

# Natural language processing for subjectivity analysis in personal narratives

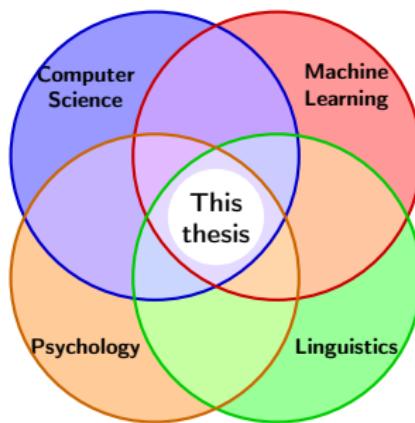
Gustave Cortal

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



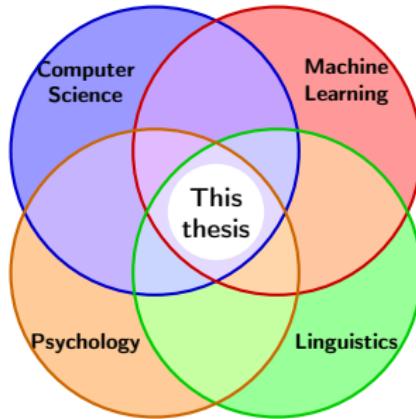
# Introduction

# Context



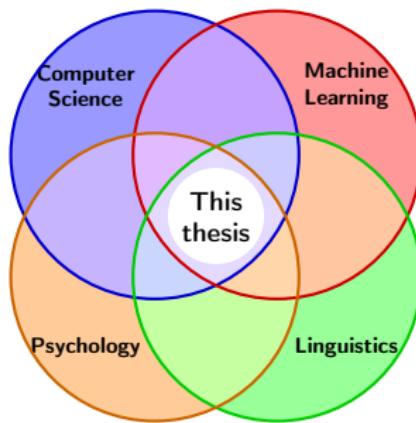
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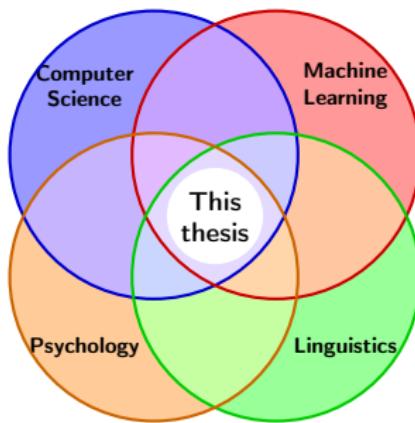
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- ▶ We study subjectivity (first-person perspective, meaning-making processes, and experiential content)
- ▶ We focus on personal narratives (emotional narratives, dream reports)

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- ▶ Emotion analysis in emotional and dream narratives

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- ▶ Cognitive science perspective on emotion analysis
- ▶ French corpus based on emotion components
- ▶ Emotion analysis in emotional and dream narratives
- ▶ Formalization of style in personal narratives

# Contributions

# Papers

## **International conferences (2):**

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# Open corpus and tools

## Corpus:

French narratives based on emotion components



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

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## Corpus:

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## Tools:

Language model for emotion and character prediction  
in dream narratives +400 downloads

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French language models for emotion component  
prediction and discrete emotion prediction +1200  
downloads

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## Cognitive science perspective on emotion analysis

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

# Psychology and emotion annotation

Psychological theories	In text, emotion is...	Example
Basic emotions theory	a <i>category</i>	"I love philosophy." → joy

Darwin (1872), Tomkins (1962), Ekman (1999), and Plutchik (2001)  
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Constructivist theories	a continuous value with an <i>affective meaning</i> Schachter and Singer (1962) and Russell and Barrett (1999) Buechel and Hahn (2017)	"His voice soothes me." → valence (4/5), arousal (1/5)

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Schachter and Singer (1962) and Russell and Barrett (1999) Buechel and Hahn (2017)		
Appraisal theory	a continuous value with a <i>cognitive</i> meaning	"I received a surprise gift." → sudden (4/5), control (0/5)
Arnold (1960) and Lazarus (1991) Troiano, Oberländer, and Klinger (2023)		

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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)."

Campagnano, Conia, and Navigli (2022) and Klinger (2023)  
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Similar to aspect-based sentiment analysis (W. Zhang, Li, et al., 2022): "The battery life is *amazing* (+), but its camera quality is *disappointing* (-)."

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- ▶ Emotion verbalization is underexplored  
(Micheli, 2013b; Etienne, Battistelli, and Lecorv , 2022)
- ▶ Benchmarks evaluate certain aspects of emotional understanding but do not consider its full complexity  
(Campagnano, Conia, and Navigli, 2022; W. Zhang, Deng, et al., 2023; Paech, 2024)

## Linguistic and cognitive science theories

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(Nathalie Blanc, 2010; Creissen and N. Blanc, 2017; Foppolo and Mazzaggio, 2024)

→ There exist an annotation scheme for emotion expression modes

(Etienne, Battistelli, and Lecorvé, 2022; Dragos et al., 2022)

## How to integrate psychological theories of emotion?

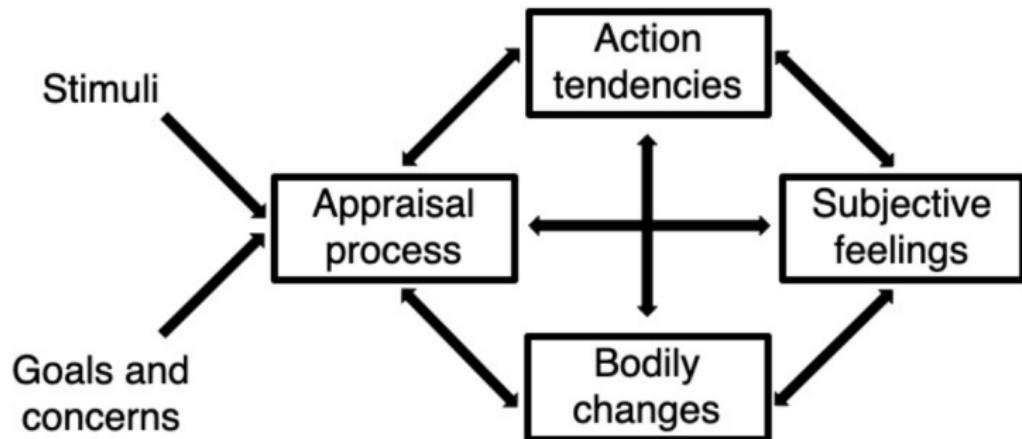


Figure: The integrated framework for emotion theories (Scherer, 2022b).

Rectangles represent the components constituting an emotional episode, and arrows represent causation.

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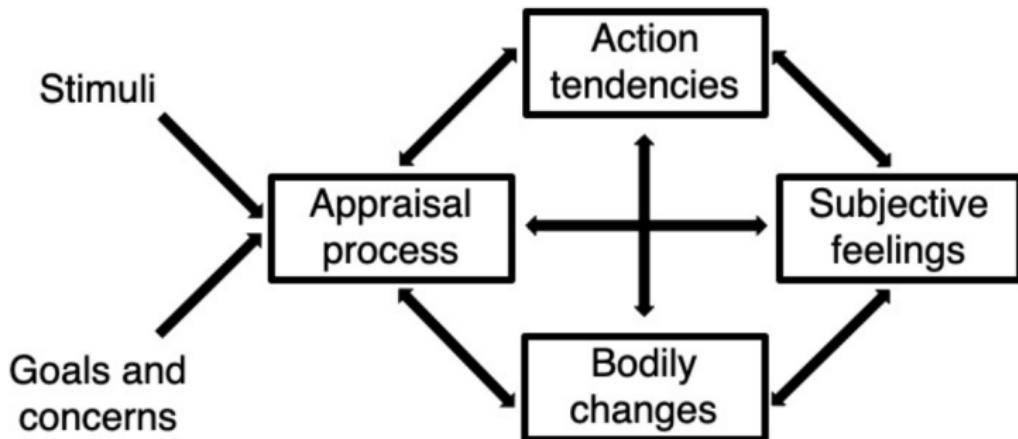


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→ We use this framework to construct a corpus based on components

## French narratives based on emotion components

The corpus is available at [hf.co/datasets/gustavecortal/FrenchEmotionalNarratives](https://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*.

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→ A new French corpus of emotional narratives structured by the authors according to their behaviors, thoughts, physical feelings, and reasons

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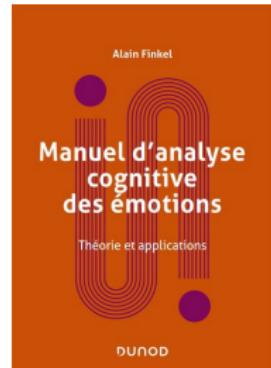
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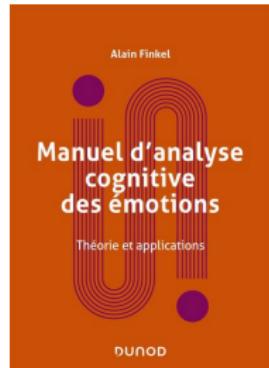
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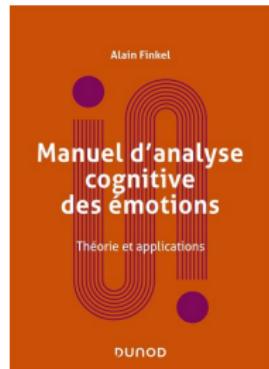
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- ▶ uses emotion components to reorganize the narrative of experienced events
- ▶ helps individuals better regulate their emotions



Finkel (2022)

## French narratives based on emotion components

**Contribution:** +1,000 narratives structured with emotion components by the writers themselves plus discrete emotion labels

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.
Reason	The student attacks my ability to be respected in class.

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

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→ A. Finkel has been collecting narratives since 2005 during emotion regulation sessions; I structured them to build a corpus for emotion classification

# Language models for emotion analysis in emotional and dream narratives

Language models are available on [hf.co/gustavecortal](https://hf.co/gustavecortal)

**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 (tf-idf)			CamemBERT		
	Precision	Recall	$F_1$	Precision	Recall	$F_1$
All	71.2 (2.6)	69.1 (2.2)	67.8 (2.3)	<b>85.1</b>	<b>84.8</b>	<b>84.7</b>

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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
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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
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; need to study static vs. contextual semantics

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→ Dream narratives possess a narrative structure and represent attempts to communicate subjective experience

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(Flanagan, 1966; Domhoff and Schneider, 2008)

The annotation process is complex and costly

## Quantitative analysis of dream narratives

*Quantitative dream analysis* studies the continuity hypothesis, and relies on dream databases and annotation schemes

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→ How to automate the annotation process using language models?

# Example of an annotated dream with HVdC

Series: Girls (tutorial) Number: 0039

CHAR.	AGGRESSION		FRIENDLINESS		SEXUALITY	SET.	OBJ.		
2MUT	1MUT 3> 1FKT		D 5= 1MUT			OU	[not coded]		
1MUT	D 2= 1MUT								
1FKT	ACTIVITIES					MOD.			
	[not coded]					[not coded]			
	FAILURE	SUCCESS	MISFORTUNE	GOOD FORT.	EMOTIONS	AP, D			

## Character:

- ▶ **Status:** individual alive (**1**), group alive (**2**), dead individual (**3**), dead group (**4**), imaginary individual (**5**), imaginary group (**6**), original form (**7**), changed form (**8**)
- ▶ **Gender:** male (**M**), female (**F**), joint (**J**), indefinite (**I**)
- ▶ **Identity:** known (**K**), prominent (**P**), occupational (**O**), ethnic (**E**), unknown (**U**)
- ▶ **Age:** adult (**A**), teen (**T**), child (**C**)

**Emotion:** anger (**AN**), apprehension (**AP**), sadness (**SD**), confusion (**CO**), and happiness (**HA**)

## Existing research on computational dream analysis

*Lexical-based approaches* associate text spans with specific categories (e.g., type of interactions) (Miller, 1994; Fogli, Aiello, and Quercia, 2020)

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McNamara et al. (2019) and Yu (2022) combine the lexical-based and distributional semantic-based approaches with machine learning

# Existing research on computational dream analysis

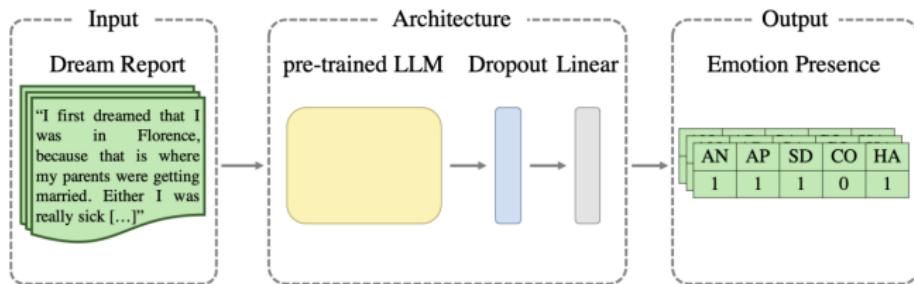


Figure: Architecture for multi-label emotion detection (Bertolini et al., 2023).

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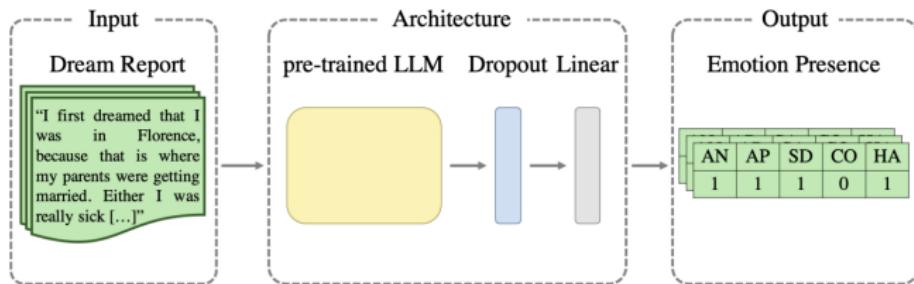


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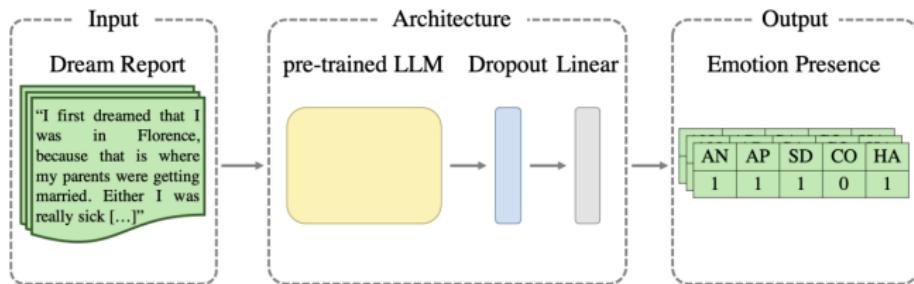


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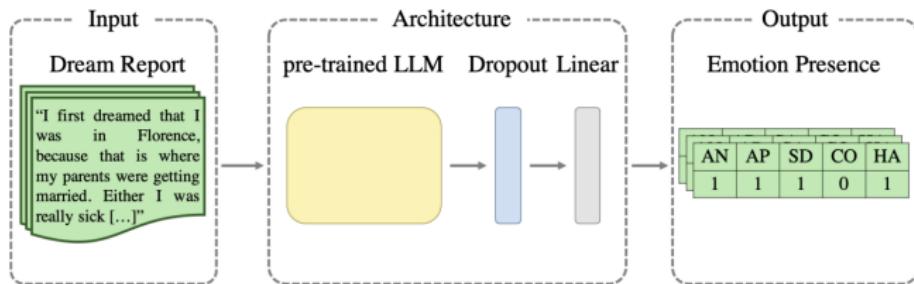


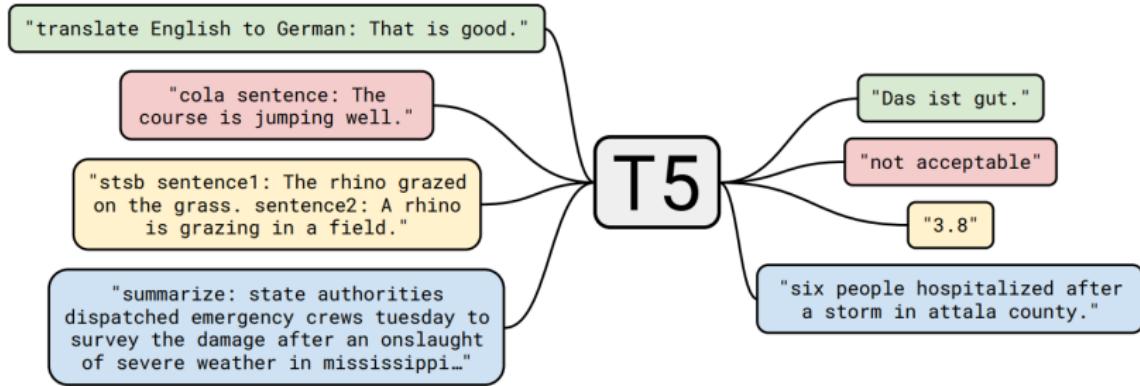
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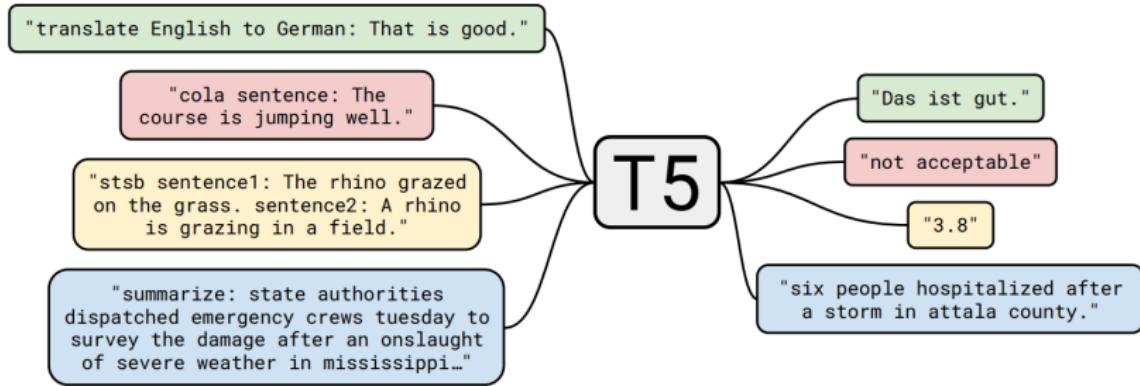
→ We address this by identifying characters and their emotions with transformer-based sequence-to-sequence models

# T5 language models



**Figure: Text-to-text framework** (Raffel et al., 2020). One model maps input text to target text for tasks such as translation, QA, and classification.

# T5 language models



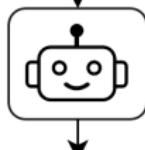
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→ 248M-parameter LaMini-Flan-T5 encoder-decoder transformer, pre-trained on 2.58M instructions across 15 tasks (Wu et al., 2023)

# Character and emotion detection in dream narratives

**Dream narrative:** Chloé called me on my phone. She was happy to tell me that she liked a boy.

**Characters:** 1FKA, 1MSA. *Chloé and the boy.*  
**Emotion:** 1FKA HA. *Chloé is happy.*



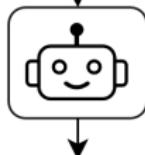
*conversion  
into natural  
language*

[CHARACTER] status is individual alive, gender is female, identity is known, age is adult [CODE] 1FKA  
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→ Our framework can be extended to include other HVdC categories

# Results

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

**Table: Character and emotion detection.**  $p < 0.05$ .

Model	Status	Gender	Identity	Age	Character	Emotion
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→ Our models can address this task; there is room for improvement

58  $F_1$ -score for gender prediction using lexical approaches (Fogli, Aiello, and Quercia, 2020)

86  $F_1$ -score for emotion presence detection using transformers (Bertolini et al., 2023)

## 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
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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

Generated annotations for DreamBank are available on [hf.co/gustavecortal](https://hf.co/gustavecortal)

## Formalization of style in personal narratives

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

## Motivation

**Limitation:** A formalization of style that captures how subjective experience is linguistically communicated is lacking

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Formalization could enable more precise identification of linguistic patterns associated with psychological states and may support interventions (White and Epston, 1990)

→ We aim to create a accessible framework that researchers can build upon in future studies

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(Hadamard, 1945; Granger, 1968; Husserl, 1982; Dilts, 1994)

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semantic content (Jin et al., 2022; Troiano, Velutharambath, and Klinger, 2023)

→ They provide operational tools to capture or control linguistic form,  
but do not focus on how such forms encode subjective experience

## How to give an operational definition of style?

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**Goal:** Map narratives to sequences based on extracted linguistic features:  
"I wake in a dark room. I feel a cold wind. I tell myself to move." → *amv*

## Contributions

- ▶ A sequence-based framework defining style as *patterns in sequences of linguistic choices that encode subjective experience*

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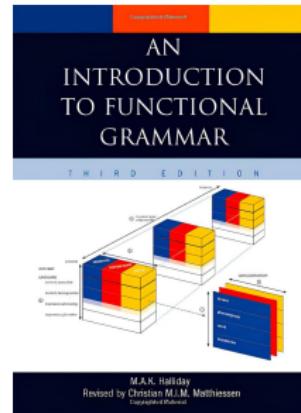
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- ▶ A case study on dream narratives

# What linguistic features encode subjective experience?

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

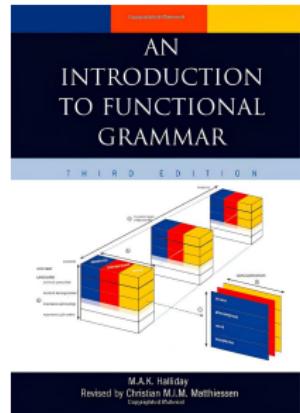


**Figure:** Halliday et al. (2014).  
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Meaning emerges through choices in systems of linguistic features to achieve communicative goals



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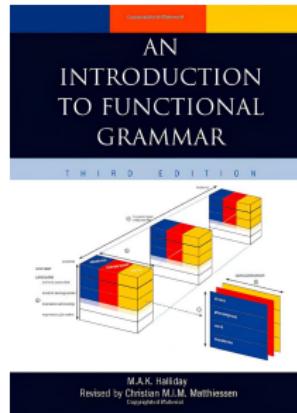
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Language achieves three functions:

- ▶ Interpersonal: language builds social relationships
- ▶ Textual: information is organized to create coherent messages
- ▶ *Ideational*: language represents experience



**Figure:** Halliday et al. (2014).  
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# What linguistic features encode subjective experience?

According to the *ideational function*, language represents experience through **processes** and **participants**

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

## Formal definition of style

**Alphabet:** Let  $\Sigma$  be the set of process types

$$\Sigma = \{\text{Action, Mental, Verbal, State}\}$$

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→ We implement  $\phi$  using a language model with in-context learning

## Formal definition style

**Style:** We define the style of text  $T$  as the set of patterns contained in its sequence  $\phi(T)$

$$\mathcal{S}(T) = \{w \in \Sigma^* \mid w \subseteq \phi(T)\}$$

where  $w \subseteq \phi(T)$  denotes a substring (contiguous symbols)

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$$\mathcal{S}(A) = \bigcup_{T \in \mathcal{C}_A} \mathcal{S}(T)$$

# Methodology for our sequence-based framework

**Narrative:** "I wake in a dark room. I feel a cold wind. I tell myself to move."

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

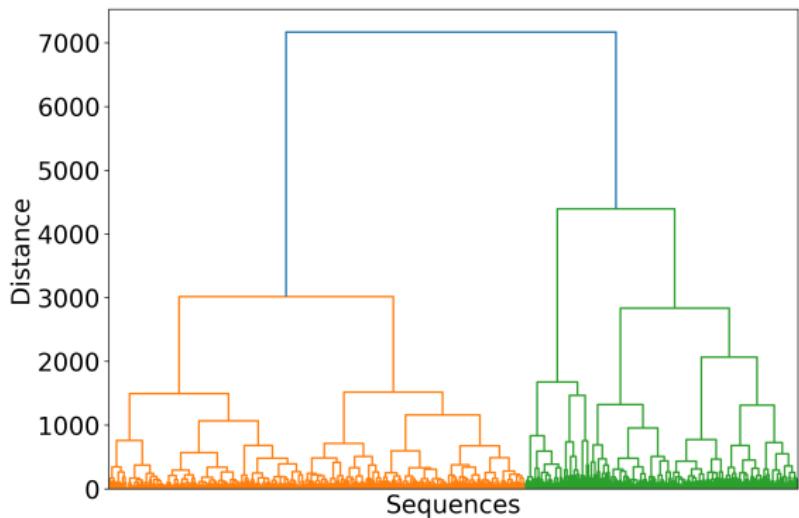


Figure: Dendrogram with Ward linkage and cosine similarity

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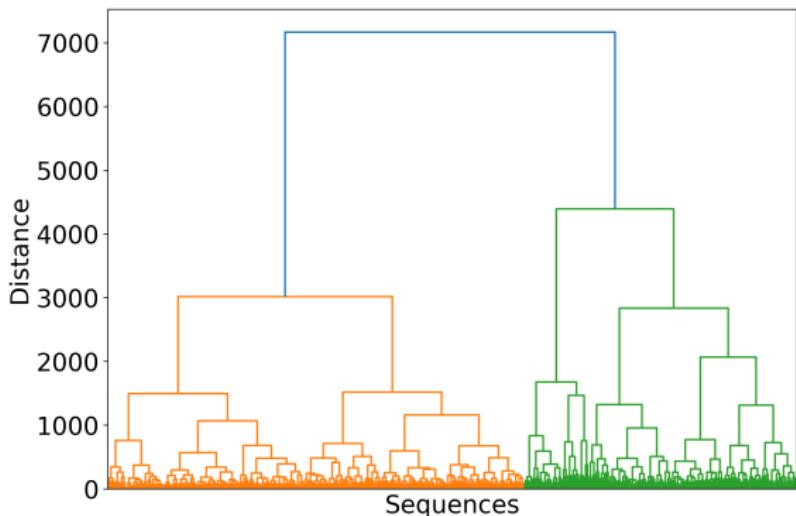


Figure: Dendrogram with Ward linkage and cosine similarity

**Representative sequences:** *savamasasaaaamaaaasavvvaaaaaaavssaaaaa*  
and *sssssavaavssvsavvvvsmasasaasasaamaamvmsss*

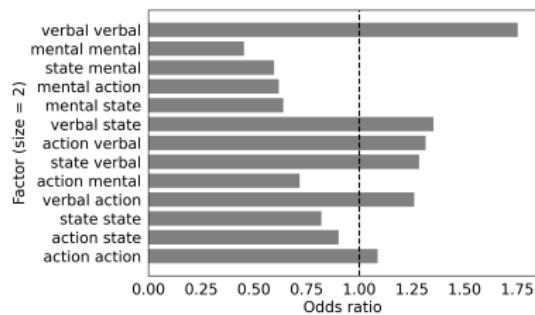
with  $a$  = action,  $m$  = mental,  $s$  = state,  $v$  = verbal

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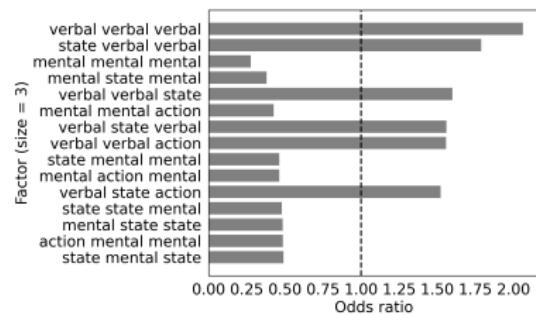
We compare the proportion of sequences containing a given substring

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(a) Size 2.

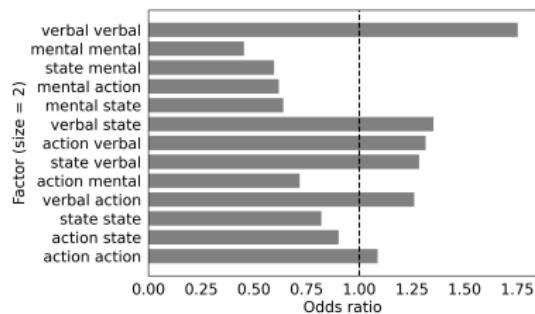


(b) Size 3.

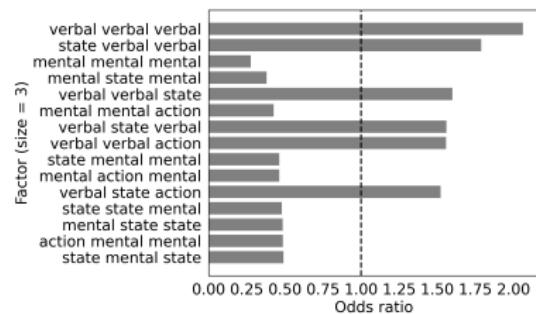
Figure: Top substring odds ratio between the veteran and the norm

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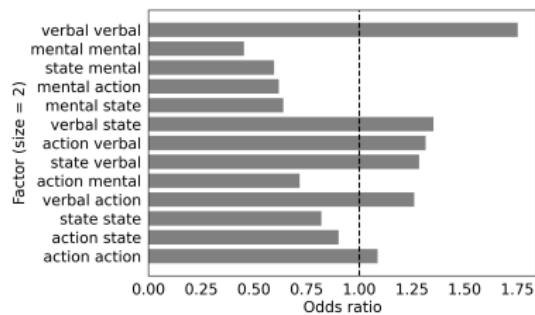
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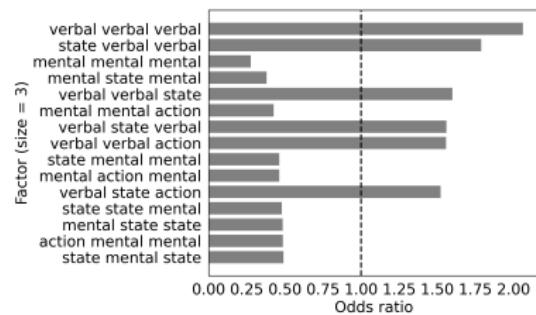
→ The veteran favors verbal processes over mental ones

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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
- Our results can inform psychological interpretations; need more individuals to generalize findings

## How can this framework be extended?

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- ▶ **Applying methods from complexity science**  
(Lempel and Ziv, 1976; Hipólito et al., 2023)

## Conclusion and perspectives

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## Perspectives

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## Perspectives

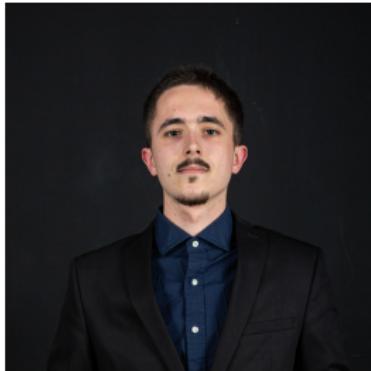
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- ▶ **Psychology of language models:** sycophancy, thought operations  
(Didolkar et al., 2025; M. Sharma et al., 2025)

# 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).

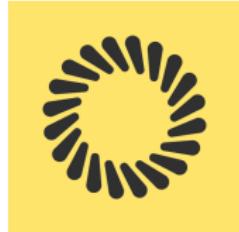
## NLP for psychiatry (industry)

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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.

## Motivation

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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

## Data collection

Narratives and clinical scores from *four cohorts*: French general population (n=1809) and three clinical cohorts (Italian n=116, Chinese n=52, Spanish n=90)

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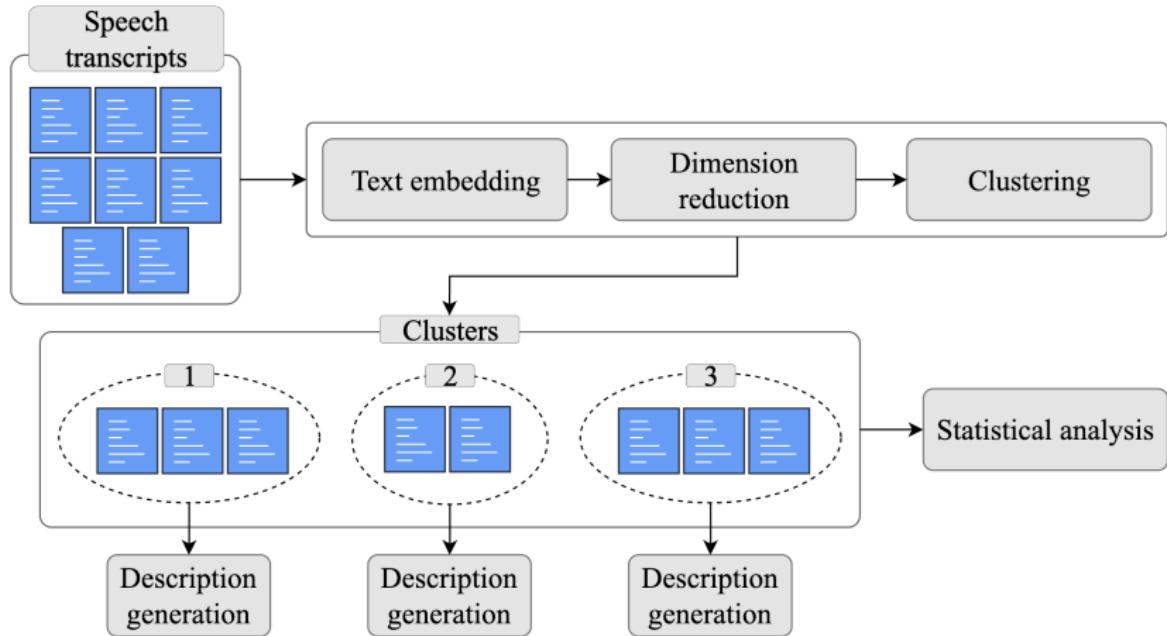
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*Clinical scores* for depression, anxiety, insomnia

*Open-ended questions* involving last 24h, positive future event, current feelings and sleep, etc.

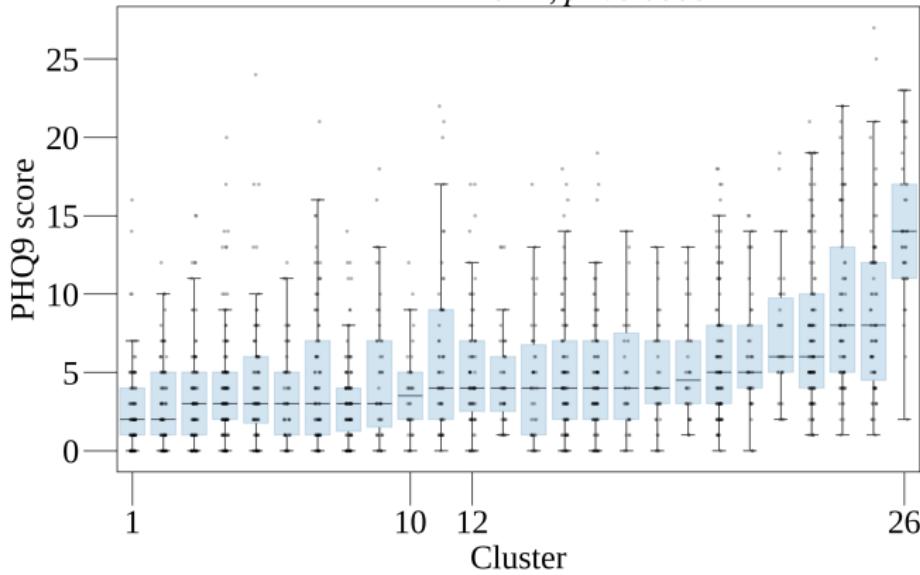
# Semantic clustering and description generation



# Distribution of depression scores across clusters

*Current feelings and sleep (n=1,786)*

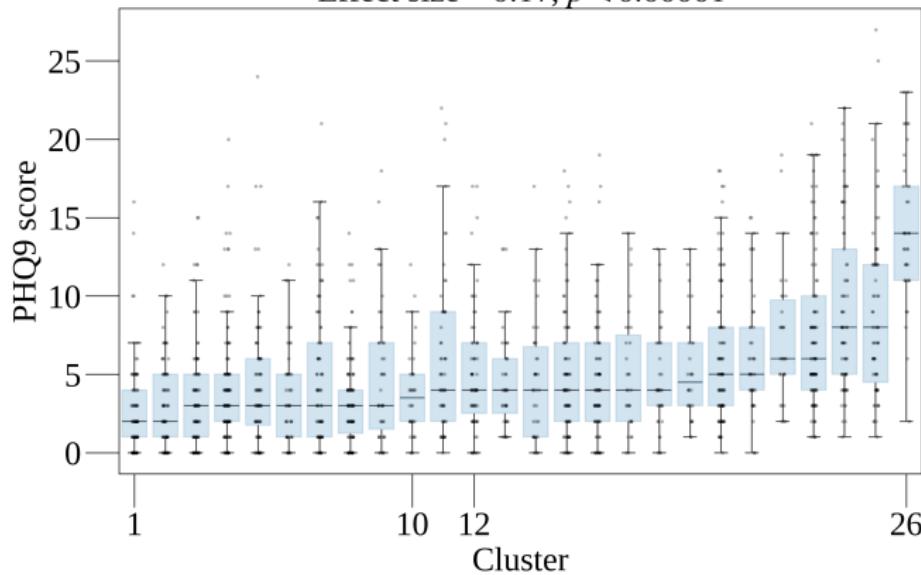
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Effect size = 0.17,  $p < 0.00001$



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

# 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

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- ▶ Cognitive science perspective on emotion analysis
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**Papers:** 2 int. conferences, 3 int. workshops, 2 national venues

**Open corpus and tools:** French corpus based on emotion components; language models for emotion analysis in emotional and dream 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 Kurabayashi et al. Bangkok, Thailand: Association for Computational Linguistics, pp. 264–277. DOI: [10.18653/v1/2024.cmcl-1.23](https://doi.org/10.18653/v1/2024.cmcl-1.23)

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# Appendix

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The formal semantics of a language is made of syntactical and lexical rules that pairs <strings of words> with [sentential meanings]

What are the psychological mechanisms used to infer what is communicated?

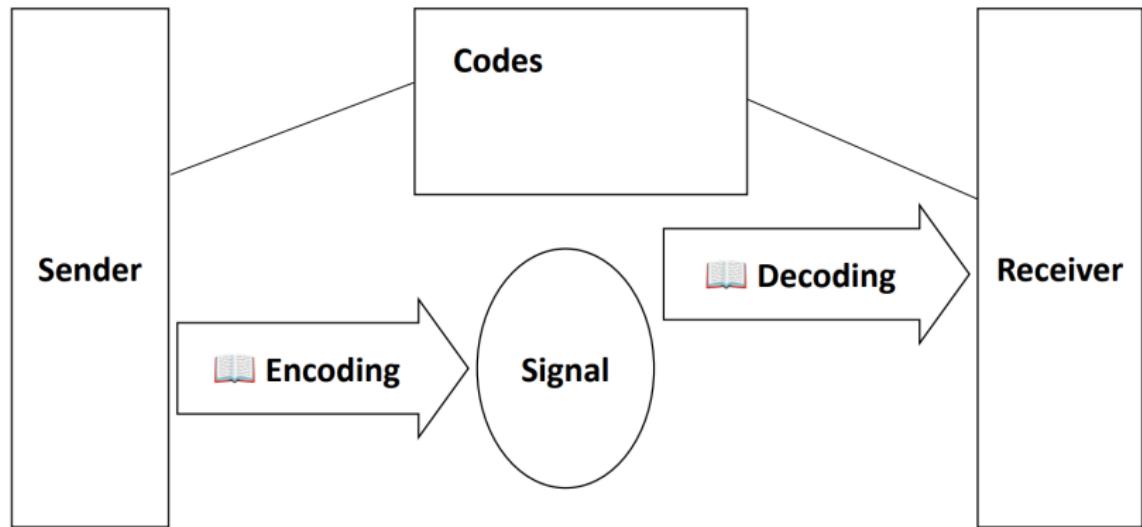


Figure: Dictionary analysis in cognitive pragmatics.

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- We rely on other sources of evidence to infer what is communicated

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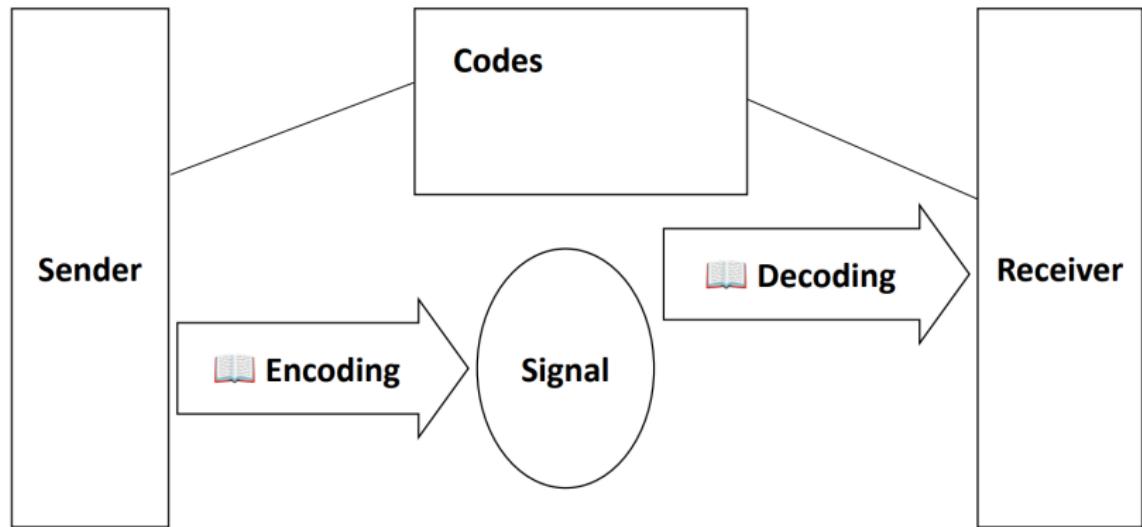


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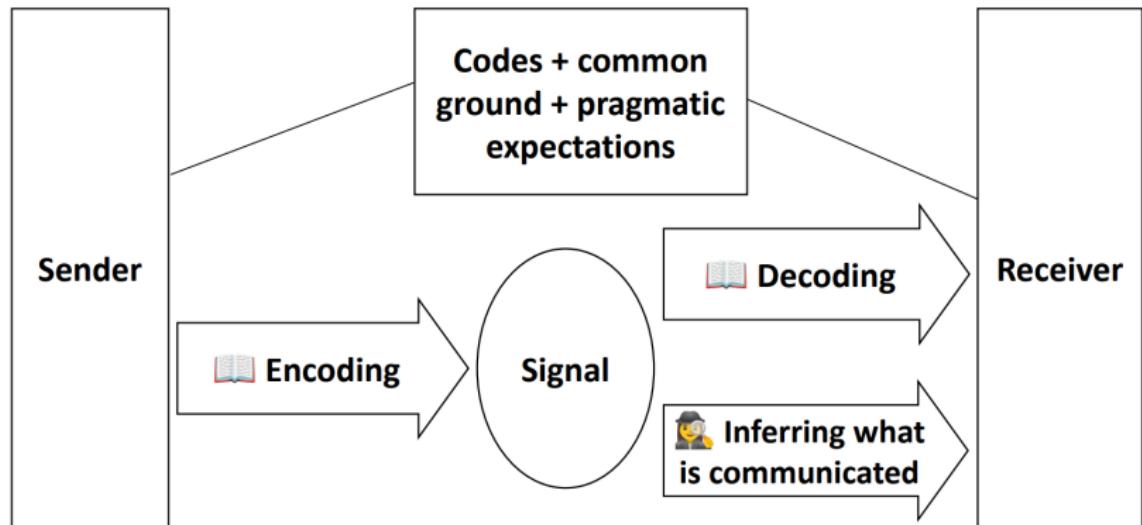


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# Component classification in emotional narratives

Model	Precision	Recall	$F_1$
Logistic Regression	84.9 (0.3)	84.3 (0.3)	84.4 (0.3)
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→ Models can be used to automatically classify unstructured narratives

## Results

StableBeluga<sub>i</sub> is a 7B model with in-context learning using  $i$  examples

Model	Status	Gender	Identity	Age	Character	Emotion
Baseline	82.87	78.02	76.17	86.21	64.74	75.13
StableBeluga <sub>1</sub>	43.95**	39.76**	31.25**	56.16**	15.65**	-
StableBeluga <sub>3</sub>	52.44**	46.49**	38.46**	63.88**	21.06**	-
StableBeluga <sub>5</sub>	55.89**	46.29**	42.61**	63.73**	24.86**	-

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

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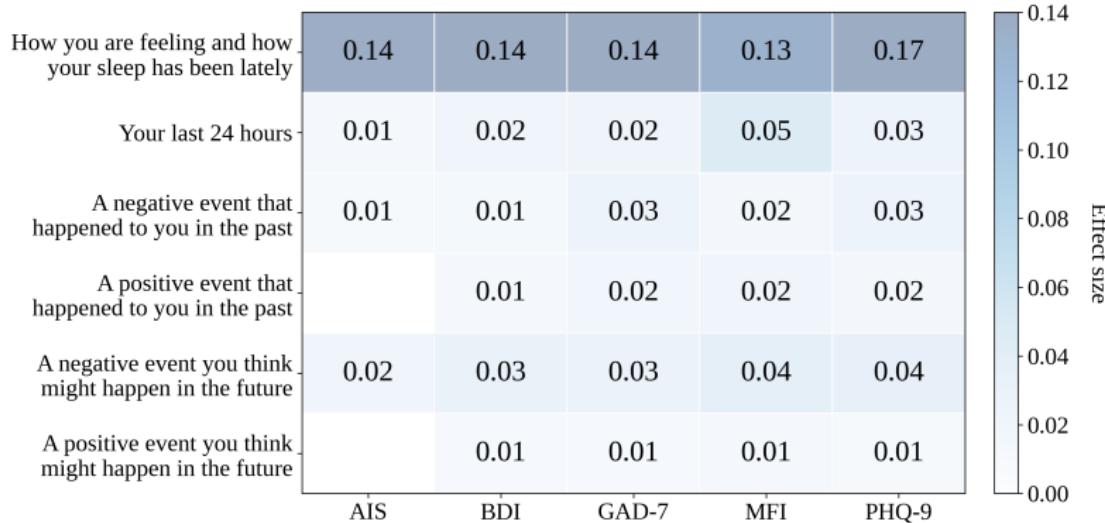
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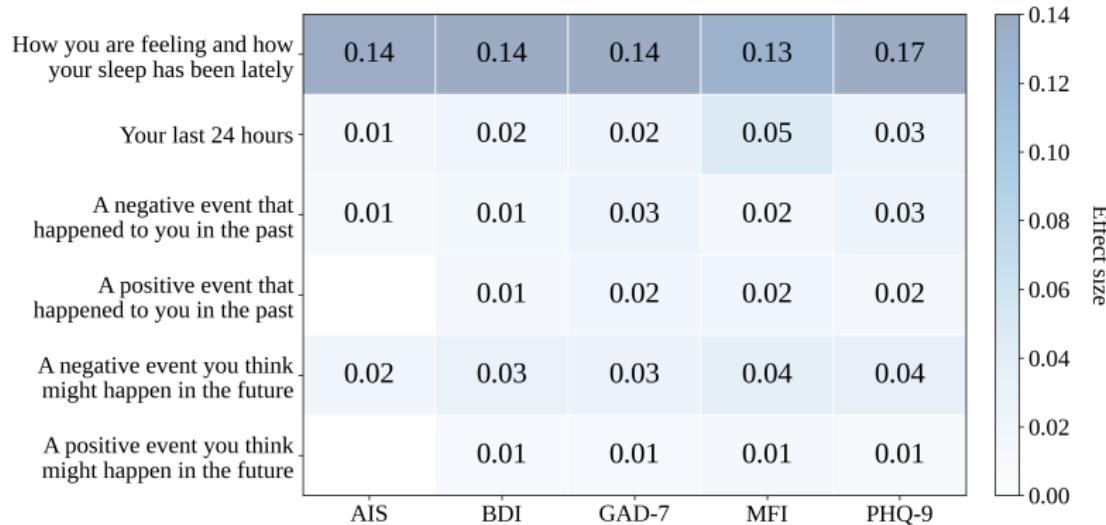
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→ Compared to StableBeluga, our supervised models perform better while having 28 times fewer parameters (248M vs. 7B)

# Effect size across questions and clinical scores

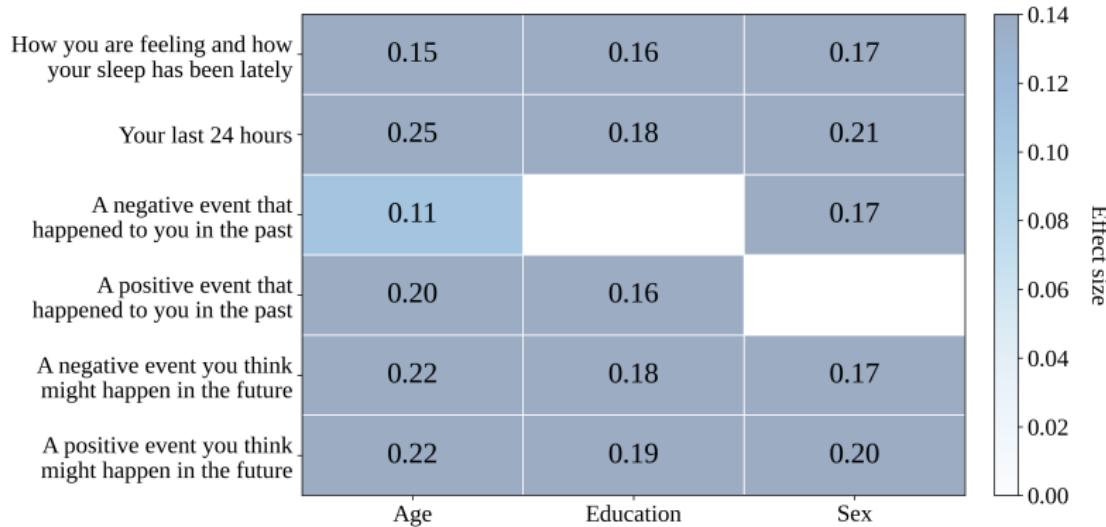


## Effect size across questions and clinical scores

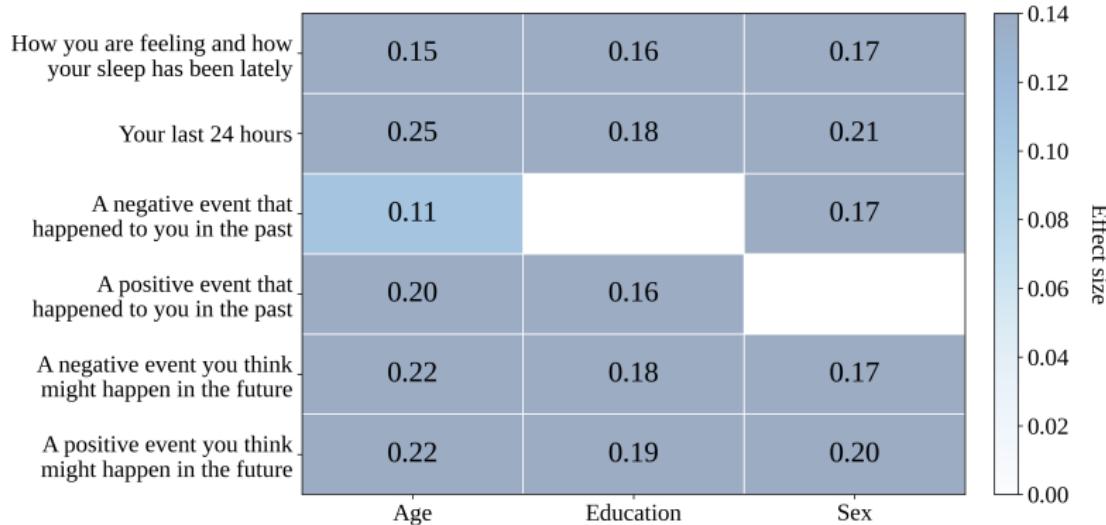


→ Certain questions better discriminate clinical scores

# Effect size across questions and sociodemographics



# Effect size across questions and sociodemographics



→ Nearly all questions discriminate sociodemographics

# Demographics

	General Population n=1809	Androids n=116	MODMA n=52	VOCES n=90
<b>Demographics</b>				
<b>Language</b>	French	Italian	Chinese	Spanish
<b>Age</b>	***	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
<b>Sex, n (%)</b>	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)
<b>Education, n (%)</b>	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
<b>C-SSRS</b>	<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)
<b>MADRS / MDD</b>	<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)	-
<b>PHQ-9</b>	<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

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