In text, emotion is...	Example
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	composed of *semantic roles*	"Louise (`experiencer`) was angry (`cue`) towards Paul (`target`), because he didn't inform her (`cause`)."

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- There is no benchmark that evaluates the richness of the emotional phenomenon [add refs]

Linguistic and cognitive science theories

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How to integrate psychological theories of emotion?

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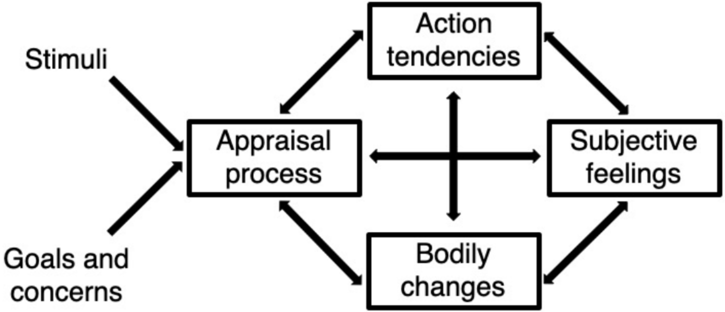


Figure: Integrated framework for emotion theories. Emotional episodes are synchronized changes in four components (Scherer, 2022).

[add Appraisal dimensions]

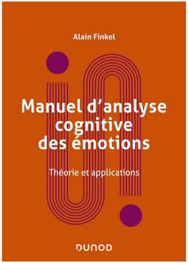
Construction of an emotion dataset

Available at hf.co/datasets/gustavecortal/FrenchEmotionalNarratives

G. Cortal, A. Finkel, P. Paroubek, L. Ye. Emotion Recognition based on Psychological Components in Guided Narratives for Emotion Regulation. *SIGHUM @ EACL 2023*.

Cognitive analysis of emotions

- explores emotions with behavioral (*behavior*), physiological (*feeling*), and cognitive (*thinking* and *territory)* components
- helps individuals better regulate their emotions
- uses psychological components to reorganize the narrative of experienced emotional events



finkel2022, april **finkel2022**

French emotional narratives based on components

Goal: A more comprehensive understanding of emotional events

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Component	**Answer**
`Behavior`	I'm giving a lecture on a Friday morning at 8:30. A student goes out and comes back a few moments later with a coffee in his hand.
`Feeling`	My heart is beating fast, and I freeze, waiting to know how to act.
`Thinking`	I think this student is disrupting my class.
`Territory`	The student attacks my ability to be respected in class.

Chosen emotion: `anger` (possible choices: `anger`, `fear`, `joy`, `sadness`)

1000 narratives were collected during emotion regulation sessions

Training language models for emotion analysis

G. Cortal, A. Finkel, P. Paroubek, L. Ye. Emotion Recognition based on Psychological Components in Guided Narratives for Emotion Regulation. *SIGHUM @ EACL 2023*

G. Cortal. Sequence-to-Sequence Language Models for Character and Emotion Detection in Dream Narratives. *LREC-COLING 2024*

Discrete emotion detection based on components

	Logistic Regression			CamemBERT		
Component	Precision	Recall	F_1	Precision	Recall	F_1
All	71.2 (2.6)	69.1 (2.2)	67.8 (2.3)	**85.1**	**84.8**	**84.7**

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Without `behavior`	77.4 (2.3)	75.8 (2.4)	74.5 (2.6)	80.3	79.8	79.7
Without `feeling`	64.3 (1.9)	61.5 (1.2)	61.3 (2.2)	81.6	79.8	79.9
Without `thinking`	70.9 (1.8)	69.1 (2.0)	68.3 (2.2)	79.6	78.5	78.7
Without `territory`	64.3 (4.1)	64.5 (2.4)	62.3 (2.8)	78.7	78.5	78.6

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Without `territory`	64.3 (4.1)	64.5 (2.4)	62.3 (2.8)	78.7	78.5	78.6
Only `behavior`	52.1 (3.5)	54.6 (2.9)	51.7 (2.9)	68.4	67.1	66.6
Only `feeling`	69.6 (1.5)	68.9 (2.1)	68.4 (2.0)	67.8	68.4	67.7
Only `thinking`	50.1 (3.4)	53.8 (2.3)	50.6 (2.7)	70.5	70.1	70.1
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→ Some components benefit from contextual understanding and world knowledge (*e.g.*, `behavior` and `thinking`)

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[add illustration dreambank, hdvc scheme]

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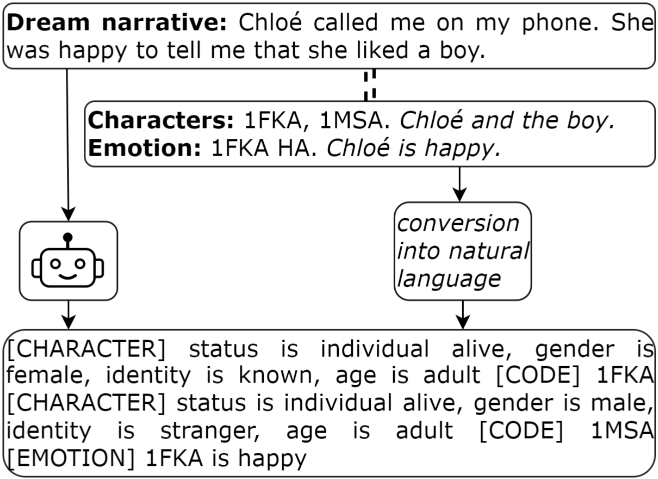
How to automate the annotation process?

Hall and Van de Castle annotation scheme

Character and emotion detection in dream narratives

[add seq2seq architecture illustration, add list of characters and emotions]



Results

Baseline is LaMini-Flan-T5 finetuned on 1823 dream narratives

Model	Status	Gender	Identity	Age	Character	Emotion
Baseline	82.87	78.02	76.17	86.21	64.74	75.13
$\texttt{No}_{\texttt{semantics}}$	71.37	56.54*	61.0	90.51	41.79*	75.79
$\texttt{No}_{\texttt{names}}$	80.66*	74.32**	74.2	83.95*	60.93**	73.04*
$\texttt{Size}_{\texttt{small}}$	78.35**	72.13**	70.25**	81.66**	56.79**	70.15**
$\texttt{Size}_{\texttt{large}}$	84.51*	80.3**	78.63**	87.29	67.63**	74.71
$\texttt{First}_{\texttt{group}}$	82.33	77.71	74.86	85.61	63.71	71.94
$\texttt{First}_{\texttt{individual}}$	80.59**	76.14	74.22*	83.87**	62.67	67.32
$\texttt{First}_{\texttt{emotion}}$	83.92	78.74	77.06	87.63	64.97	72.03
$\texttt{Conversion}_{\texttt{comma}}$	84.02**	79.84**	77.67**	87.08*	66.69**	73.68
$\texttt{Conversion}_{\texttt{marker}}$	82.39	78.45	76.53	86.09	65.44	74.36
Cross-validation	86.28	81.9	79.51	89.52	68.64	76.18

Table: F_1-scores for character and emotion detection. Significant differences from baseline: ** ($p < 0.01$), * ($p < 0.05$).

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→ Language models can address character and emotion detection in dream narratives, while there is still room for improvement

Case study on the war veteran

Group	Category	% Vet	% Total	Δ
Identity	known*	24.9	51.6	-26.7
	prominent	1.9	2.5	-0.6
	occupational*	22.4	8.0	14.4
	ethnic*	4.1	0.9	3.1
	unknown*	46.8	37.0	9.8
Gender	male*	56.2	43.0	13.1
	female*	24.1	33.1	-9.0
	joint	10.9	12.2	-1.3
	undefined	7.9	8.7	-0.9

Table: Identity and gender proportions for the veteran (n=566 narratives) versus other dreamers. Δ shows the difference in percentage points. * indicates significant difference ($p < 0.05$).

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→ The war veteran dreams more about *occupational*, *ethnic*, and *unknown* identities compared to other dreamers.

Formalization of style in personal narratives

G. Cortal and A. Finkel. Formalizing Style in Personal Narratives. *EMNLP 2025*.

Expand the Cognitive Model of Isabelle Tellier

Tellier was a PhD student of Alain (30 years ago)

- Tellier's cognitive model proposes formally capturing redundancies in decision-making texts, characterizing a *cognitive style*; using algebraic languages and finite automata.
- For implementation, Tellier performs a partial automatic analysis using categorial grammars.

We propose:

- to fully implement the cognitive model using language models
- to linguistically justify the relevant traits to capture and organize
- to extend the model to account for the attention mechanisms involved in expressing subjective experience

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[for second slide, give a formal definition]

We narrow the general definition of style: *a distinctive manner of communicating subjective experience in narratives*

How to give an operational definition of style?

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Hypothesis: An individual uses some redundant choices of features that characterize its style

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3. A case study on dream narratives

What linguistic features encode subjective experience?

We ground our framework in *systemic functional linguistics* (Halliday et al., 2014)

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Language achieves three functions: interpersonal (language builds social relationships), textual (information is organized to create coherent messages), and *ideational* (language represents experience)

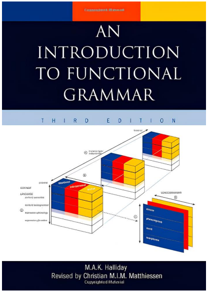

Figure: (Halliday et al., 2014). +57,000 citations.

What linguistic features encode subjective experience?

Processes	Examples
Action: actions and events in the physical world.	He$_{\texttt{Actor}}$ **takes**$_{\texttt{Action}}$ the valuable$_{\texttt{Affected}}$ I$_{\texttt{Actor}}$ **give**$_{\texttt{Action}}$ her$_{\texttt{Recipient}}$ a chance$_{\texttt{Range}}$
Mental: internal experiences such as thoughts, perceptions, and feelings.	The moon$_{\texttt{Senser}}$ **sees**$_{\texttt{Mental}}$ the earth$_{\texttt{Phenomenon}}$ He$_{\texttt{Senser}}$ **disliked**$_{\texttt{Mental}}$ Gilbert's writing$_{\texttt{Phenomenon}}$
Verbal: acts of communication.	David$_{\texttt{Sayer}}$ **said**$_{\texttt{Verbal}}$ "the corrupt, [...]"$_{\texttt{Verbiage}}$
State: states of being, having, or existence.	John$_{\texttt{Carrier}}$ **is**$_{\texttt{State}}$ an interesting teacher$_{\texttt{Attribute}}$ Chloé$_{\texttt{Possessor}}$ **has**$_{\texttt{State}}$ a cat$_{\texttt{Possessed}}$

Table: Examples of processes and their participants. Language represents experience through **processes** and participants.

Pipeline for our sequence-based framework

[remove bullet points, make it more visual]

Clause	**Process (symbol)**	**Participants**
I wake in a dark room	`Action` (**a**)	`Actor`
I feel a cold wind	`Mental` (**m**)	`Senser, Phenomenon`
I tell myself to move	`Verbal` (**v**)	`Sayer, Recipient`

Sequence: *amv* | **Substrings:** {am, mv}

Results on the war veteran

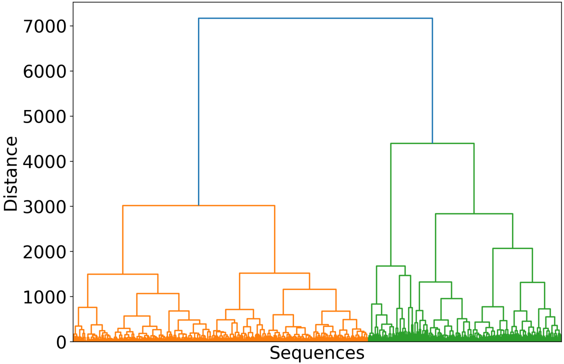

Figure: Dendrogram with Ward linkage and cosine similarity

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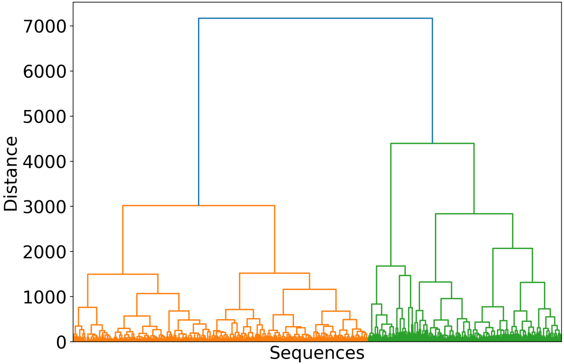

Figure: Dendrogram with Ward linkage and cosine similarity

Representative sequences: *savamasasaaamaaasavvvaaaaaaavssaaaaa* and *sssssavaavssvsavvvvsmasasaasasaamaamvmsss* with a = action, m = mental, s = state, v = verbal

Results on the war veteran

We compare the proportion of sequences containing a given substring

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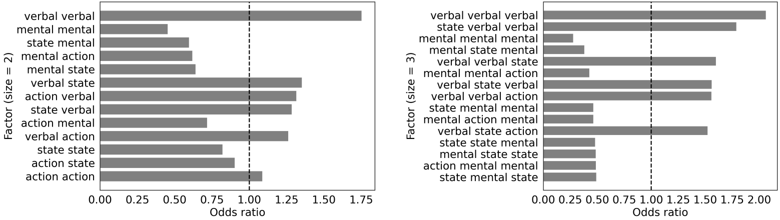

(a) Size 2.

(b) Size 3.

Figure: Top substring odds ratio between the veteran and the norm

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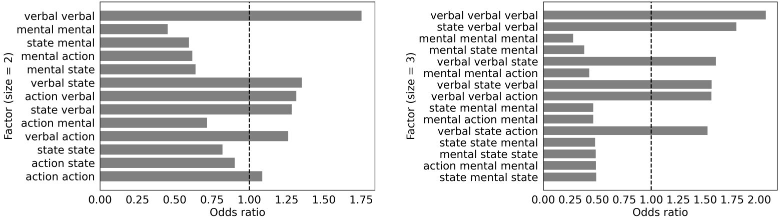

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→ The veteran favors verbal processes over mental ones

How can this framework be extended?

- Authorship profiling

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- Style-conditioned narrative generation

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- Style-conditioned narrative generation
- Applying methods from complexity science and formal language theory

Conclusion and perspectives

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How to model subjective experience in personal narratives?

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- Definition of objectives and scope using cognitive science

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How to model subjective experience in personal narratives?

- Definition of objectives and scope using cognitive science
- Construction of an emotion dataset
- Training of language models for emotion analysis
- Formalization of style in personal narratives

Impact

(a) Amine Haddou on cognitive distortions (2025).

(b) Raphael Faure on style analysis (2025).

(c) Nicolas Richet on emotion multimodal recognition (2024).

Figure: Co-supervised PhD topics.

During my PhD internship at Callyope, *Fine-grained mental health topic modeling in different cohorts using large language models*

Automatic thematic analysis in mental health narratives using language models

G. Cortal, S. Guessoum, X. Cao, R. Riad. *Fine-grained mental health topic modeling in different cohorts using large language models* (preprint). 2025.

Introduction

- Qualitative analysis of speech content is central to clinical practice

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→ We developed a pipeline that (a) clusters narratives from different cohorts, (b) generates descriptions for each cluster, and (c) links clusters to variation in clinical scores and sociodemographic factors

Data collection

We collected clinical scores and narratives from **four cohorts**. A French general population cohort (n=1809), and three clinical populations: Italian (n=116), Chinese (n=52), and Spanish (n=90) cohorts

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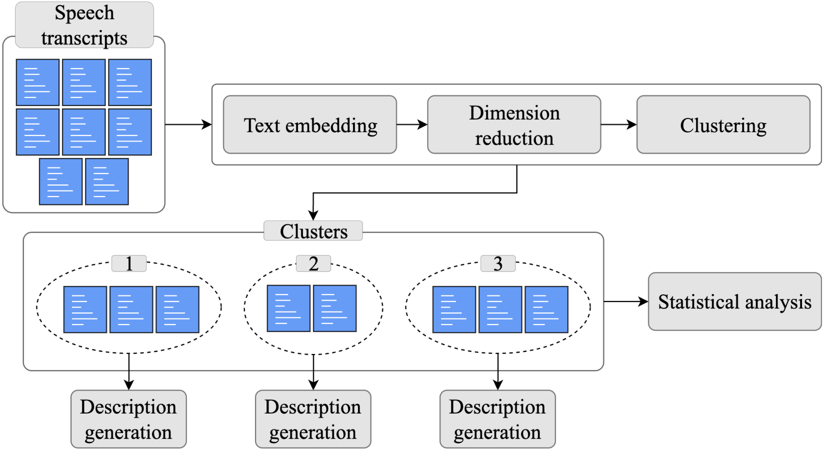
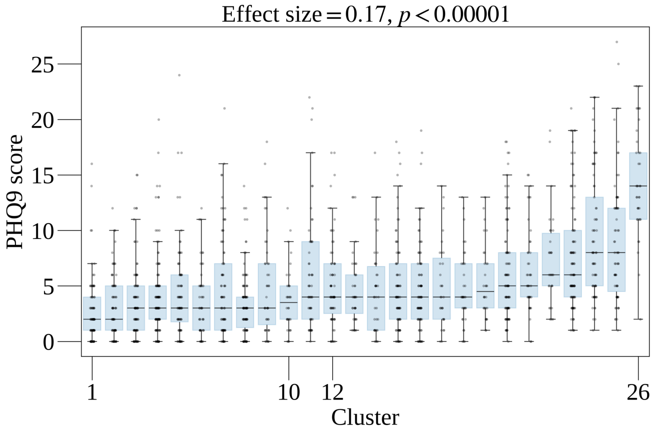
Open-ended questions: *Describe your last 24 hours / a negative event that happened to you in the past / a positive event that happened to you in the past / a negative event you think might happen in the future / a positive event you think might happen in the future / Describe how you are feeling at the moment and how your sleep has been lately*

Pipeline for semantic clustering and description generation



Distribution of depression scores across clusters

How you are feeling and how your sleep has been lately



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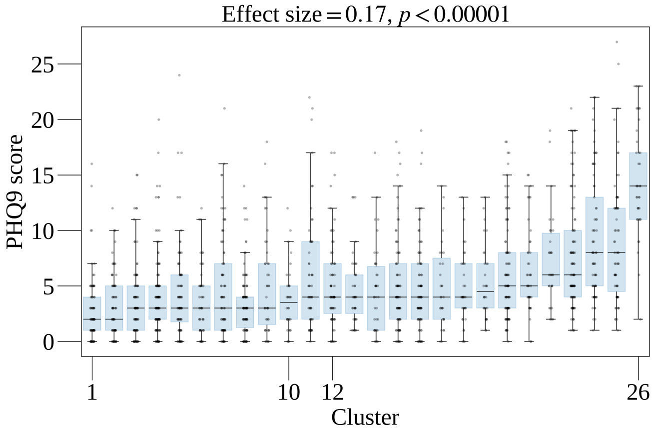

→ Depression scores vary significantly: cluster 26 highest (13.4±5.4), cluster 1 lowest (2.6±2.2)

Generated cluster descriptions

Cluster 1 description: The individuals express consistent satisfaction with their current well-being, emphasizing good sleep quality, restful or pleasant nights, and a general sense of relaxation, even when noting variations in sleep duration or occasional fatigue. (age=39±19, n=92)

Cluster 10 description: The individuals express frequent nighttime urinary interruptions disrupting sleep, often attributed to age-related conditions like prostate issues or overactive bladder, alongside mixed reports of physical well-being, mental resilience, and lifestyle factors such as retirement or exercise influencing their overall health and sleep patterns. (age=69±15, n=34)

Cluster 12 description: The individuals express stress related to academic exams, significant life decisions, and workloads, alongside sleep disturbances caused by lifestyle changes, increased responsibilities, or environmental adjustments, while some also highlight temporary relief from pressures through personal achievements or upcoming positive events. (age=24±9, n=67)

Cluster 26 description: The individuals express sleep disturbances characterized by insomnia, frequent awakenings, and restless sleep, alongside pervasive anxiety, emotional instability, and self-esteem issues, which collectively contribute to persistent fatigue, impaired daily functioning, and a diminished sense of well-being. (age=25±9, n=37)

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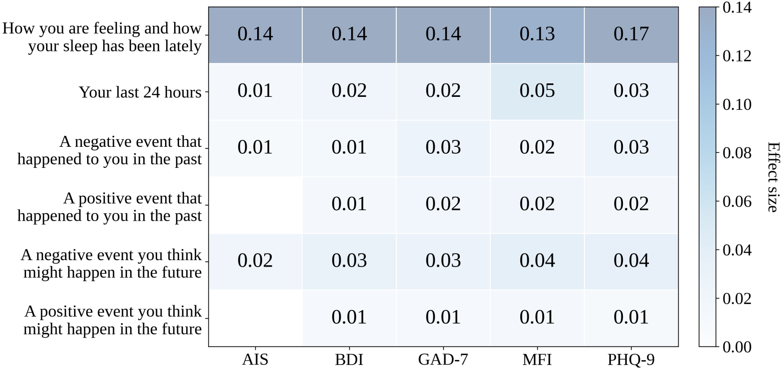
→ Clustering captures symptom severity and age-related circumstances

Effect size across questions and clinical scores



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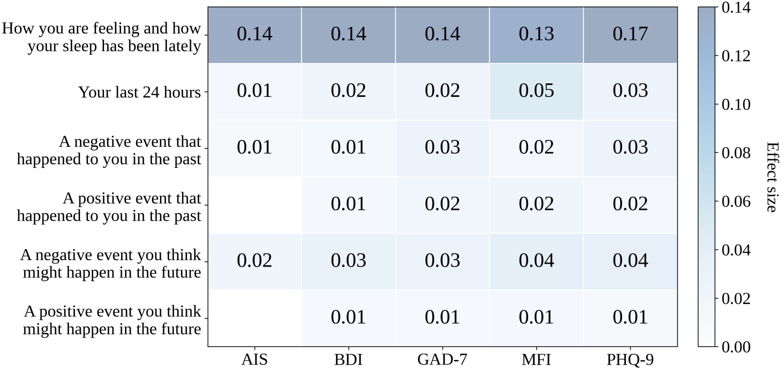
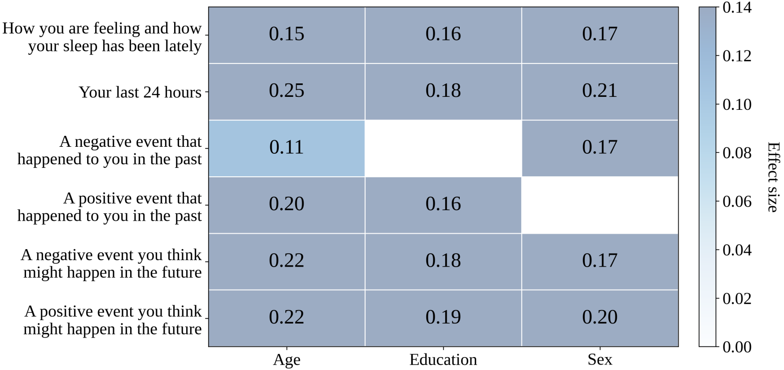


→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



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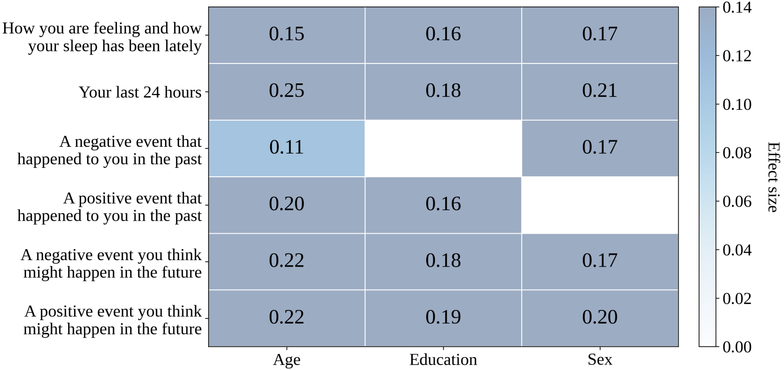

→ Nearly all questions discriminate sociodemographics

Perspectives

- Emotion analysis for mental health (empathic support, cognitive distortions, theory of mind)

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- Post-training for psychology (preferences and reasoning data)

Selected research papers

Constant Bonard and Gustave Cortal (2024). "Improving Language Models for Emotion Analysis: Insights from Cognitive Science". In: *Proceedings of the Workshop on Cognitive Modeling and Computational Linguistics*. Ed. by Tatsuki Kuribayashi et al. Bangkok, Thailand: Association for Computational Linguistics, pp. 264–277. DOI: 10.18653/v1/2024.cmcl-1.23

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Appendix

Component classification in emotional narratives

Model	Precision	Recall	F_1
Logistic Regression	84.9 (0.3)	84.3 (0.3)	84.4 (0.3)
CamemBERT	**93.2**	**93.0**	**93.1**

Table: Scores ($\pm$ std) for emotion component classification.

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$\rightarrow$ Models can be used to automatically classify unstructured narratives

Demographics

	General Population n=1809	Androids n=116	MODMA n=52	VOCES n=90
Demographics				
Language	French	Italian	Chinese	Spanish
Age	***	*n.s.*	*n.s.*	***
Mean (SD)	37.8 (18.2)	37.4 (12.0)	31.3 (9.2)	38.6 (14.9)
Range	18–91	19–71	18–52	21–76
Sex, n (%)	*n.s.*	*n.s.*	*n.s.*	*n.s.*
Female	1187 (66.2)	84 (72.4)	16 (30.8)	39 (43.3)
Male	595 (33.2)	32 (27.6)	36 (69.2)	48 (53.3)
Other	11 (0.6)	0 (0.0)	0 (0.0)	3 (3.3)
Education, n (%)	*n.s.*	*n.s.*	*n.s.*	*n.s.*
No diploma	52 (2.9)	11 (9.5)	7 (13.5)	-
Secondary	291 (16.2)	37 (31.9)	8 (15.4)	-
Higher short	213 (11.9)	52 (44.8)	0 (0.0)	-
Higher long	1236 (69.0)	16 (13.8)	37 (71.2)	-

Clinical evaluation

	General Population n=1809	Androids n=116	MODMA n=52	VOCES n=90
C-SSRS	*n.s.*	*n.s.*	*n.s.*	*n.s.*
Suicidal risk, n (%)	-	-	-	60 (66.7)
No suicidal risk, n (%)	-	-	-	30 (33.3)
MADRS / MDD	*n.s.*	*n.s.*	*n.s.*	*n.s.*
Depression, n (%)	-	64 (55.2)	23 (44.2)	-
No depression, n (%)	-	52 (44.8)	29 (55.8)	-
PHQ-9	*n.s.*	*n.s.*	***	***
Mean (SD)	5.2 (4.6)	-	9.4 (8.5)	10.5 (6.8)
Range	0–27	-	0–25	0.0–26.0

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Bonard, Constant and Gustave Cortal (2024). "Improving Language Models for Emotion Analysis: Insights from Cognitive Science". In: *Proceedings of the Workshop on Cognitive Modeling and Computational Linguistics*. Ed. by Tatsuki Kuribayashi et al. Bangkok, Thailand: Association for Computational Linguistics, pp. 264–277. DOI: `10.18653/v1/2024.cmcl-1.23`.

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