

Natural language processing for subjectivity analysis in personal narratives

Gustave Cortal

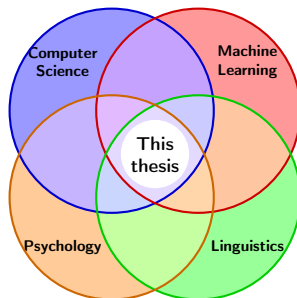
Thesis director: Alain Finkel

Co-advisors: Patrick Paroubek and Lina Ye



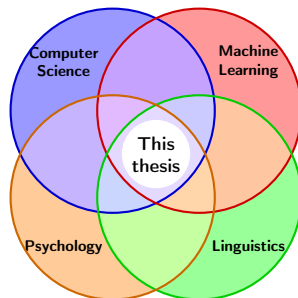
Introduction

Context



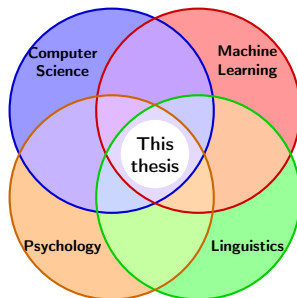
- Natural language processing for psychology is underexplored

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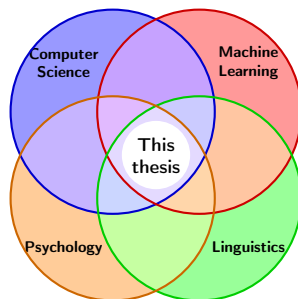
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- ▶ We study subjectivity (e.g., first-person perspective, meaning-making processes, and experiential content)

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- ▶ We study subjectivity (e.g., first-person perspective, meaning-making processes, and experiential content)
- ▶ We focus on personal narratives (emotional narratives, dream reports)

Introduction

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2 international conferences (EMNLP, LREC-COLING); 3 international workshops; 2 national conferences and journals (TALN)

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 <i>semantic roles</i>	"Louise (experiencer) was angry (cue) towards Paul (target), because he didn't inform her (cause)."

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- ▶ Some linguistic and cognitive science theories are not considered [reformulate, not some]
- ▶ 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?

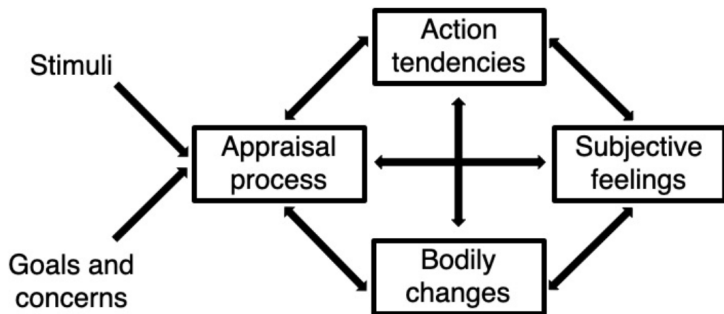


Figure: Integrated framework for emotion theories. Emotional episodes are synchronized changes in four components (Scherer, 2022).

→ There is no dataset of personal narratives structured according to emotion components [add refs]

Construction of an emotion dataset

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

French emotional narratives based on components

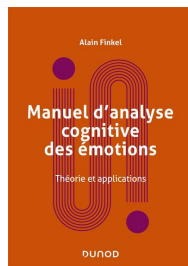
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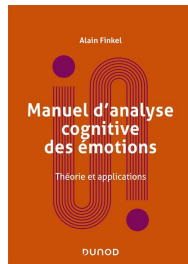
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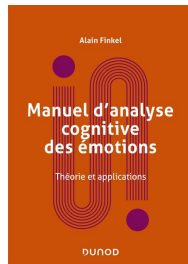
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- ▶ explores emotions with behavioral (*behavior*), physiological (*feeling*), and cognitive (*thinking* and *territory*) components
- ▶ uses emotion components to reorganize the narrative of experienced events
- ▶ helps individuals better regulate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



finkel2022, april
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Contribution: 1000 narratives from emotion regulation sessions, providing 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)

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

Component	Logistic Regression			CamemBERT		
	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)

Quantitative analysis of dream narratives

[add illustration dreambank, hdvc scheme]

Need other datasets with narrative structure, emotional content, and available for research

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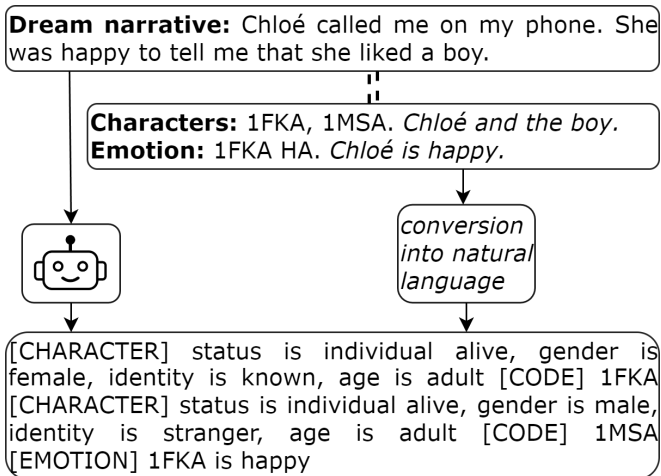
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How to automate the annotation process?

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

Table: Character and emotion detection. ** ($p < 0.01$), * ($p < 0.05$).

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No _{names}	80.66*	74.32**	74.2	83.95*	60.93**	73.04*

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	82.33	77.71	74.86	85.61	63.71	71.94
First _{group}						
First _{individual}	80.59**	76.14	74.22*	83.87**	62.67	67.32
First _{emotion}	83.92	78.74	77.06	87.63	64.97	72.03

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→ Our models can address this task, 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
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→ The 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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1. A sequence-based framework defining style as patterns in sequences of linguistic choices

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Contributions:

1. A sequence-based framework defining style as patterns in sequences of linguistic choices
2. A methodology for identifying patterns using sequence analysis
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)

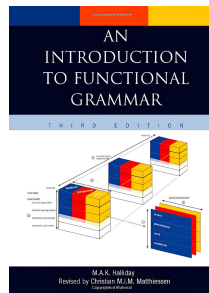


Figure: Halliday et al. (2014).
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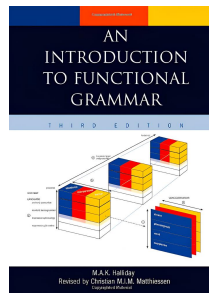


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Language achieves three functions: interpersonal (language builds social relationships), textual (information is organized to create coherent messages), and *ideational* (language represents experience)

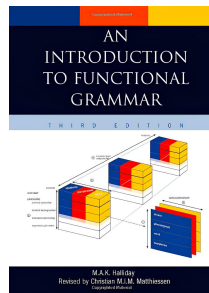


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What linguistic features encode subjective experience?

Processes	Examples
Action: actions and events in the physical world.	<p>He_{Actor} takes_{Action} the valuable_{Affected}</p> <p>I_{Actor} give_{Action} her_{Recipient} a chance_{Range}</p>
Mental: internal experiences such as thoughts, perceptions, and feelings.	<p>The moon_{Senser} sees_{Mental} the earth_{Phenomenon}</p> <p>He_{Senser} disliked_{Mental} Gilbert's writing_{Phenomenon}</p>
Verbal: acts of communication.	<p>David_{Sayer} said_{Verbal} "the corrupt, [...]"_{Verbiage}</p>
State: states of being, having, or existence.	<p>John_{Carrier} is_{State} an interesting teacher_{Attribute}</p> <p>Chloé_{Possessor} has_{State} a cat_{Possessed}</p>

Table: According to *systemic functional linguistics*, 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
<hr/>		
Sequence: <i>amv</i> Substrings: {am, mv}		

Results on the war veteran

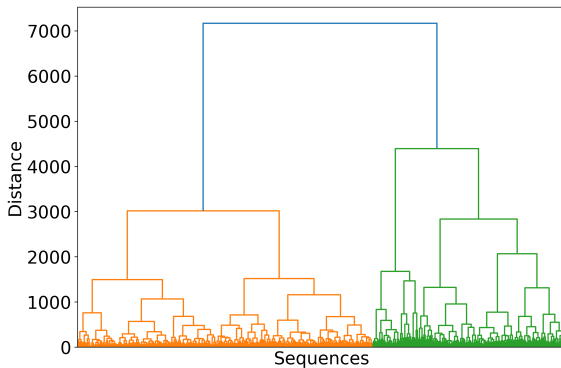


Figure: Dendrogram with Ward linkage and cosine similarity

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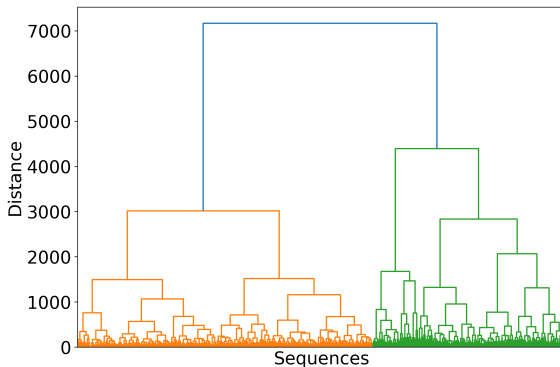


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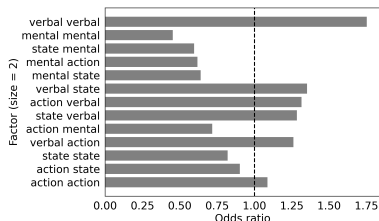
Representative sequences: *savamasasaaamaasavvvaaaaaaavssaaaaa* and *sssssavaavssvsavvvvsmasasaasasaamaamvmssss* with
a = action, *m* = mental, *s* = state, *v* = verbal

Results on the war veteran

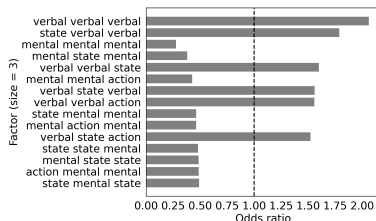
We compare the proportion of sequences containing a given substring

Results on the war veteran

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(a) Size 2.

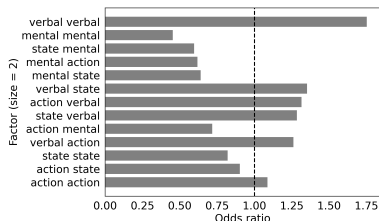


(b) Size 3.

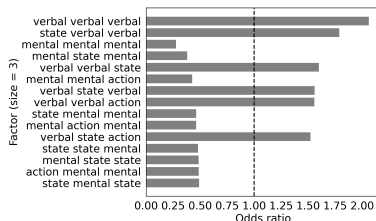
Figure: Top substring odds ratio between the veteran and the norm

Results on the war veteran

We compare the proportion of sequences containing a given substring



(a) Size 2.



(b) Size 3.

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

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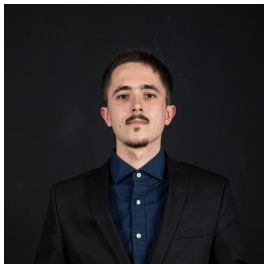
My research models are publicly hosted on Hugging Face and were trained using the Jean Zay supercomputer

Impact

Impact: Ongoing PhD thesis related to my works



(a) A. Haddou on cognitive distortions (2025, ENS Paris-Saclay).



(b) R. Faure on style analysis (2025, ENS Paris-Saclay).



(c) N. Richet on multimodal emotion (2024, ETS Montréal).

Impact: NLP for psychiatry (industry)

6-month PhD internship at Callyope on *NLP for quantifying memory, future thinking, and the self in mental health narratives*



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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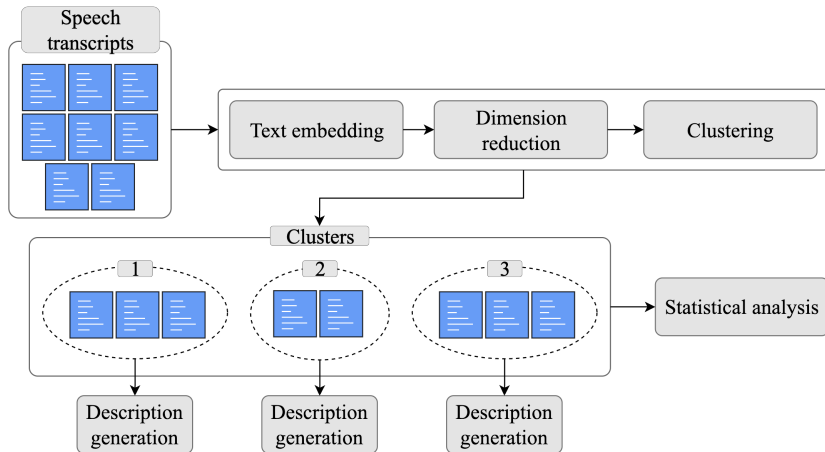
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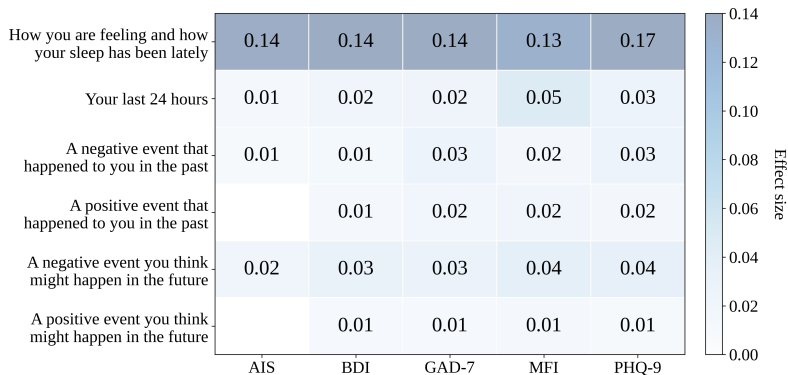
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- ▶ Qualitative analysis of speech content is central to clinical practice
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- ▶ Computational approaches offers time savings, can analyze a larger amount of data

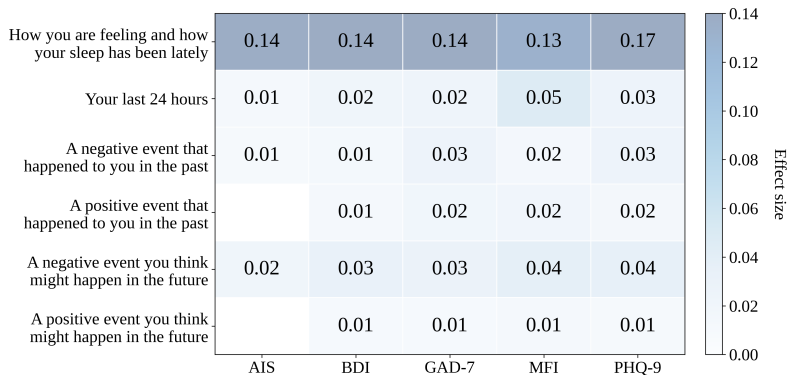
Semantic clustering and description generation



Effect size across questions and clinical scores

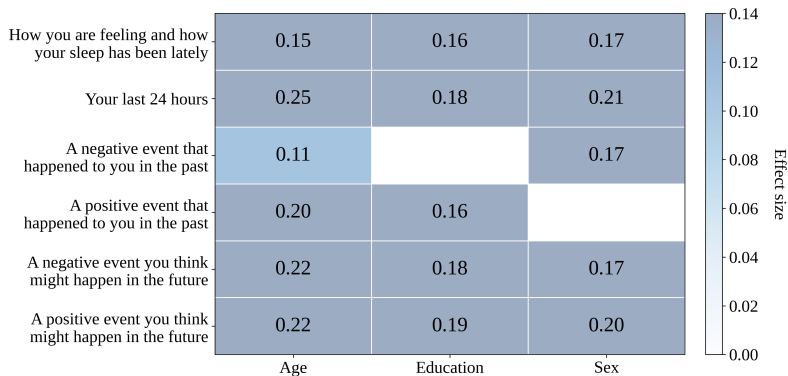


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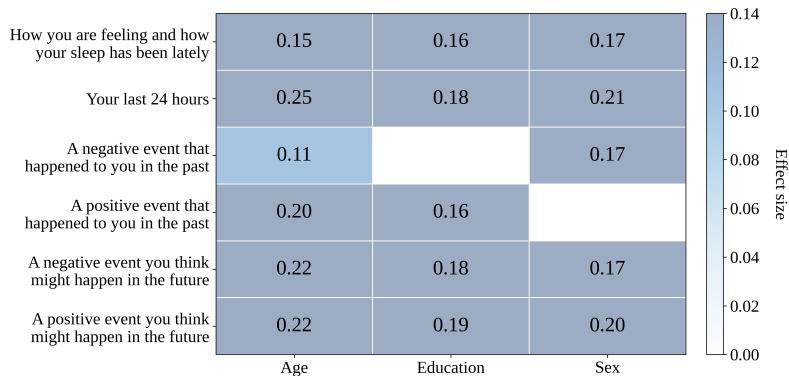


→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



Effect size across questions and sociodemographics



→ Nearly all questions discriminate sociodemographics

Perspectives

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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

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.cmc1-1.23

Gustave Cortal, Alain Finkel, et al. (2023). "Emotion Recognition Based on Psychological Components in Guided Narratives for Emotion Regulation". In: *Proceedings of the 7th Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*. Ed. by Stefania Degaetano-Ortlieb et al. Dubrovnik, Croatia: Association for Computational Linguistics, pp. 72–81. DOI: 10.18653/v1/2023.latechc1f1-1.8

Gustave Cortal (2024). "Sequence-to-Sequence Language Models for Character and Emotion Detection in Dream Narratives". In: *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*. Ed. by Nicoletta Calzolari et al. Torino, Italia: ELRA and ICCL, pp. 14717–14728

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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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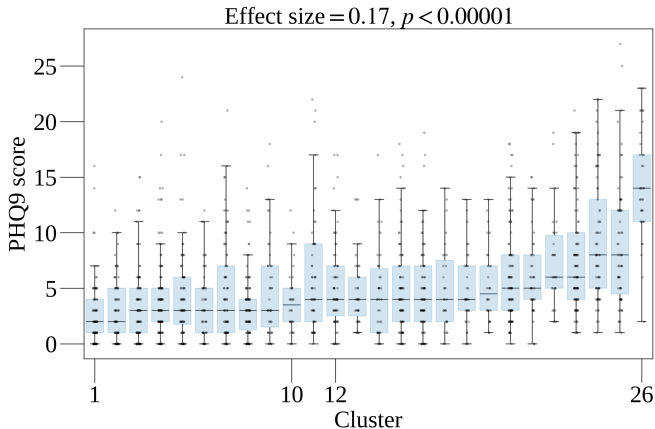
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→ Models can be used to automatically classify unstructured narratives

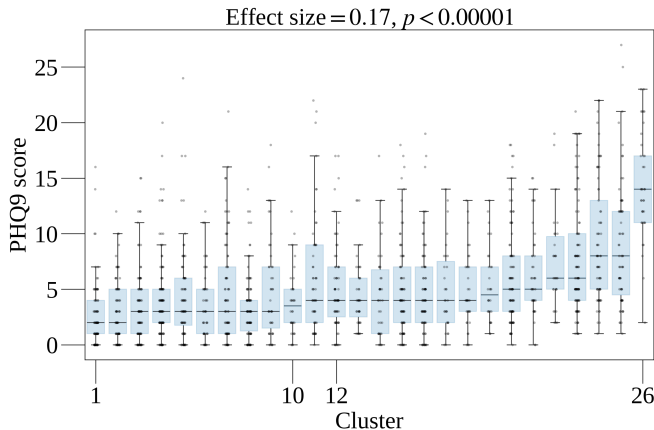
Distribution of depression scores across clusters

How you are feeling and how your sleep has been lately



Distribution of depression scores across clusters

How you are feeling and how your sleep has been lately



→ 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

Demographics




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

References




References I

-  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.cmc1-1.23](https://doi.org/10.18653/v1/2024.cmc1-1.23).
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