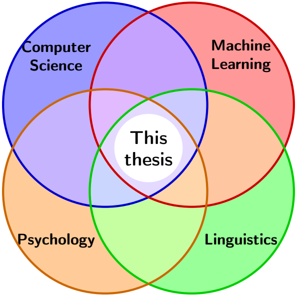
Natural language processing for subjectivity analysis in personal narratives

Gustave Cortal

Thesis director: Alain Finkel
Co-advisors: Patrick Paroubek and Lina Ye

Introduction

Context



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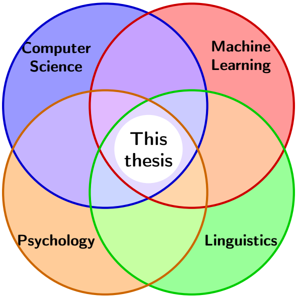

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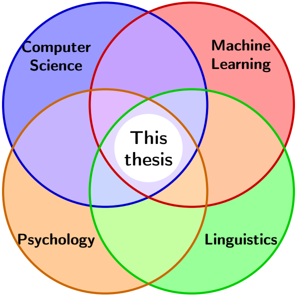

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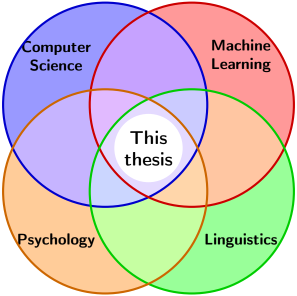

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- We build on an existing subfield: sentiment and emotion analysis
- We study subjectivity (*e.g.*, first-person perspective, meaning-making processes, and experiential content)
- We focus on personal narratives (emotional narratives, dream reports)

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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**
Basic emotions theory	a *category*	"I love philosophy." $\rightarrow$ `joy`

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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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- Different emotion theories lead to divergences in how to annotate them in the text [add refs]

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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?

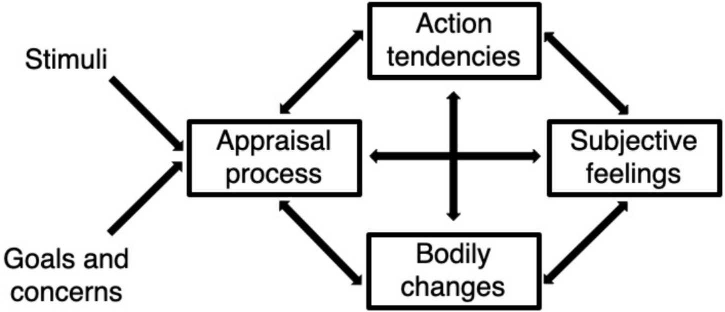

Figure: **Integrated framework for emotion theories**. Emotional episodes are synchronized changes in four components (Scherer, 2022).

→ 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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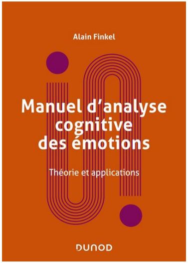

finkel2022, april **finkel2022**

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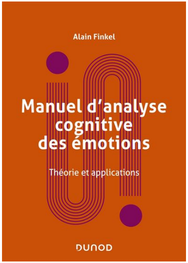

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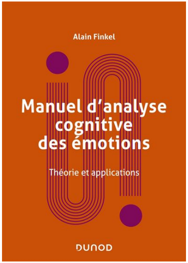
- uses emotion components to reorganize the narrative of experienced events
- helps individuals better regulate their emotions



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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

	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 `feeling`	64.3 (1.9)	61.5 (1.2)	61.3 (2.2)	81.6	79.8	79.9
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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
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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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How to automate the annotation process?

Hall and Van de Castle annotation scheme

Series: **Girls (tutorial)** Number: **0039**

<table>
<tr><th>CHAR.</th><th colspan="2">AGGRESSION</th><th colspan="2">FRIENDLINESS</th><th>SEXUALITY</th><th>SET.</th><th>OBJ.</th></tr>
<tr><td rowspan="5">2MUT
1MUT
1FKT</td><td colspan="2">1MUT 3> 1FKT
D 2= 1MUT</td><td colspan="2">D 5= 1MUT</td><td></td><td>OU</td><td rowspan="5">[not coded]</td></tr>
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<tr><td></td><td></td><td></td><td></td><td>AP, D</td></tr>
</table>

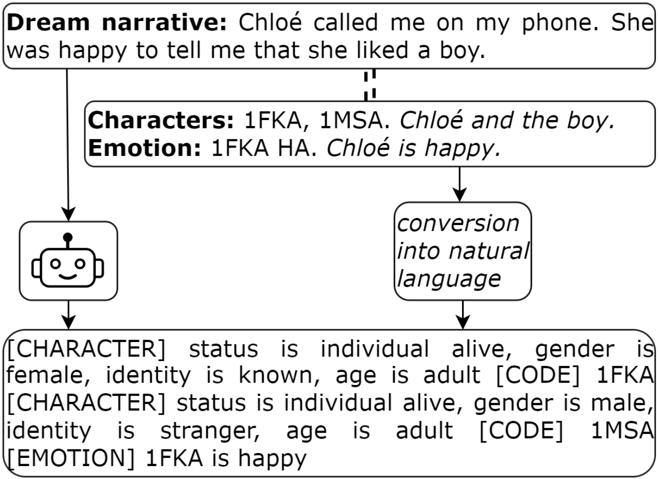
#0039
It was my birthday and I was having a party but in a place I've never been before. It was in a forest type area. All I remember is that at the same time I had two boyfriends. Only one was at my party, though he had just broken up with my best friend so I kinda felt uncomfortable being with him. We had got in an argument so he left. I don't quite remember how but we did make up but I don't remember when or why even got in the argument. I woke up when I heard the telephone ringing. (103 words)

Figure: **Hall and Van de Castle (HVC) annotation scheme**. Categories for character and emotion detection in dream narratives (**hallContentAnalysisDream1966**).

[add related works, what we propose]

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

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$\texttt{First}_{\texttt{group}}$	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

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$\texttt{Conversion}_{\texttt{comma}}$	84.02**	79.84**	77.67**	87.08*	66.69**	73.68
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$\text{Conversion}_{\text{comma}}$	84.02**	79.84**	77.67**	87.08*	66.69**	73.68
$\text{Conversion}_{\text{marker}}$	82.39	78.45	76.53	86.09	65.44	74.36

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

→ Our models can address this task; there is room for improvement

Case study on the war veteran

Group	Category	% Vet	% Total	Δ
	known*	24.9	51.6	-26.7
	prominent	1.9	2.5	-0.6
Identity	occupational*	22.4	8.0	14.4
	ethnic*	4.1	0.9	3.1
	unknown*	46.8	37.0	9.8

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

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

→ 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

How is subjective experience communicated in narratives?

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We use narratives to express our representations of reality and make sense of the world (Bruner, 1990) [add more recents refs]

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[better transition]

In everyday usage, style refers to a distinctive manner of expression

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We use style as a proxy to study how subjective experience is linguistically communicated

[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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Contributions:

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)

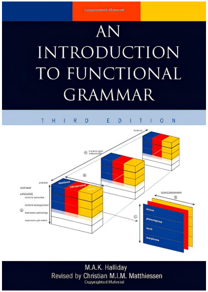

Figure: Halliday et al. (2014). $+57,000$ citations.

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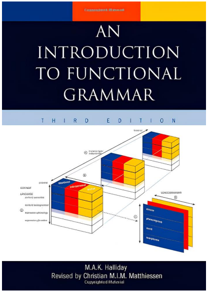
Meaning emerges through choices in systems of linguistic features to achieve communicative goals



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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)

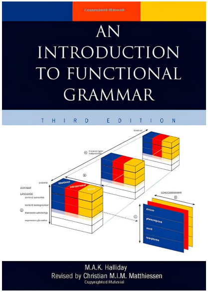

Figure: Halliday et al. (2014). +57,000 citations.

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: 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`

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

Results on the war veteran

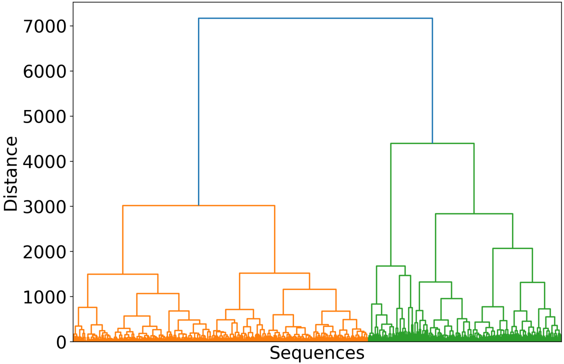

Figure: Dendrogram with Ward linkage and cosine similarity

Results on the war veteran

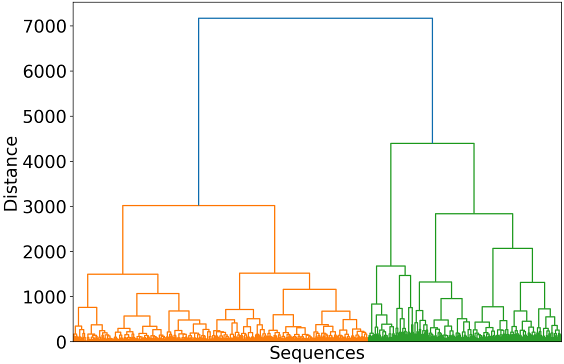

Figure: Dendrogram with Ward linkage and cosine similarity

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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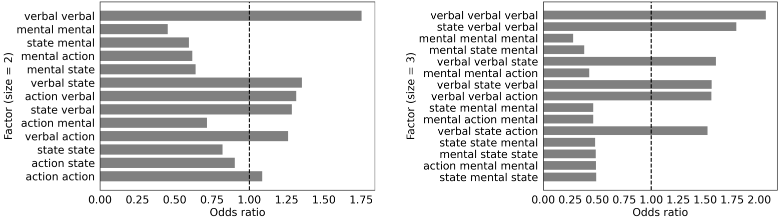

(a) Size 2.

(b) Size 3.

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

Results on the war veteran

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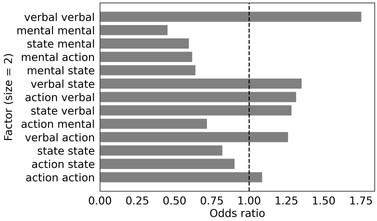

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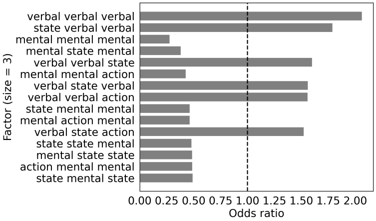

(b) Size 3.

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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- Authorship profiling
- 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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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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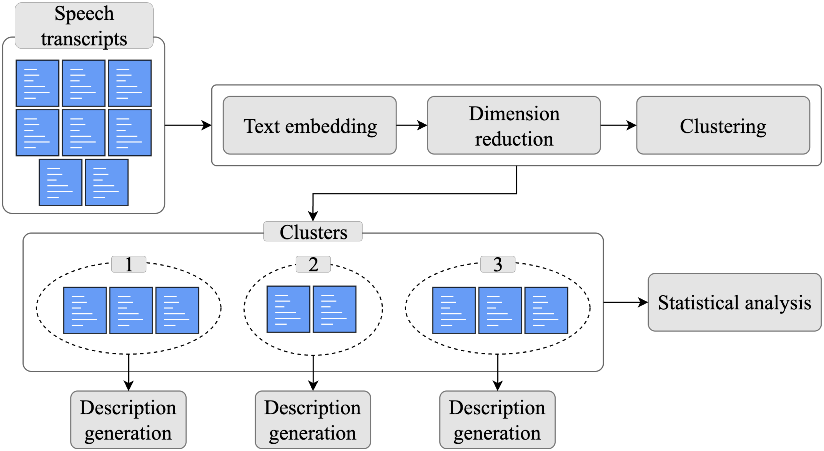
- Thematic analysis studies how people construct meaning
- Thematic analysis is time-consuming, often constrained to small, monolingual corpora
- Computational approaches offers time savings, can analyze a larger amount of data

Semantic clustering and description generation



Effect size across questions and clinical scores

	AIS	BDI	GAD-7	MFI	PHQ-9
How you are feeling and how your sleep has been lately	0.14	0.14	0.14	0.13	0.17
Your last 24 hours	0.01	0.02	0.02	0.05	0.03
A negative event that happened to you in the past	0.01	0.01	0.03	0.02	0.03
A positive event that happened to you in the past		0.01	0.02	0.02	0.02
A negative event you think might happen in the future	0.02	0.03	0.03	0.04	0.04
A positive event you think might happen in the future		0.01	0.01	0.01	0.01

Effect size (0.00–0.14)

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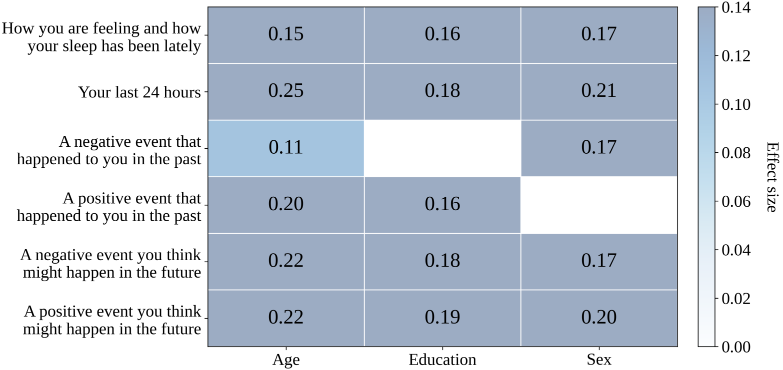
→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



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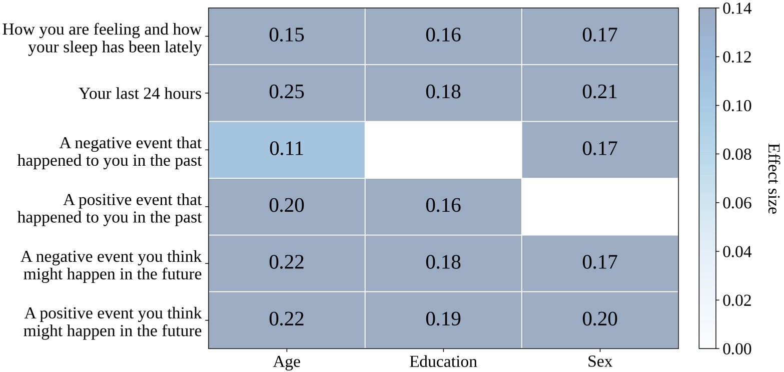

→ Nearly all questions discriminate sociodemographics

Perspectives

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

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- Post-training for psychology (preferences and reasoning data) [add refs]

Conclusion

How to model subjective experience in personal narratives?

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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

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.latechclfl-1.8

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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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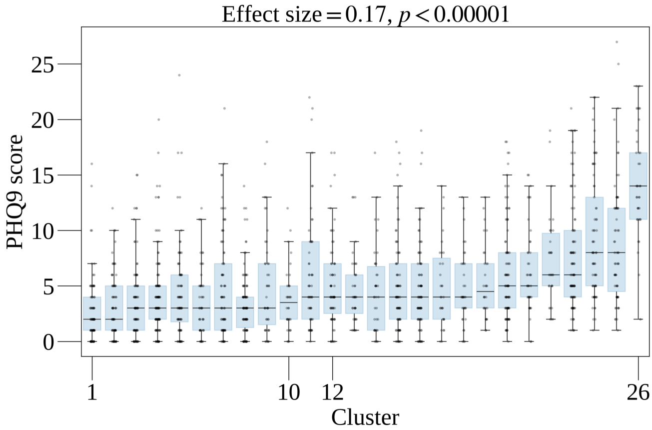
Table: Scores (± std) for emotion component classification.

→ 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



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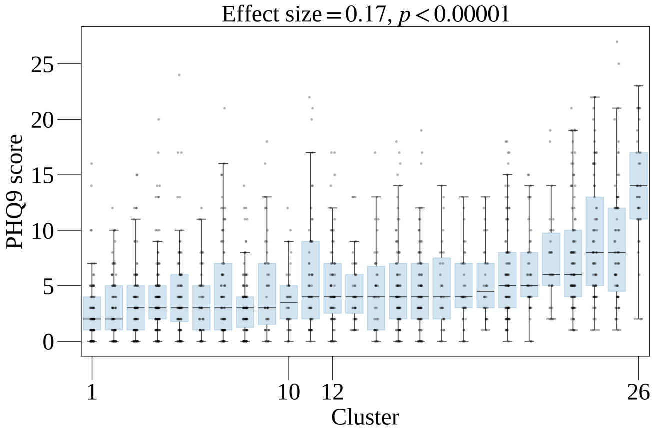

→ Depression scores vary significantly: cluster 26 highest (13.4±5.4), cluster 1 lowest (2.6±2.2)

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

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

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.cmcl-1.23`.

Bruner, Jerome (1990). *Acts of Meaning*. Acts of Meaning. Cambridge, MA, US: Harvard University Press. ISBN: 978-0-674-00360-6.

Cortal, Gustave (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.

References II

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- Domhoff, G. William and Adam Schneider (2008). "Studying Dream Content Using the Archive and Search Engine on DreamBank.Net". In: *Consciousness and Cognition* 17.4, pp. 1238–1247. ISSN: 10538100. DOI: `10.1016/j.concog.2008.06.010`.

References III

Halliday, M.A.K. et al. (2014). *An Introduction to Functional Grammar*. 0th ed. Routledge. ISBN: 978-1-4441-1908-4. DOI: 10.4324/9780203783771.

Micheli, Raphaël (2013). "Esquisse d'une typologie des différents modes de sémiotisation verbale de l'émotion". In: *Semen. Revue de sémio-linguistique des textes et discours* 35. ISSN: 0761-2990. DOI: 10.4000/semen.9795.

Scherer, Klaus R. (2022). "Theory Convergence in Emotion Science Is Timely and Realistic". In: *Cognition and Emotion* 36.2, pp. 154–170. ISSN: 0269-9931. DOI: 10.1080/02699931.2021.1973378.