

Natural language processing for subjectivity analysis in personal narratives

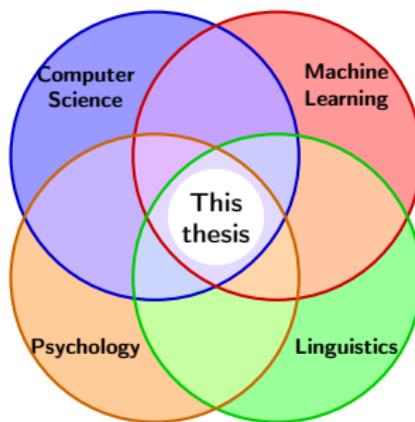
Gustave Cortal

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



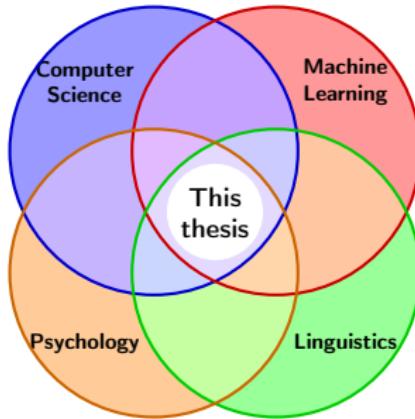
Introduction

Context



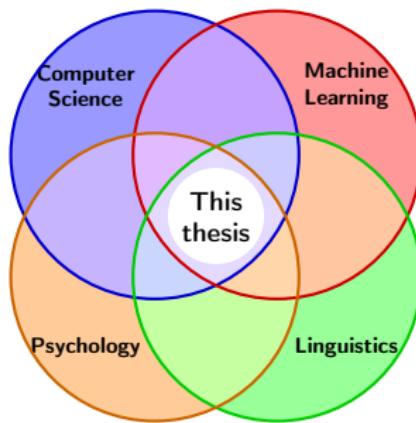
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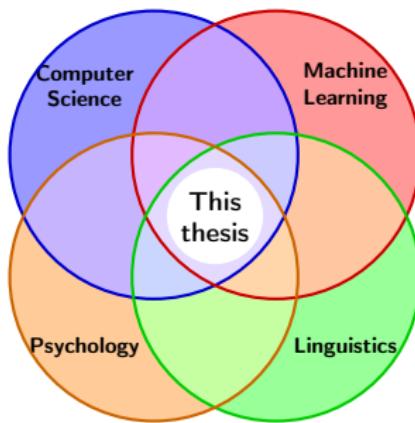
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- ▶ We study subjectivity (first-person perspective, meaning-making processes, and experiential content)

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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

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Open corpus and tools

Corpus:

French narratives based on emotion components



hf.co/gustavecortal

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

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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

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Demszky et al. (2020) and Greschner et al. (2025)

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

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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)."

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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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- ▶ 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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→ [add refs] (Etienne, Battistelli, and Lecorv , 2022; Dragos et al., 2022)

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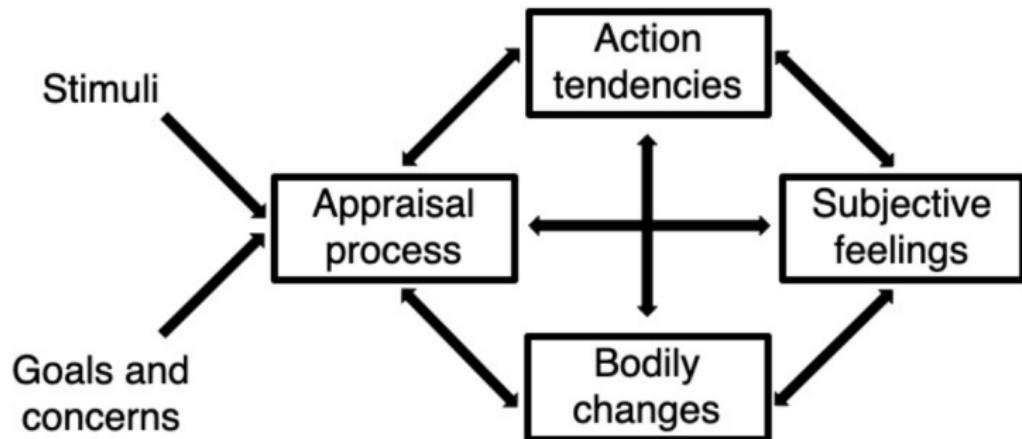


Figure: The integrated framework for emotion theories (Scherer, 2022b).

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

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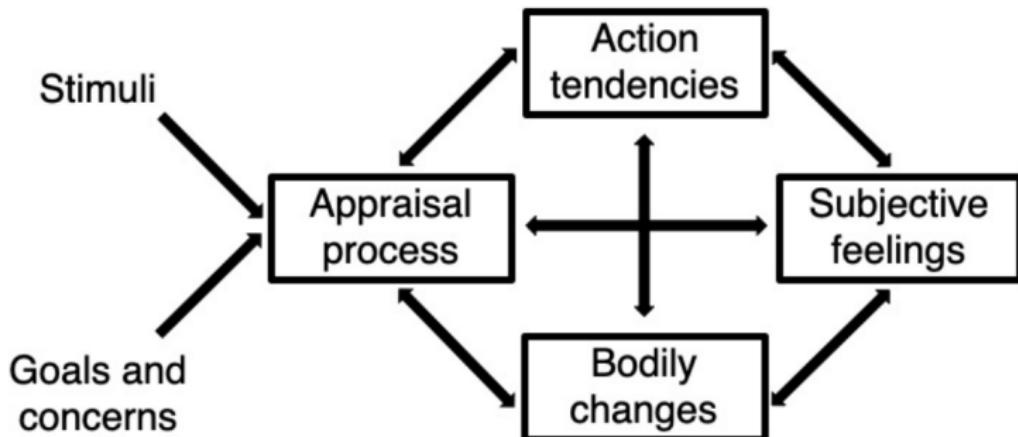


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→ We use this framework to construct a corpus based on components

French narratives based on emotion components

The corpus is available at hf.co/datasets/gustavecortal/FrenchEmotionalNarratives

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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→ We structure emotional narratives according to behaviors, thoughts, physical feelings, and reasons

Cognitive Analysis of Emotions

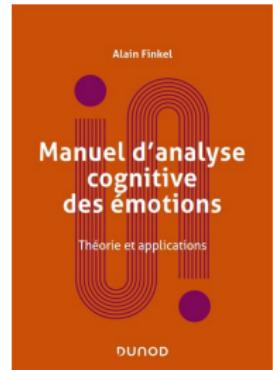
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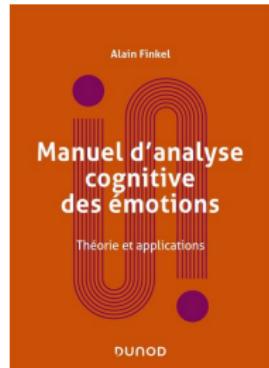
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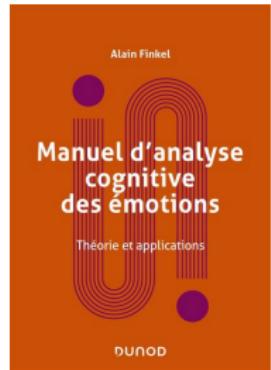
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- ▶ uses emotion components to reorganize the narrative of experienced events
- ▶ helps individuals better regulate their emotions



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

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 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 (behavior and thinking)

Motivation for dream analysis

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

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), stranger (S)
- ▶ **Age:** adult (A), child (C)

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

Existing research on computational dream analysis

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Distributional semantic-based approaches represent text spans in a vector space to identify prototypical situations
(Gutman Music, Holur, and Bulkeley, 2022)

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

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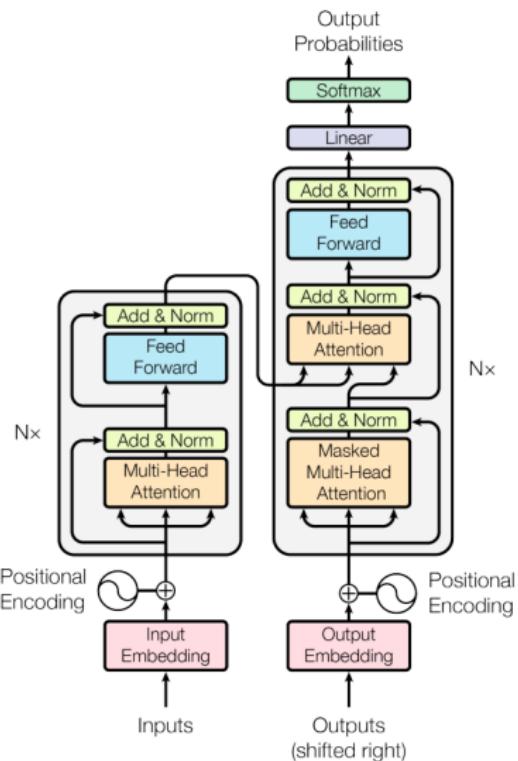
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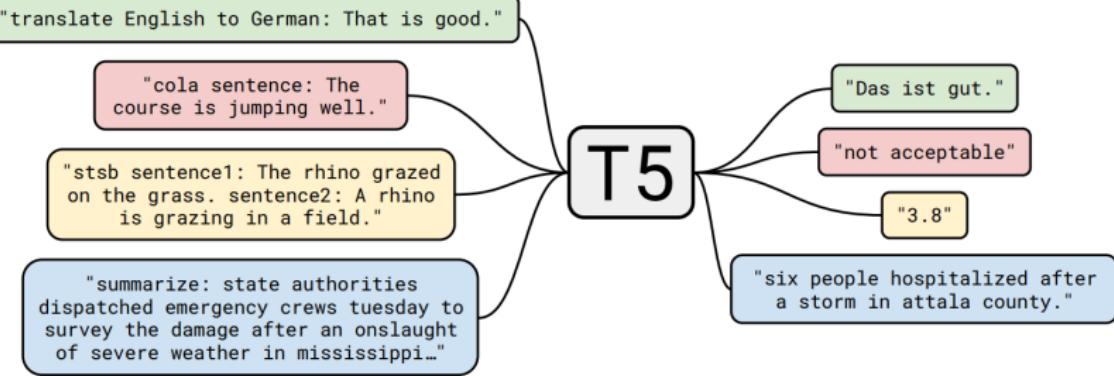
→ We address this by identifying characters and their emotions with transformer-based sequence-to-sequence models

Encoder-decoder transformer architecture



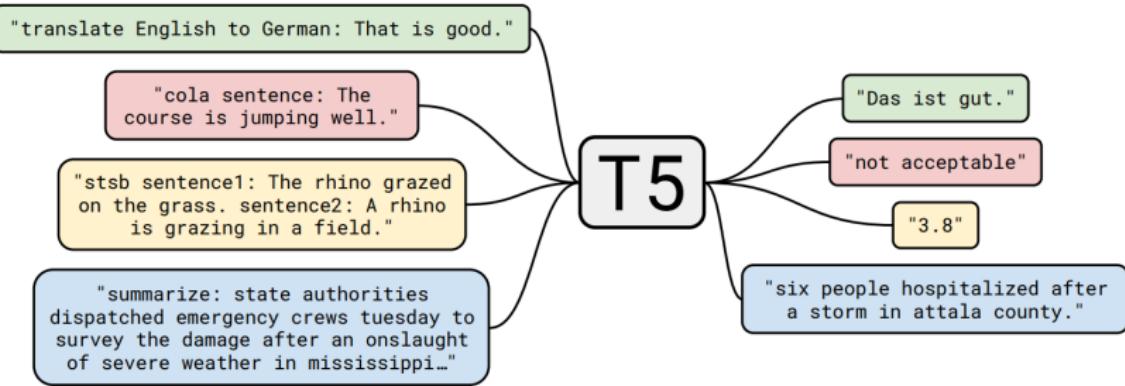
Vaswani et al. (2017)

T5 sequence-to-sequence framework



Raffel et al. (2020)

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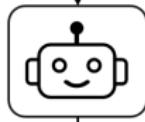
Raffel et al. (2020)

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
[CHARACTER] status is individual alive, gender is male, identity is stranger, age is adult [CODE] 1MSA
[EMOTION] 1FKA is happy

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
Baseline	82.9	78.0	76.2	86.2	64.7	75.1

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First _{individual}	80.6	76.1	74.2	83.9	62.7	67.3
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→ Our models can address this task; there is 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

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

Generated annotations for DreamBank are available on 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

Motivation

Scholarly work has examined personal modes of reasoning and expression
(Hadamard, 1945; Granger, 1968; Husserl, 1982; Dilts, 1994)

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

Motivation

Tellier and Finkel (1995) define linguistic style as lexical and syntactical patterns using formal language theory

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→ Drawing on these ideas, we provide a sequence-based framework to analyze how personal narratives convey subjective experience

How to give an operational definition of style?

Intuitive definition: a distinctive manner of communicating subjective experience in personal narratives

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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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- ▶ A methodology for identifying patterns using sequence analysis
- ▶ A case study on dream narratives

What linguistic features encode subjective experience?

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

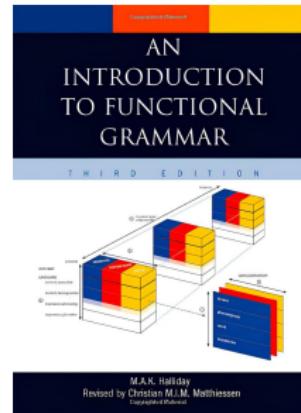


Figure: Halliday et al. (2014).
+57,000 citations.

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

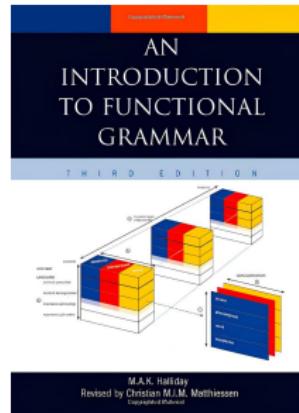


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Language achieves three functions:

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

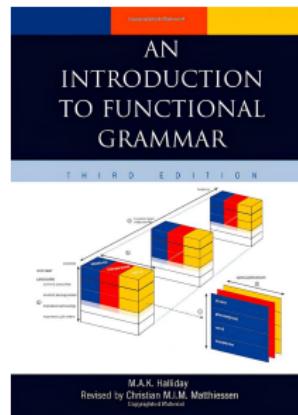


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What linguistic features encode subjective experience?

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

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

Formal definition of style

Alphabet: Let Σ be a finite alphabet grounded in the ideational function of language

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→ We implement ϕ using a language model with in-context learning

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

(where $w \subseteq u$ denotes that w is a substring of u)

Methodology for our sequence-based framework

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}

Substrings are contiguous sequences of symbols within a sequence

Results on the war veteran

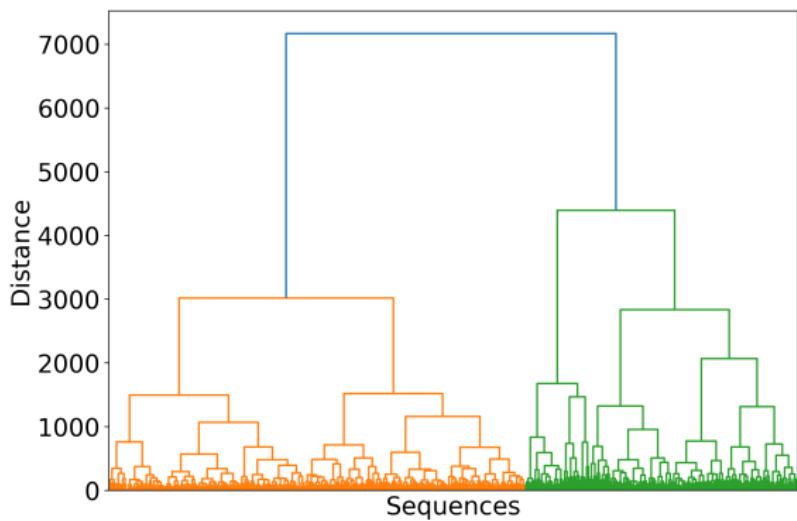


Figure: Dendrogram with Ward linkage and cosine similarity

Results on the war veteran

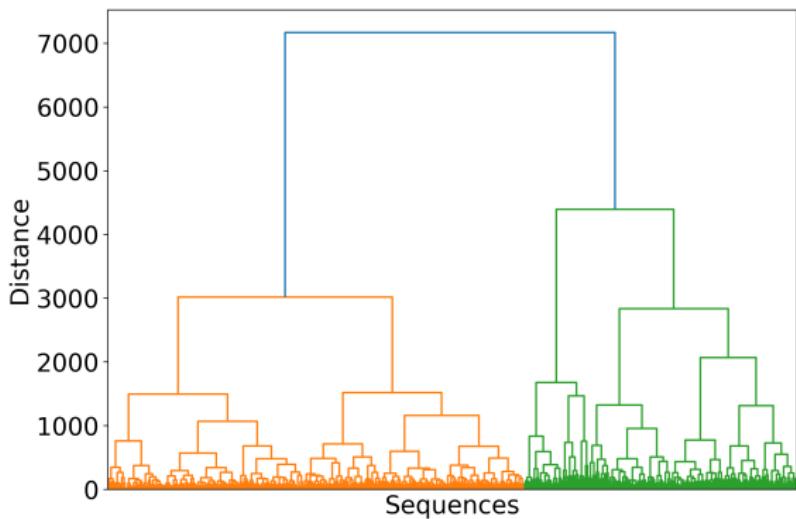


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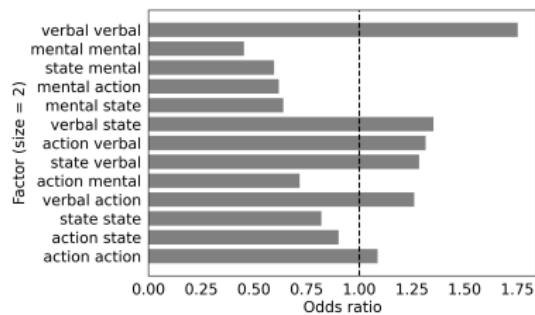
Representative sequences: *savamasasaaaamaaaasavvvaaaaaaavssaaaaa* and
ssssavaavssvsavvvvsmasasaasasaamaamvmsss with
 a = action, m = mental, s = state, v = verbal

Results on the war veteran

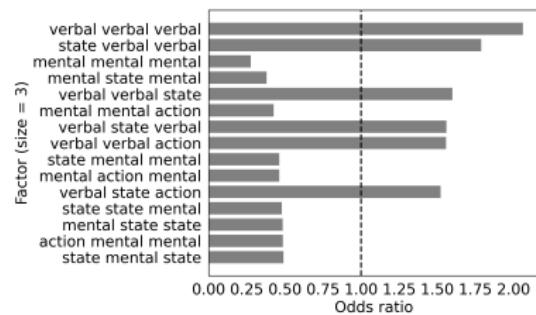
We compare the proportion of sequences containing a given substring

Results on the war veteran

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(a) Size 2.

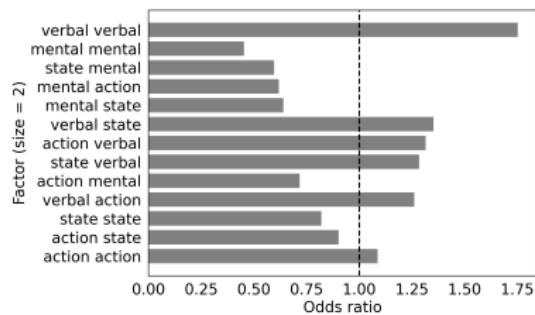


(b) Size 3.

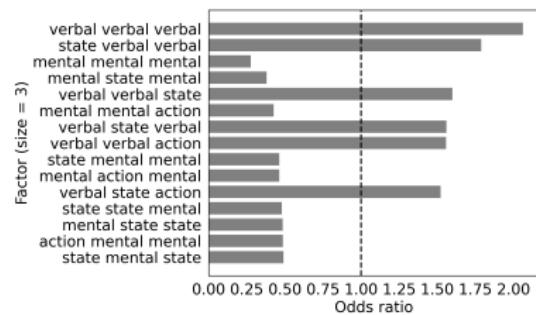
Figure: Top substring odds ratio between the veteran and the norm

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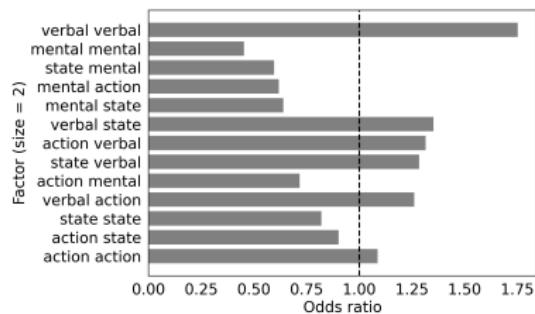
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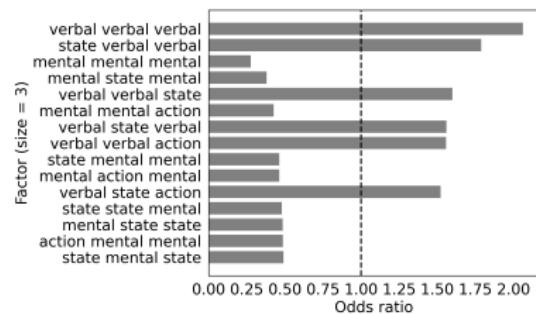
→ The veteran favors verbal processes over mental ones

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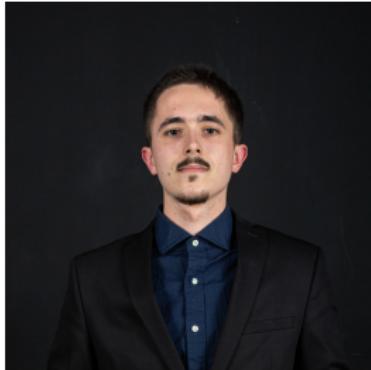
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- ▶ **Psychology of language models:** sycophancy, thought operations
(Didolkar et al., 2025; M. Sharma et al., 2025)

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).

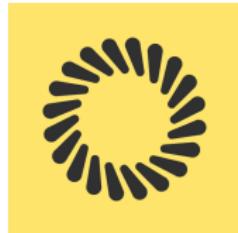
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Automatic thematic analysis in mental health narratives using language models

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

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- ▶ Computational approaches offers time savings, can analyze a larger amount of data

Data collection

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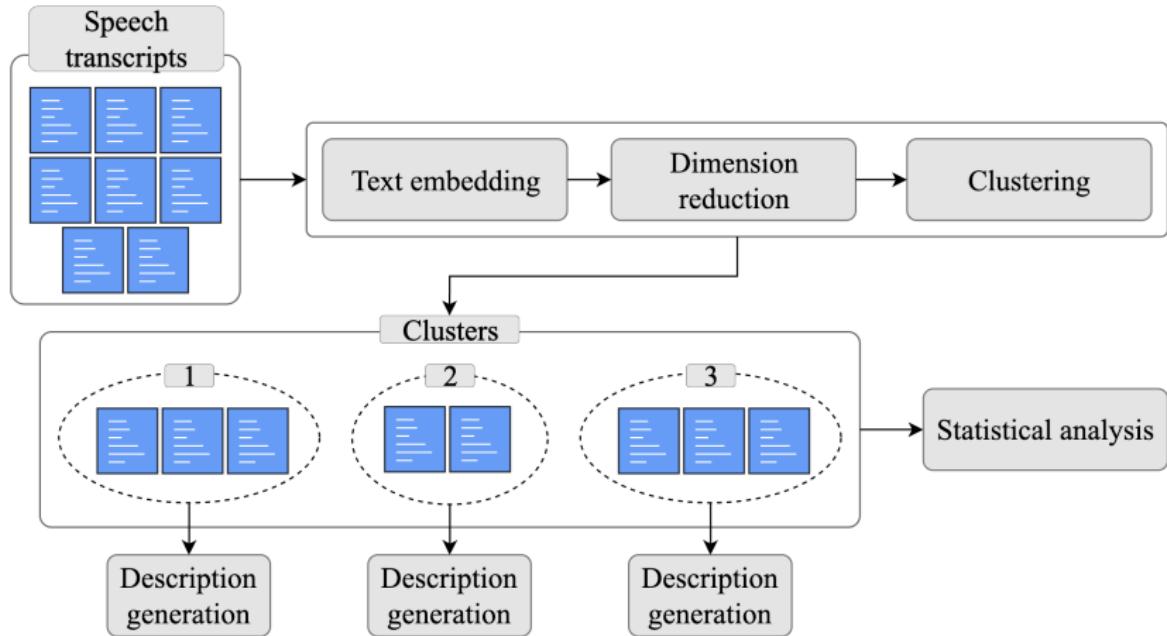
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Open-ended questions involving last 24h, positive future event, current feelings and sleep, etc.

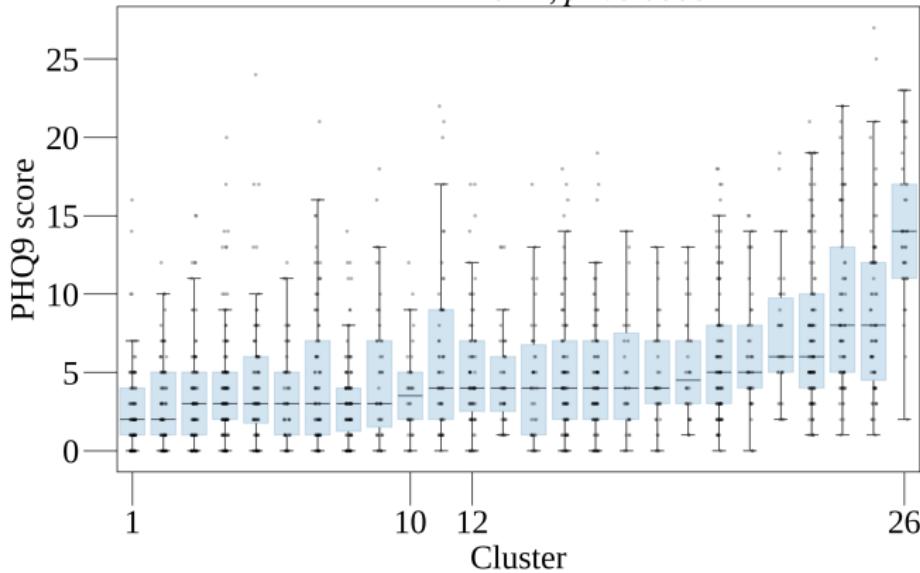
Semantic clustering and description generation



Distribution of depression scores across clusters

Current feelings and sleep (n=1,786)

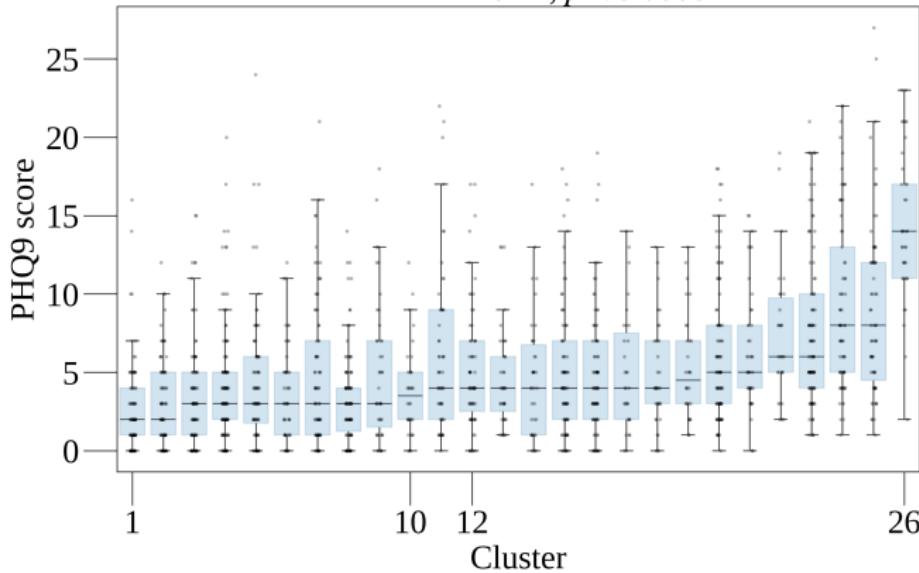
Effect size = 0.17, $p < 0.00001$



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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

Perspectives

Conclusion

How to model subjective experience in personal narratives?

- ▶ 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)

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.latechclf1-1.8](https://doi.org/10.18653/v1/2023.latechclf1-1.8)

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Gustave Cortal and Alain Finkel (2025). "Formalizing Style in Personal Narratives". In: *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing*. Ed. by Christos Christodoulopoulos et al. Suzhou, China: Association for Computational Linguistics, pp. 7322–7337. ISBN: 979-8-89176-332-6

Appendix

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

A *code* is a pre-established pairing between stimuli and sets of information

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The Morse code is a pairing between <combination of short and long signals> and [letters]

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?

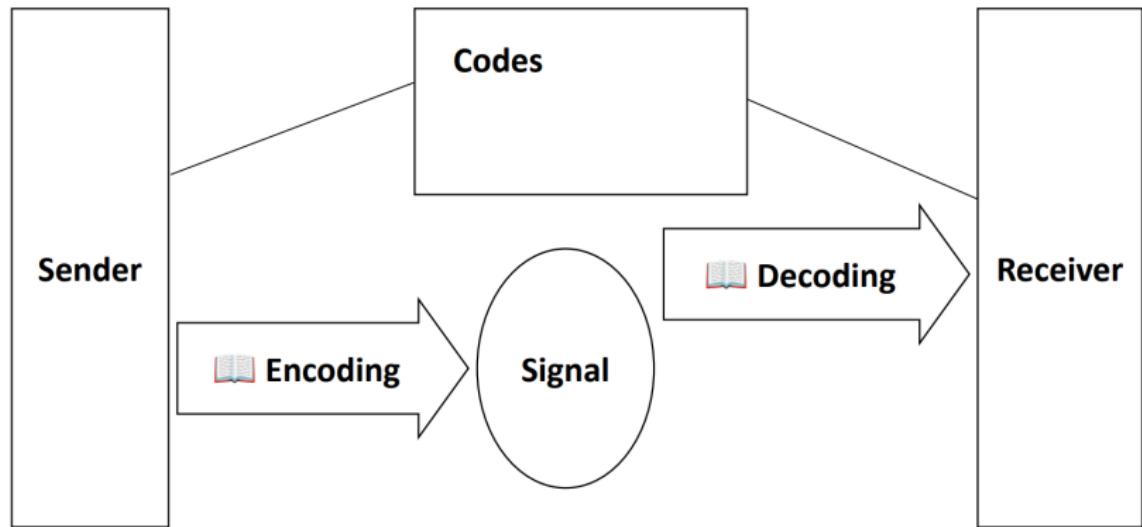


Figure: Dictionary analysis in cognitive pragmatics.

Codes underdetermine emotion meaning

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

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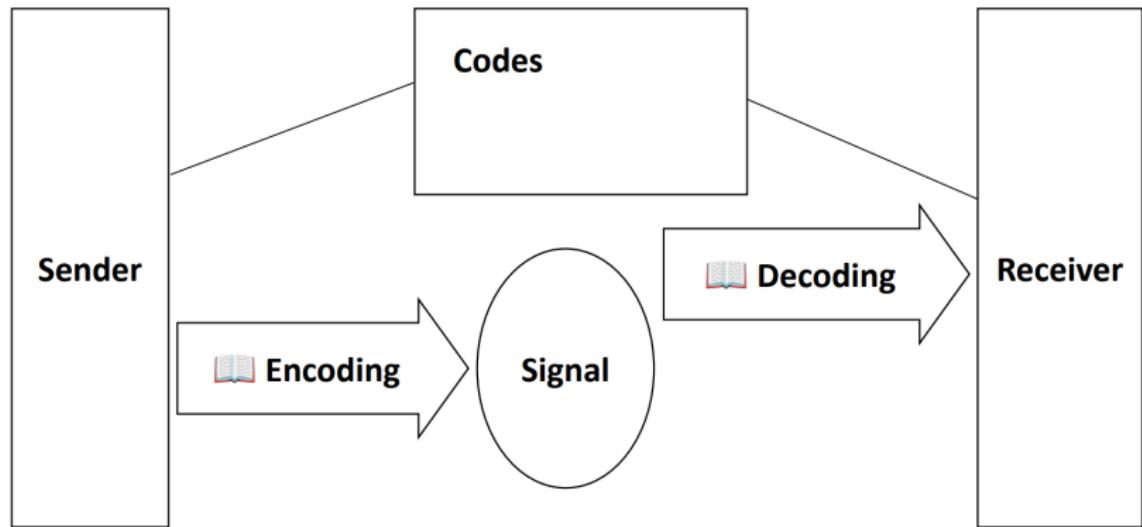


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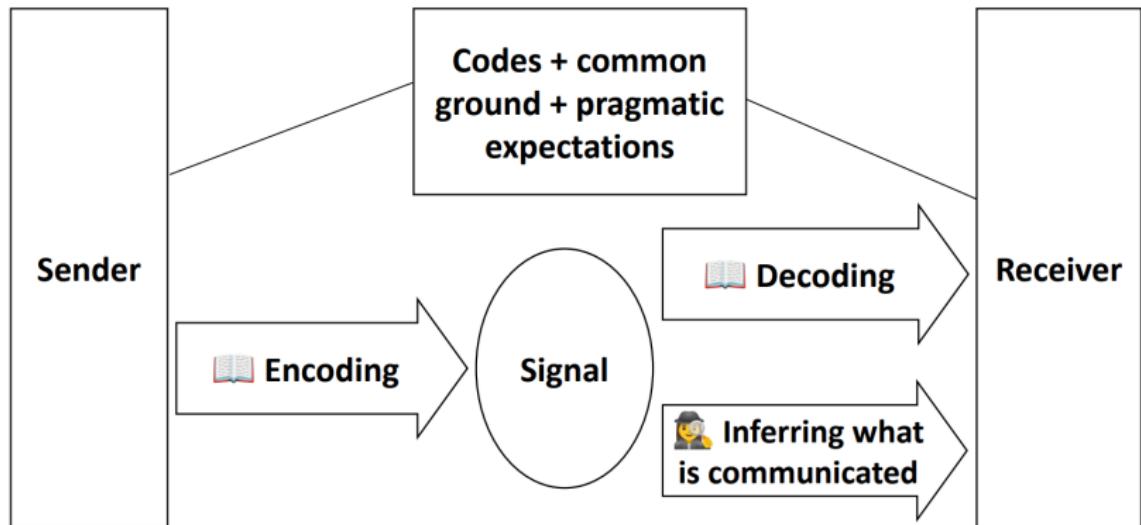


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Component classification in emotional narratives

Model	Precision	Recall	F_1
Logistic Regression	84.9 (0.3)	84.3 (0.3)	84.4 (0.3)
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Table: Scores (\pm std) for emotion component classification.

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→ Models can be used to automatically classify unstructured narratives

Results

StableBeluga_i 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 ₁	43.95**	39.76**	31.25**	56.16**	15.65**	-
StableBeluga ₃	52.44**	46.49**	38.46**	63.88**	21.06**	-
StableBeluga ₅	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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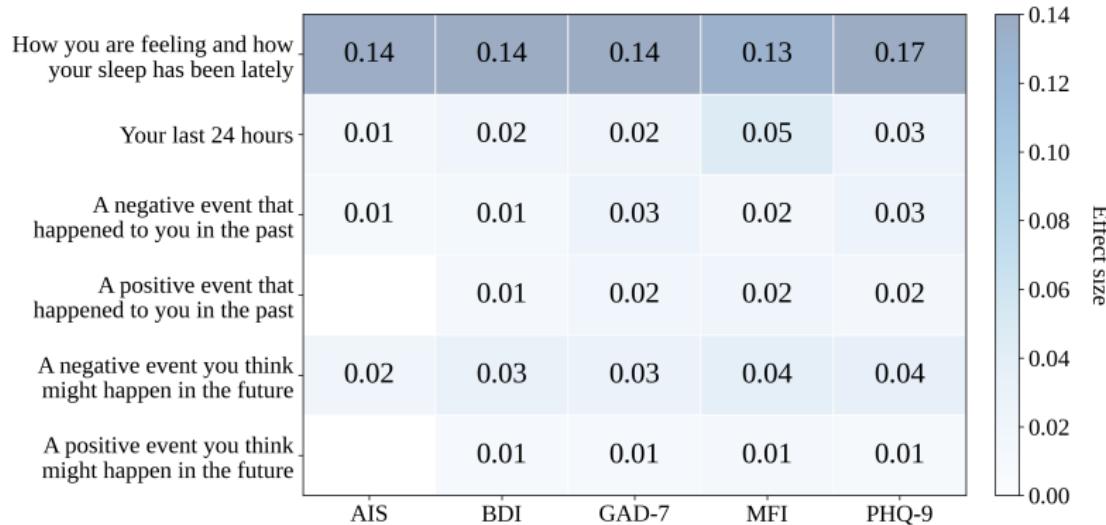
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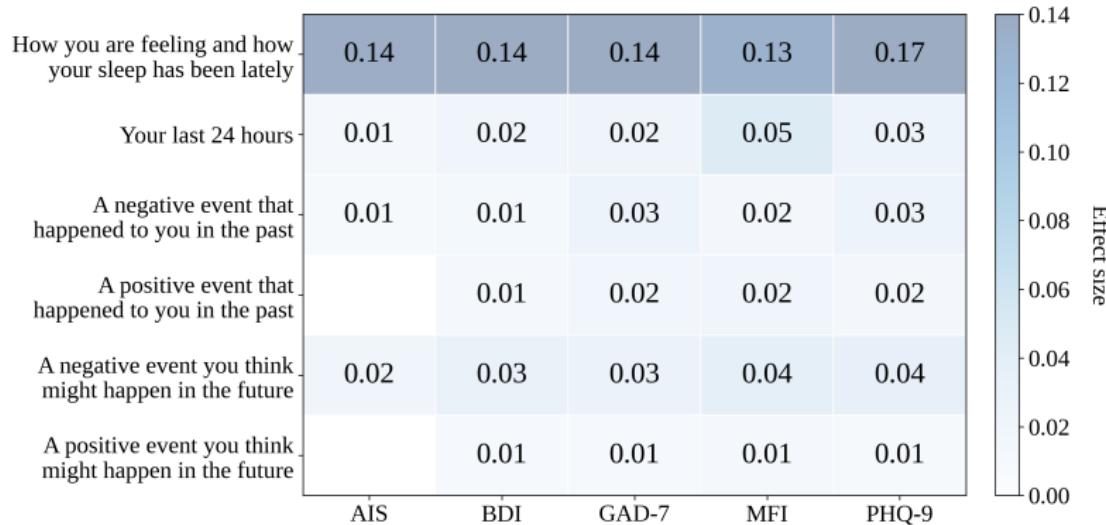
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→ Compared to StableBeluga, our supervised models perform better while having 28 times fewer parameters (248M vs. 7B)

Effect size across questions and clinical scores

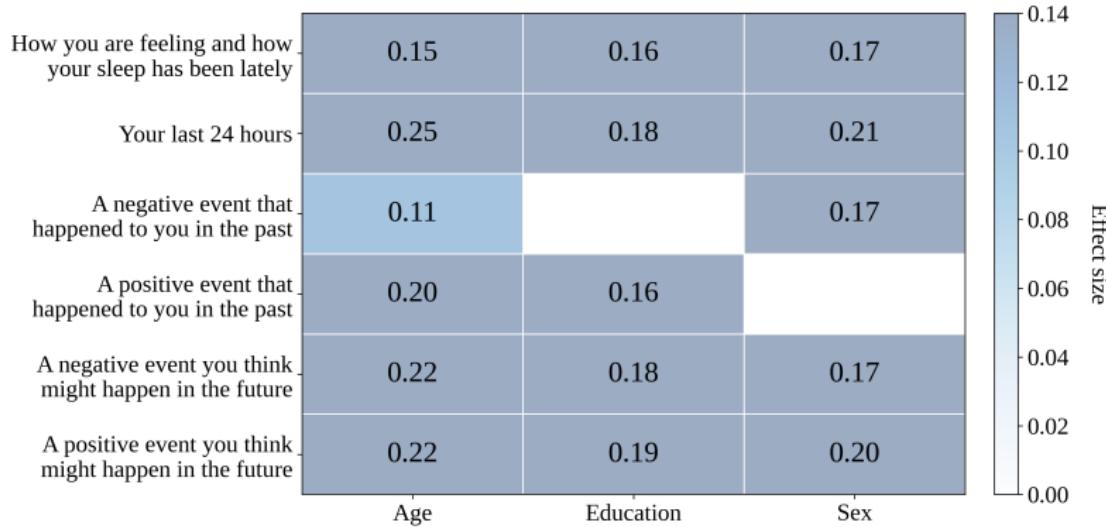


Effect size across questions and clinical scores

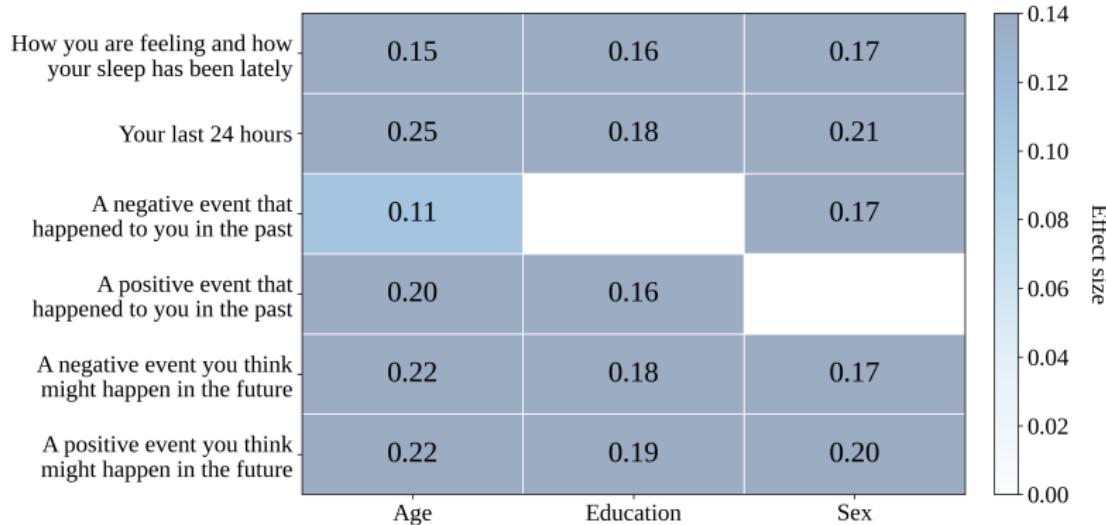


→ Certain questions better discriminate clinical scores

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
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	<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

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