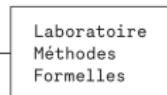


Natural language processing for subjectivity analysis in personal narratives

Gustave Cortal

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



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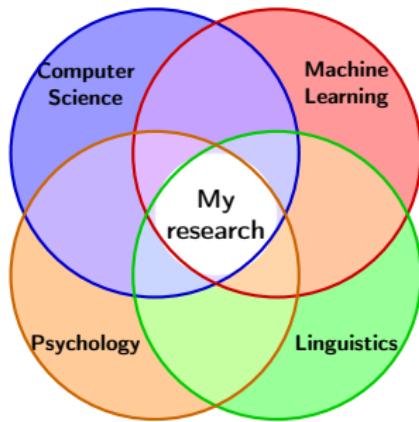
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LISN The LISN logo features the letters "LISN" in a large, dark blue, bold font. To the right is a graphic element composed of vertical bars in orange, teal, and yellow.
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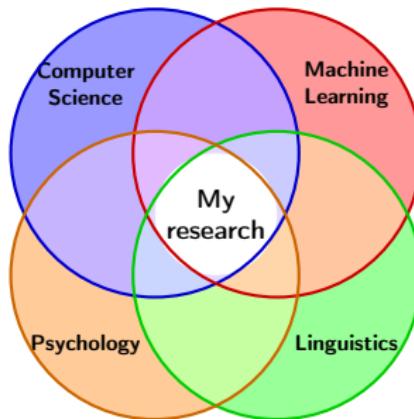
Introduction

Context



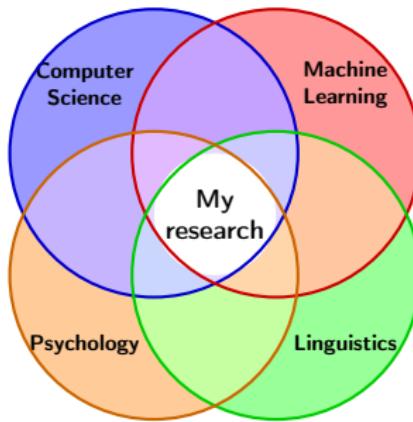
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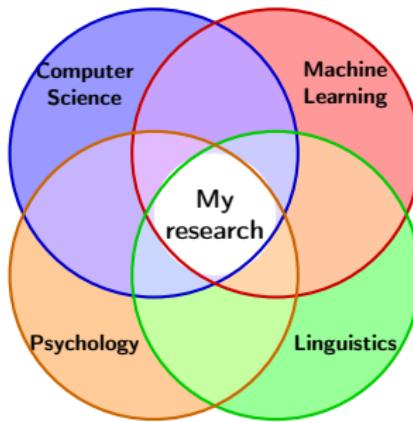
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- ▶ We build on an existing subfield: sentiment and emotion analysis
- ▶ We study subjectivity (first-person perspective, meaning-making processes, and experiential content)
- ▶ We focus on personal narratives (emotional narratives, dream reports)

Introduction

How to model subjective experience in personal narratives?

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- ▶ Cognitive science perspective on emotion analysis

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- ▶ Automatic thematic analysis in mental health narratives

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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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)

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

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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]

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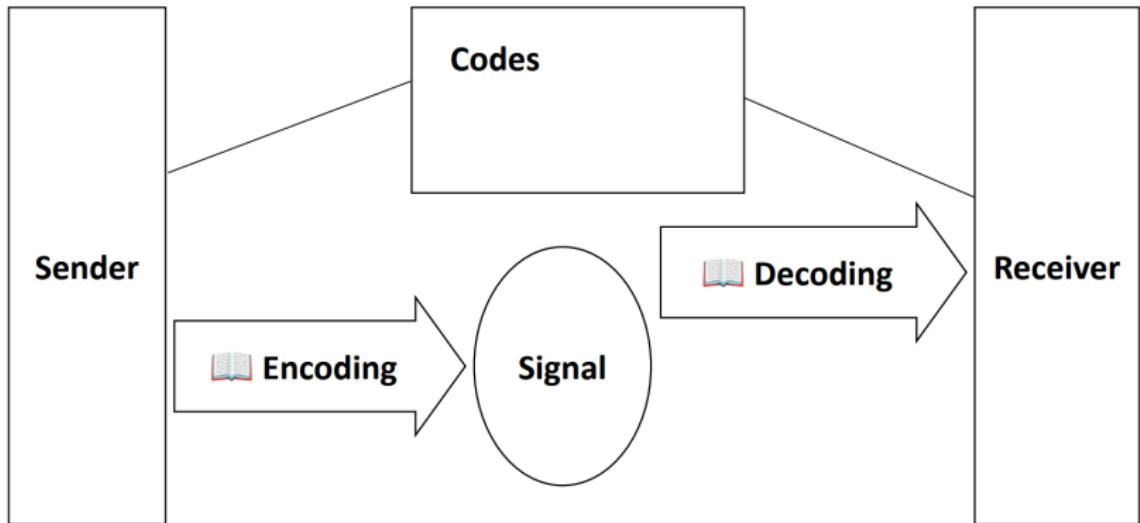


Figure: Dictionary analysis in cognitive pragmatics.

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

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

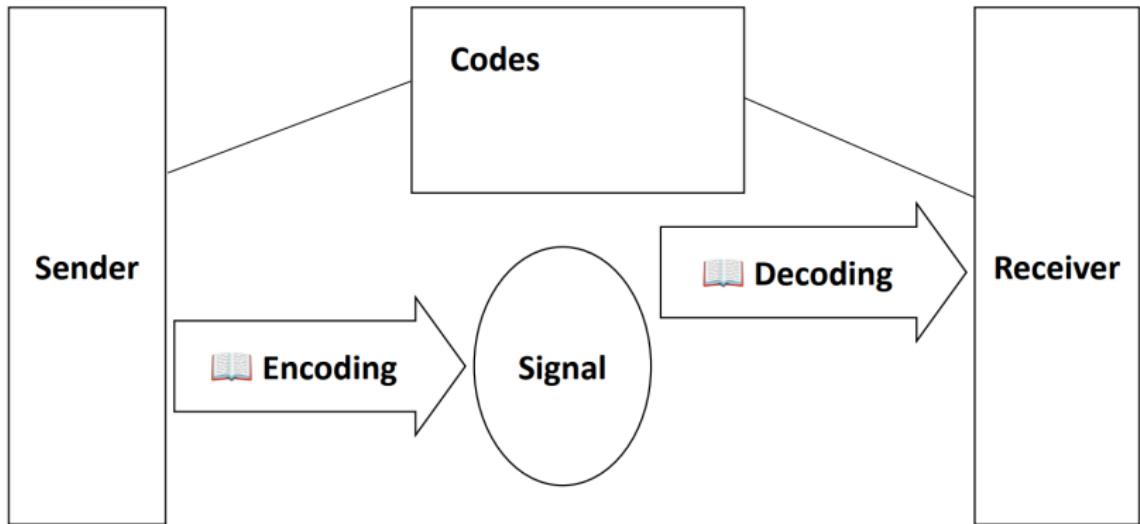


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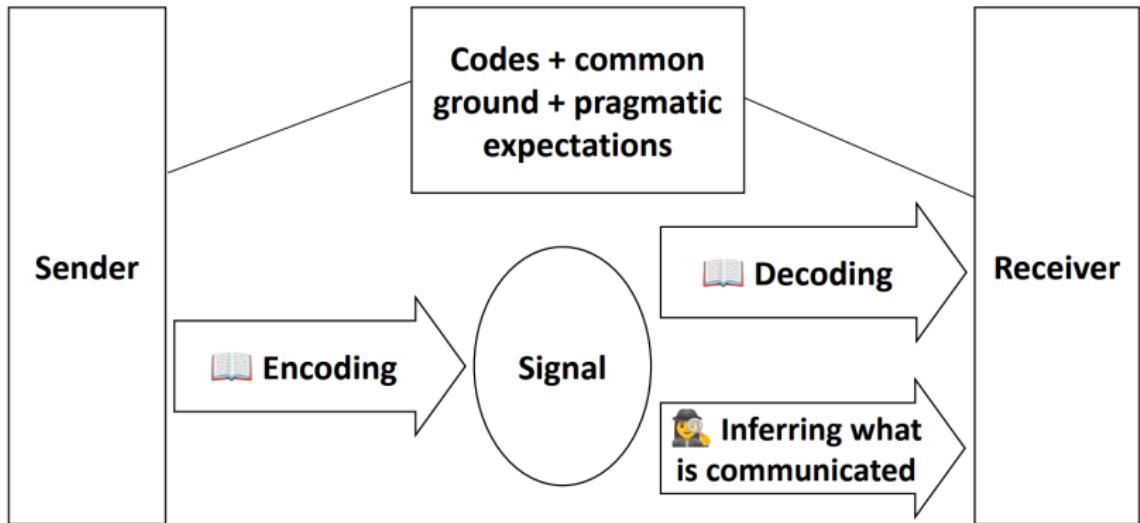


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How to integrate psychological theories of emotion?

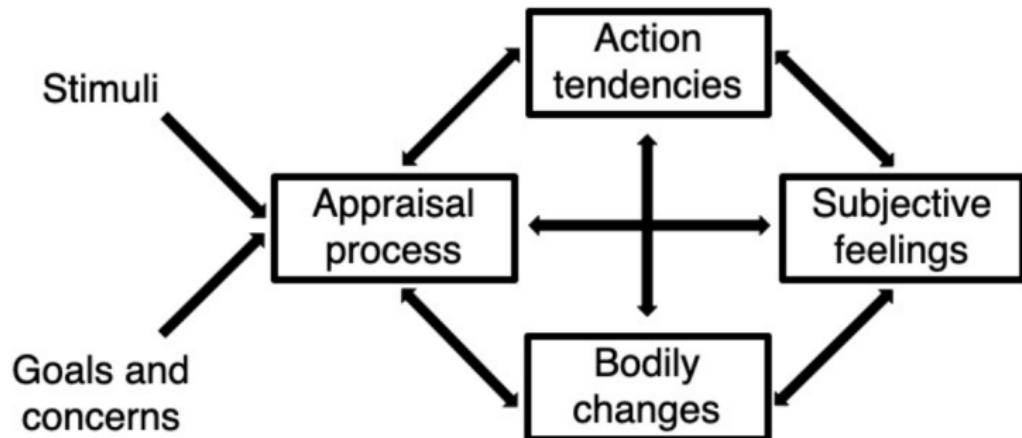


Figure: The integrated framework for emotion theories (Scherer, 2022b).

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

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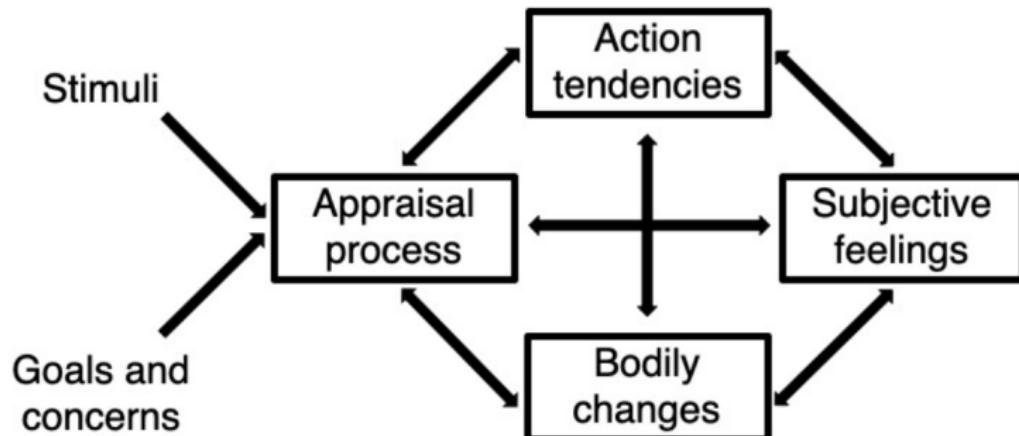


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→ We use this framework to construct a corpus based on components

French narratives based on emotion components

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

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

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 real-life and oniric situations

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 (tf-idf)			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
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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

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**), 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

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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

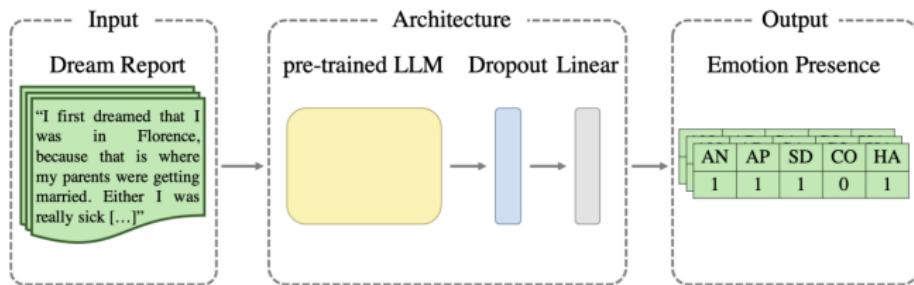


Figure: Architecture for multi-label emotion detection (Bertolini et al., 2023).

Existing research on computational dream analysis

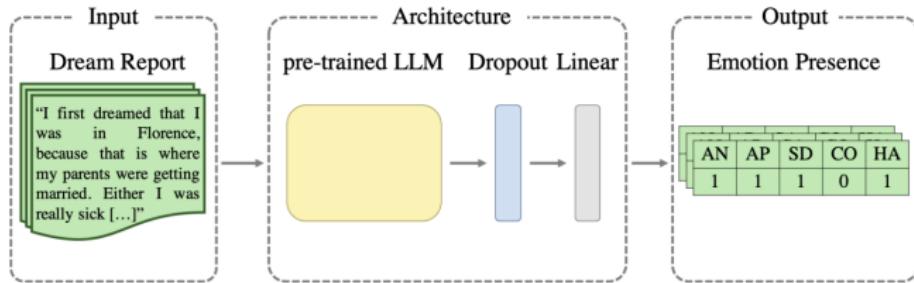


Figure: Architecture for multi-label emotion detection (Bertolini et al., 2023).

They use full context and compare predictions with gold annotations

Existing research on computational dream analysis

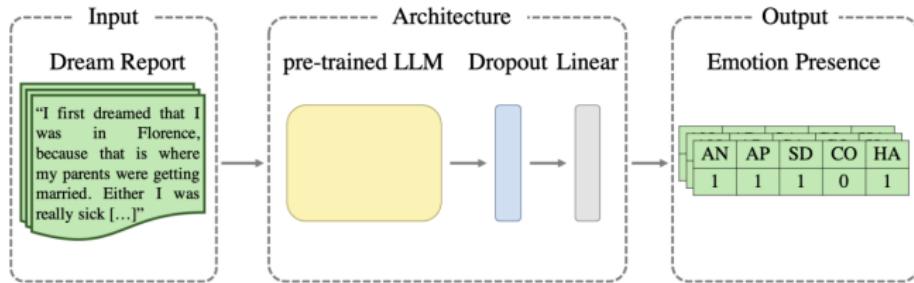


Figure: Architecture for multi-label emotion detection (Bertolini et al., 2023).

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Limitations: emotions without characters; frequency not captured

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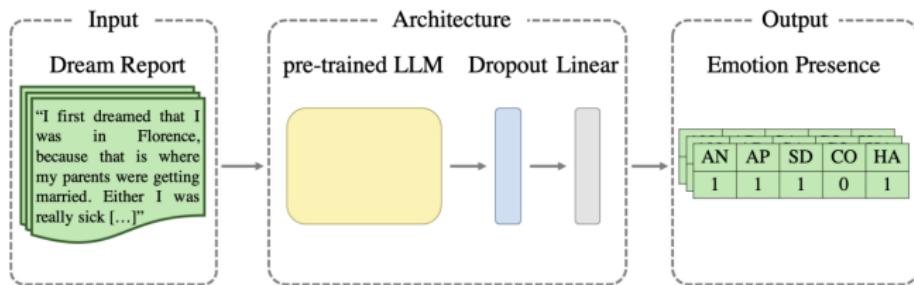


Figure: Architecture for multi-label emotion detection (Bertolini et al., 2023).

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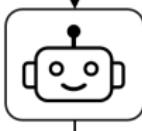
Limitations: emotions without characters; frequency not captured

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

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.

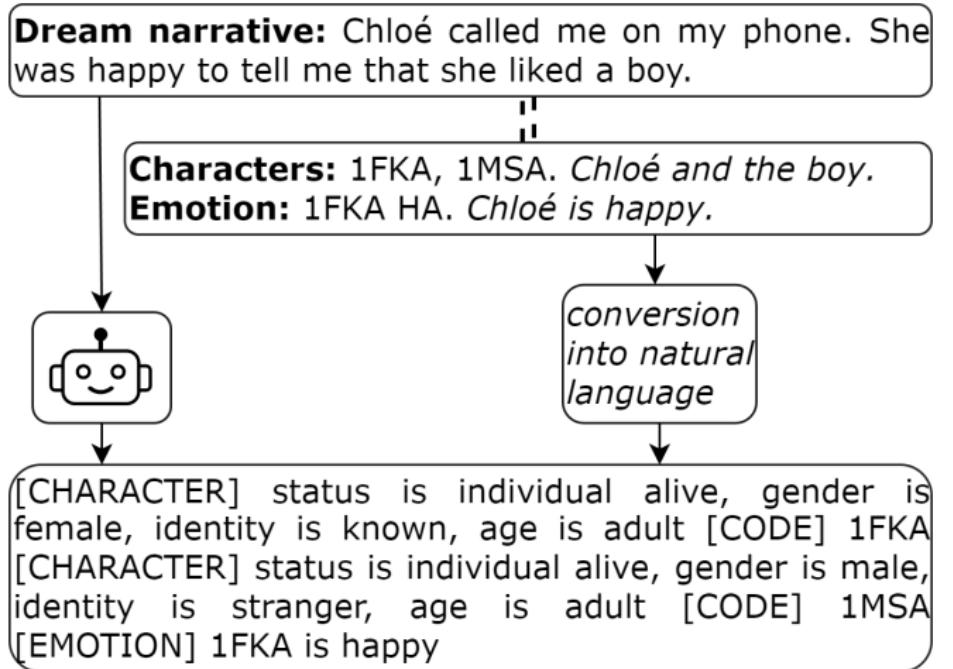
Characters: 1FKA, 1MSA. *Chloé and the boy.*
Emotion: 1FKA HA. *Chloé is happy.*



*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

Character and emotion detection in dream narratives



→ 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
Baseline	82.9	78.0	76.2	86.2	64.7	75.1

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Model	Status	Gender	Identity	Age	Character	Emotion
Baseline	82.9	78.0	76.2	86.2	64.7	75.1
No _{semantics}	71.4	56.5	61.0	90.5	41.8	75.8
No _{names}	80.7	74.3	74.2	84.0	60.9	73.0

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No _{semantics}	71.4	56.5	61.0	90.5	41.8	75.8
No _{names}	80.7	74.3	74.2	84.0	60.9	73.0
Size _{small}	78.4	72.1	70.3	81.7	56.8	70.2
Size _{large}	84.5	80.3	78.6	87.3	67.6	74.7

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Size _{small}	78.4	72.1	70.3	81.7	56.8	70.2
Size _{large}	84.5	80.3	78.6	87.3	67.6	74.7
First _{group}	82.3	77.7	74.9	85.6	63.7	71.9
First _{individual}	80.6	76.1	74.2	83.9	62.7	67.3
First _{emotion}	83.9	78.7	77.1	87.6	65.0	72.0

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First _{individual}	80.6	76.1	74.2	83.9	62.7	67.3
First _{emotion}	83.9	78.7	77.1	87.6	65.0	72.0
Conversion _{comma}	84.0	79.8	77.7	87.1	66.7	73.7
Conversion _{marker}	82.4	78.5	76.5	86.1	65.4	74.4

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Conversion _{comma}	84.0	79.8	77.7	87.1	66.7	73.7
Conversion _{marker}	82.4	78.5	76.5	86.1	65.4	74.4

→ 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
	undefined	7.9	8.7	-0.9

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

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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

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

- ▶ Qualitative analysis of speech content is central to clinical practice

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- ▶ Qualitative analysis of speech content is central to clinical practice
- ▶ Thematic analysis studies how people construct meaning
- ▶ Thematic analysis is time-consuming, often constrained to small, monolingual corpora (Stanghellini et al., 2023)
- ▶ Computational approaches offers time savings, can analyze a larger amount of data

Methodology

We developed a pipeline that:

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- ▶ generates fine-grained natural language descriptions for each cluster
- ▶ links clusters to variation in clinical scores and sociodemographics

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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Clinical scores for depression (BDI, PHQ9, MADRS), anxiety (GAD7), insomnia (AIS), and fatigue (MFI)

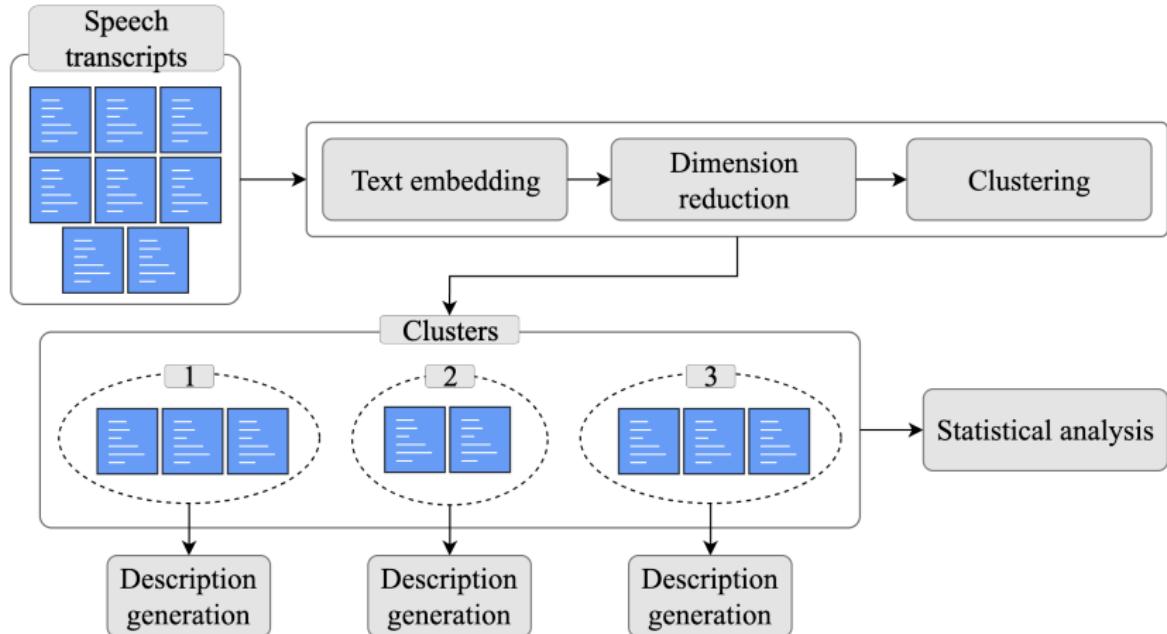
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Open-ended questions involving last 24h, negative past event, positive future event, current feelings and sleep, etc.

Semantic clustering and description generation



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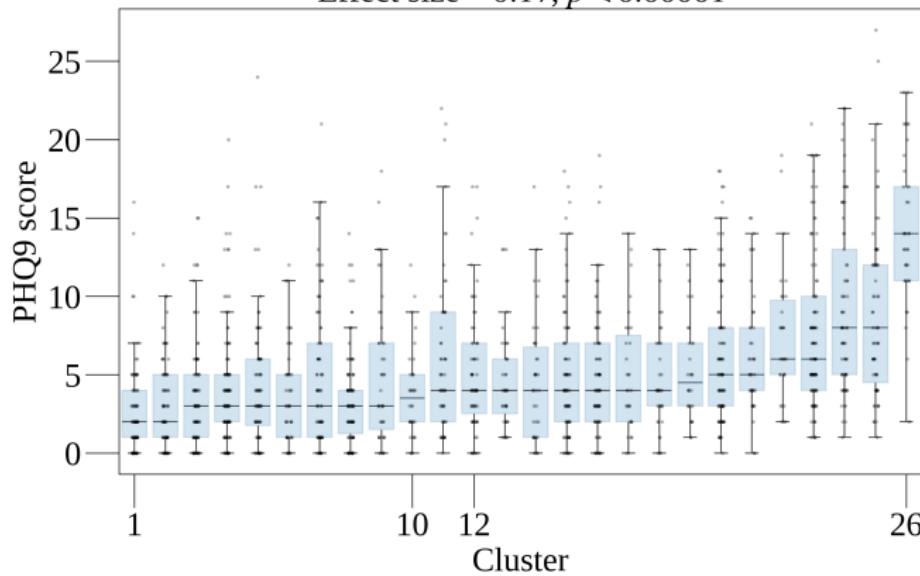
Contributions

- ▶ First topic modeling *across different languages and cohorts* using language models
- ▶ Replaced keywords ("family") with *context-rich descriptions* to capture symptom co-occurrence and clinical nuance ("family conflicts", "family relationships")
- ▶ Identified *risk* ("sleep disturbance") and *protective* ("physical activity") topics for depression, consistent with psychiatric literature

Distribution of depression scores across clusters

Current feelings and sleep (n=1786)

Effect size = 0.17, $p < 0.00001$



→ 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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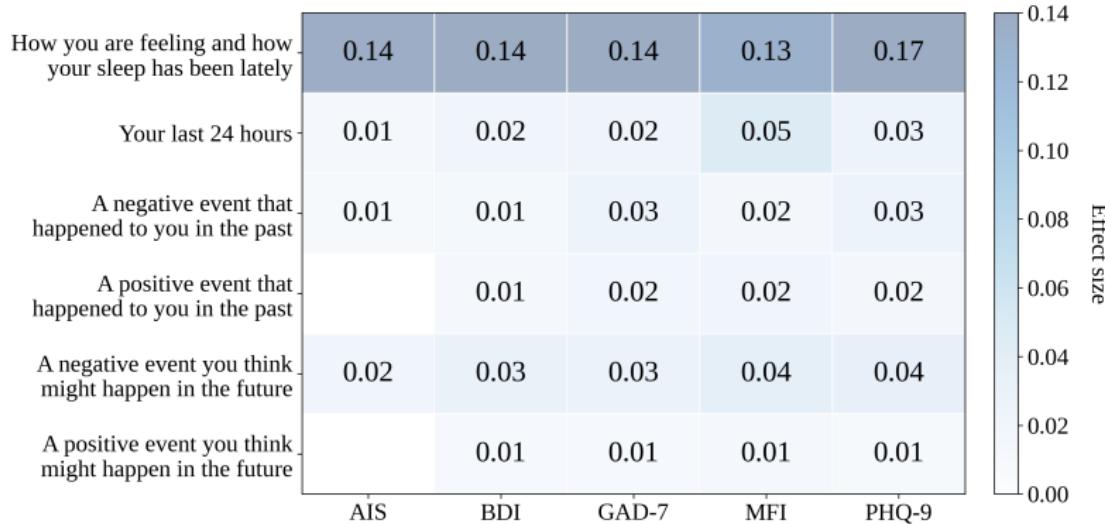
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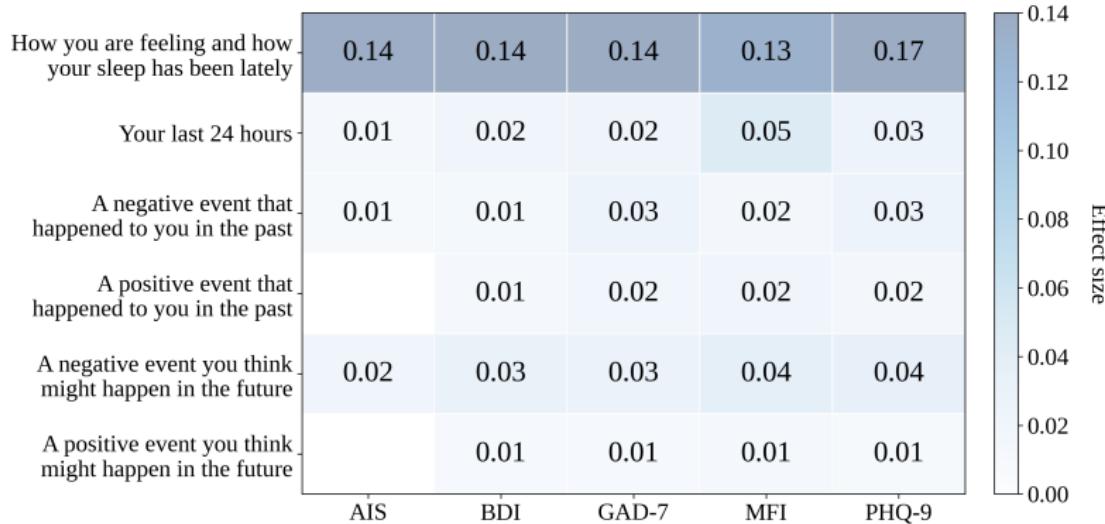
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→ Clustering captures symptom severity and age-related circumstances

Effect size across questions and clinical scores

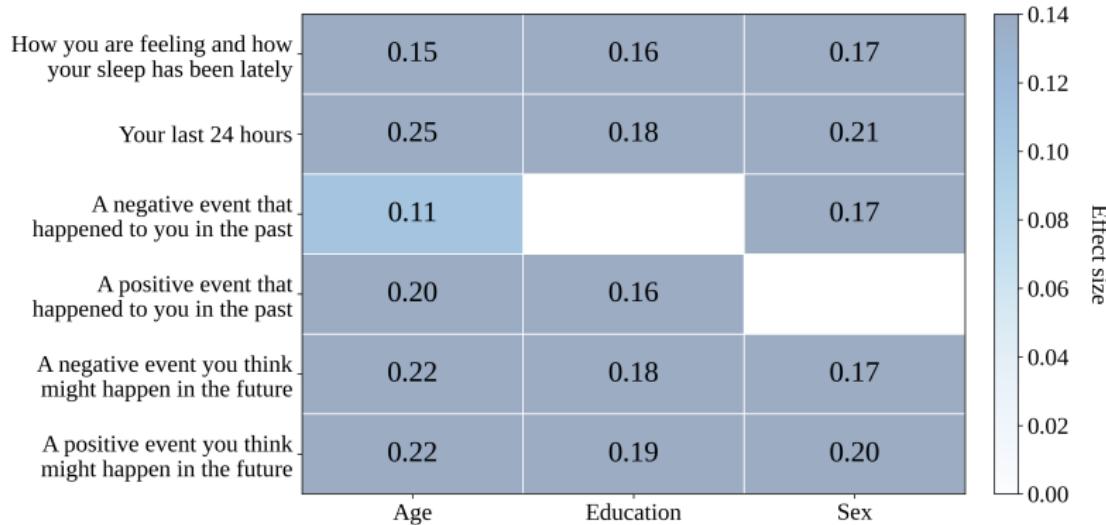


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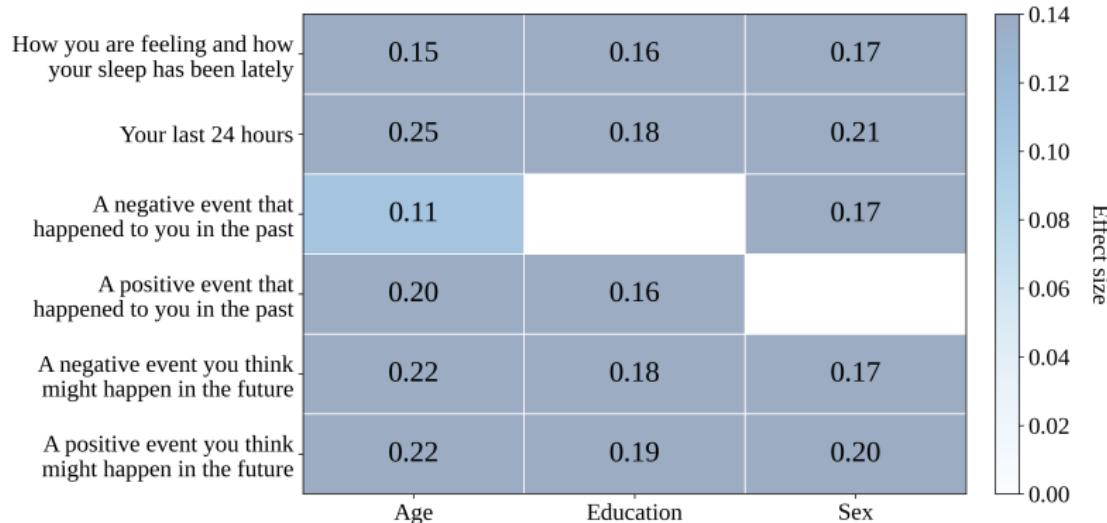


→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



Effect size across questions and sociodemographics



→ Nearly all questions discriminate sociodemographics

Risk and protective topics for depression

→ NLP and psychiatry researchers reviewed generated cluster descriptions to identify risk and protective topics for depression

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 - ▶ **Protective topics:** arts and creative activity (Fancourt and Finn, 2019); gardening and nature (Soga, Gaston, and Yamaura, 2017); holidays and travel (Bloom, Geurts, and Kompier, 2013); physical activity (Pearce et al., 2022)

Potential applications and future work

- ▶ **Risk stratification:** flagging individuals in high-severity clusters for clinical review

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- Do cluster descriptions improve clinician decision-making?

Conclusion and 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)

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)

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

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

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

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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-  Arena, Andrew F. et al. (2023). "Mental health and unemployment: A systematic review and meta-analysis of interventions to improve depression and anxiety outcomes". In: *Journal of Affective Disorders* 335, pp. 450–472. ISSN: 0165-0327. DOI: 10.1016/j.jad.2023.05.027. URL: <https://www.sciencedirect.com/science/article/pii/S0165032723006638> (visited on Aug. 12, 2025).
-  Arnold, Magda B. (1960). *Emotion and Personality*. New York: Columbia University Press.
-  Bertolini, Lorenzo et al. (2023). *Automatic scoring of dream reports' emotional content with large language models*. arXiv: 2302.14828 [cs.CL].

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