Natural language processing for subjectivity analysis in personal narratives

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Introduction

Context

- Natural language processing for psychology is underexplored
- We build on an existing subfield: sentiment and emotion analysis
- We study subjectivity (involving first-person perspective, meaning-making processes, and experiential content)
- We focus on personal narratives (*e.g.*, emotional narratives, dream reports, mental health narratives)

We first address the *content* by classifying elements of personal narratives. Then, we study the *form* through the concept of style

Introduction

How to model subjective experience in personal narratives?

- Definition of objectives and scope using cognitive science
- Construction of an emotion dataset
- Training of language models for emotion analysis
- Formalization of style in personal narratives

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

Definition of objectives using cognitive science

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

Psychology and emotion annotations

[add refs to klinger, etc.]

Psychological theories	In text, emotion is...	Example
Basic emotions theory	a **category**	"I love philosophy." → `joy`
Constructivist theories	a continuous value with an **affective** meaning	"His voice soothes me." → `valence` (4/5), `arousal` (1/5)
Appraisal theory	a continuous value with a **cognitive** meaning	"I received a surprise gift." → `sudden` (4/5), `control` (0/5)
	composed of **semantic roles**	"Louise (`experiencer`) was angry (`cue`) towards Paul (`target`), because he didn't inform her (`cause`)."

Limitations in emotion analysis

- Different emotion theories lead to divergences in how to annotate them in the text [add refs]
- Some linguistic and cognitive science theories are not considered [reformulate, not some]
- There is no benchmark that evaluates the richness of the emotional phenomenon [add refs]

Linguistic and cognitive science theories

Which verbal signs are used to infer expressed emotions?

Raphaël Micheli categorizes a range of linguistic markers into three *emotion expression modes* (Micheli, 2013). The emotion can be:

- *labeled* explicitly with an emotional term ("I am sad")
- *shown* with utterance features such as interjections and punctuations ("Ah! That's great!")
- *suggested* with the description of a situation which generally, in a given sociocultural context, leads to an emotion ("She gave me a gift")

→ Different emotion expression modes are more or less difficult to interpret [add refs psycholinguistic, psychiatry, refs aline etienne]

→ [add refs aline etienne]

How to integrate psychological theories of emotion?

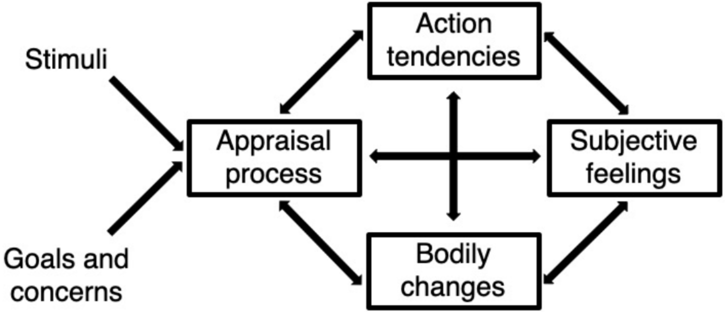


Figure: Integrated framework for emotion theories. Emotional episodes are synchronized changes in four components (Scherer, 2022).

[add Appraisal dimensions]

Construction of an emotion dataset

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*.

French emotional narratives based on components

Goal: A more comprehensive understanding of emotional events

Component	**Answer**
`Behavior`	I'm giving a lecture on a Friday morning at 8:30. A student goes out and comes back a few moments later with a coffee in his hand.
`Feeling`	My heart is beating fast, and I freeze, waiting to know how to act.
`Thinking`	I think this student is disrupting my class.
`Territory`	The student attacks my ability to be respected in class.

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

One thousand narratives were collected during emotion regulation sessions

Training language models for emotion analysis

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

G. Cortal. Sequence-to-Sequence Language Models for Character and Emotion Detection in Dream Narratives. *LREC-COLING 2024*

Discrete emotion detection based on components

	Logistic Regression			CamemBERT		
Component	Precision	Recall	F_1	Precision	Recall	F_1
All	71.2 (2.6)	69.1 (2.2)	67.8 (2.3)	**85.1**	**84.8**	**84.7**
Without `behavior`	77.4 (2.3)	75.8 (2.4)	74.5 (2.6)	80.3	79.8	79.7
Without `feeling`	64.3 (1.9)	61.5 (1.2)	61.3 (2.2)	81.6	79.8	79.9
Without `thinking`	70.9 (1.8)	69.1 (2.0)	68.3 (2.2)	79.6	78.5	78.7
Without `territory`	64.3 (4.1)	64.5 (2.4)	62.3 (2.8)	78.7	78.5	78.6
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
Only `territory`	68.2 (1.8)	66.8 (2.2)	66.6 (2.3)	71.4	68.4	68.9

→ Each component improves prediction performance, the best results are achieved by jointly considering all components

→ Some components benefit from contextual understanding and world knowledge (*e.g.*, `behavior` and `thinking`)

Quantitative analysis of dream narratives

[add illustration dreambank, hdvc scheme]

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

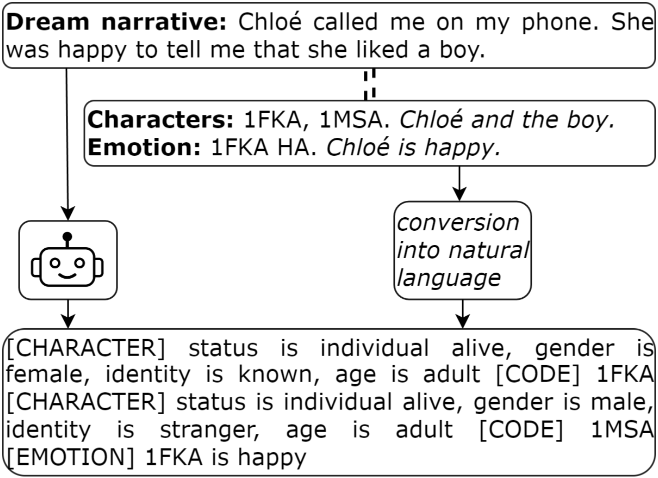
Quantitative dream analysis most relies on dream databases (*e.g.*, DreamBank composed of 27,000 dreams) and annotation schemes (*e.g.*, Hall and Van de Castle system) (Domhoff and Schneider, 2008)

The annotation process is complex and costly

How to automate the annotation process?

Character and emotion detection in dream narratives

[add seq2seq architecture illustration, add list of characters and emotions]



Results

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

Model	Status	Gender	Identity	Age	Character	Emotion
Baseline	82.87	78.02	76.17	86.21	64.74	75.13
$\texttt{No}_{\texttt{semantics}}$	71.37	56.54*	61.0	90.51	41.79*	75.79
$\texttt{No}_{\texttt{names}}$	80.66*	74.32**	74.2	83.95*	60.93**	73.04*
$\texttt{Size}_{\texttt{small}}$	78.35**	72.13**	70.25**	81.66**	56.79**	70.15**
$\texttt{Size}_{\texttt{large}}$	84.51*	80.3**	78.63**	87.29	67.63**	74.71
$\texttt{First}_{\texttt{group}}$	82.33	77.71	74.86	85.61	63.71	71.94
$\texttt{First}_{\texttt{individual}}$	80.59**	76.14	74.22*	83.87**	62.67	67.32
$\texttt{First}_{\texttt{emotion}}$	83.92	78.74	77.06	87.63	64.97	72.03
$\texttt{Conversion}_{\texttt{comma}}$	84.02**	79.84**	77.67**	87.08*	66.69**	73.68
$\texttt{Conversion}_{\texttt{marker}}$	82.39	78.45	76.53	86.09	65.44	74.36
Cross-validation	86.28	81.9	79.51	89.52	68.64	76.18

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

$\rightarrow$ Language models can effectively address character and emotion detection in dream 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: ** ($p < 0.01$), * ($p < 0.05$).

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

Case study on the war veteran

Group	Category	% Vet	% Total	Δ
	known*	24.9	51.6	-26.7
	prominent	1.9	2.5	-0.6
Identity	occupational*	22.4	8.0	14.4
	ethnic*	4.1	0.9	3.1
	unknown*	46.8	37.0	9.8
	male*	56.2	43.0	13.1
Gender	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. * indicates significant difference ($p < 0.05$).

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

Formalization of style in personal narratives

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

How is subjective experience communicated in narratives?

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

[better transition]

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

Style has been studied in stylometry and stylistics [add refs, maybe cognitive linguistics]

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

[for second slide, give a formal definition]

We narrow the general definition of style: *a distinctive manner of communicating subjective experience in narratives*

How to give an operational definition of style?

Hypothesis: An individual uses some redundant choices of features that characterize its style

1. A sequence-based framework defining style as patterns in sequences of linguistic choices
2. A methodology for identifying patterns using sequence analysis
3. A case study on dream narratives

What linguistic features encode subjective experience?

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

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

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

[add photo of book and number of citations]

What linguistic features encode subjective experience?

Language represents experience through *processes*, *participants* and *circumstances*

Processes	**Examples**
`Action`: actions and events in the physical world.	[He]$_{\text{Actor}}$ [**takes**]$_{\text{Action}}$ [the valuable]$_{\text{Affected}}$ [Members of my cult]$_{\text{Actor}}$ [**have made**]$_{\text{Action}}$ [1500 euros]$_{\text{Result}}$ [I]$_{\text{Actor}}$ [**give**]$_{\text{Action}}$ [her]$_{\text{Recipient}}$ [a chance]$_{\text{Range}}$
`Mental`: internal experiences such as thoughts, perceptions, and feelings.	[We]$_{\text{Senser}}$ [**believe**]$_{\text{Mental}}$ [women are the leaders of change]$_{\text{Phenomenon}}$ [The moon]$_{\text{Senser}}$ [**sees**]$_{\text{Mental}}$ [the earth]$_{\text{Phenomenon}}$ [He]$_{\text{Senser}}$ [**disliked**]$_{\text{Mental}}$ [Gilbert's writing]$_{\text{Phenomenon}}$
`Verbal`: acts of communication.	[David]$_{\text{Sayer}}$ [**said**]$_{\text{Verbal}}$ ["the corrupt, criminals and money launderers"]$_{\text{Verbiage}}$
`State`: states of being, having, or existence.	There [**was**]$_{\text{Existential}}$ [a swimming pool]$_{\text{Existent}}$ [John]$_{\text{Carrier}}$ [**is**]$_{\text{State}}$ [an interesting teacher]$_{\text{Attribute}}$ [Hadrian's Wall]$_{\text{Possessor}}$ [**has**]$_{\text{State}}$ [something for everyone]$_{\text{Possessed}}$

[make it more visual, less text-heavy, maybe with colors]

Pipeline for our sequence-based framework

[remove bullet points, make it more visual]

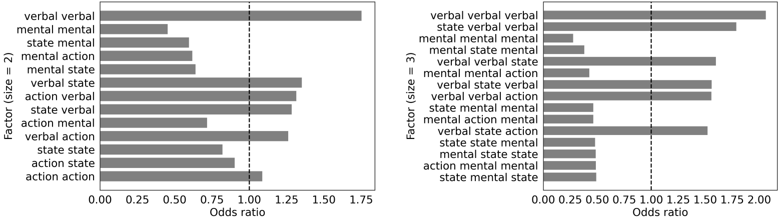
Clause	Process (symbol)	Participants
I wake in a dark room	`Action` (**a**)	`Actor`
I feel a cold wind	`Mental` (**m**)	`Senser`, `Phenomenon`
I tell myself to move	`Verbal` (**v**)	`Sayer`, `Recipient`

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

1. We first segment *"I wake in a dark room. I feel a cold wind. I tell myself to move."* into clauses
2. Identify features (*e.g.*, processes and participants) for each clause using in-context learning with large language models
3. Each narrative is mapped to a symbolic sequence using an alphabet based on identified features
4. We perform sequence analysis to identify patterns such as frequent substrings and representative sequences

Results on the war veteran

We compare the proportion of sequences containing a given substring



(a) Size 2.

(b) Size 3.

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

→ The veteran favors verbal processes over mental ones

Results on the war veteran

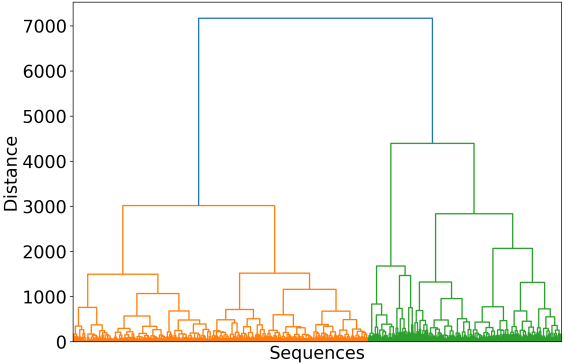


Figure: Dendrogram with Ward linkage and cosine similarity

Representative sequences: *savamasasaaamaaasavvvaaaaaaavssaaaaa* and *sssssavaavssvsavvvvsmasasaasasaamaamvmsss* with $a =$ action, $m =$ mental, $s =$ state, $v =$ verbal

Perspectives

- Authorship profiling
- Style-conditioned narrative generation
- Applying methods from complexity science and formal language theory

Conclusion and perspectives

Conclusion

How to model subjective experience in personal narratives?

- Definition of objectives and scope using cognitive science
- Construction of an emotion dataset
- Training of language models for emotion analysis
- Formalization of style in personal narratives

Impact

I co-supervised ongoing PhD thesis: Nicolas Richet (multimodal emotion recognition), Amine Haddou (cognitive distortions), and Raphael Faure (style analysis)

Callyope

Automatic thematic analysis in mental health narratives using language models

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

Introduction

- Qualitative analysis of speech content is central to clinical practice
- Thematic analysis studies how people construct meaning
- Thematic analysis is time-consuming, and typically constrained to small, monolingual corpora
- Computational approaches offers time savings over manual annotation, and the power to analyze a larger amount of data

→ We developed a pipeline that (a) clusters narratives from different cohorts, (b) generates descriptions for each cluster, and (c) links clusters to variation in clinical scores and sociodemographic factors

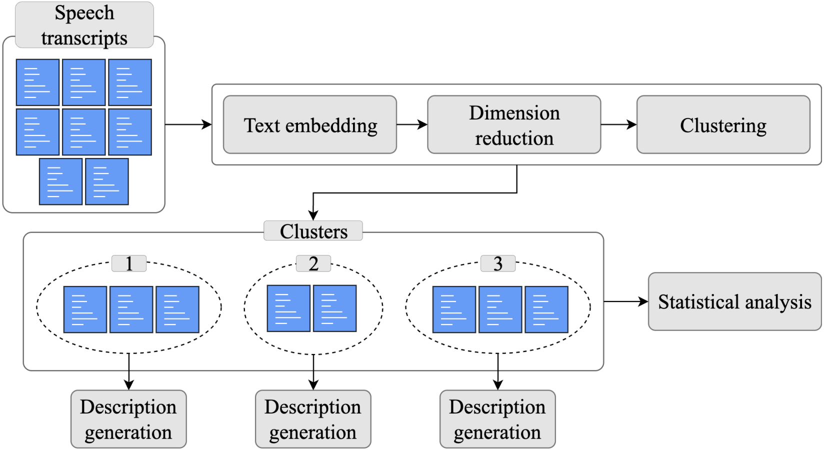
Data collection

We collected clinical scores and narratives from **four cohorts**. A French general population cohort (n=1809), and three clinical populations: Italian (n=116), Chinese (n=52), and Spanish (n=90) cohorts

Clinical scores were assessed using various scales such as: AIS (Athens Insomnia Scale); BDI (Beck Depression Inventory); GAD-7 (Generalized Anxiety Disorder 7-item scale); MFI (Multidimensional Fatigue Inventory); PHQ-9 (Patient Health Questionnaire-9 for depression)

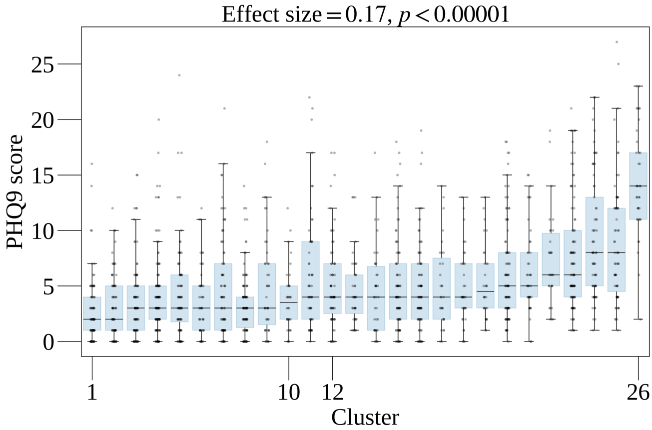
Open-ended questions: *Describe your last 24 hours / a negative event that happened to you in the past / a positive event that happened to you in the past / a negative event you think might happen in the future / a positive event you think might happen in the future / Describe how you are feeling at the moment and how your sleep has been lately*

Pipeline for semantic clustering and description generation



Distribution of depression scores across clusters

How you are feeling and how your sleep has been lately



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

Generated cluster descriptions

Cluster 1 description: The individuals express consistent satisfaction with their current well-being, emphasizing good sleep quality, restful or pleasant nights, and a general sense of relaxation, even when noting variations in sleep duration or occasional fatigue. (age=39±19, n=92)

Cluster 10 description: The individuals express frequent nighttime urinary interruptions disrupting sleep, often attributed to age-related conditions like prostate issues or overactive bladder, alongside mixed reports of physical well-being, mental resilience, and lifestyle factors such as retirement or exercise influencing their overall health and sleep patterns. (age=69±15, n=34)

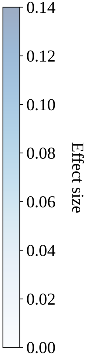
Cluster 12 description: The individuals express stress related to academic exams, significant life decisions, and workloads, alongside sleep disturbances caused by lifestyle changes, increased responsibilities, or environmental adjustments, while some also highlight temporary relief from pressures through personal achievements or upcoming positive events. (age=24±9, n=67)

Cluster 26 description: The individuals express sleep disturbances characterized by insomnia, frequent awakenings, and restless sleep, alongside pervasive anxiety, emotional instability, and self-esteem issues, which collectively contribute to persistent fatigue, impaired daily functioning, and a diminished sense of well-being. (age=25±9, n=37)

→ Clustering captures symptom severity and age-related circumstances

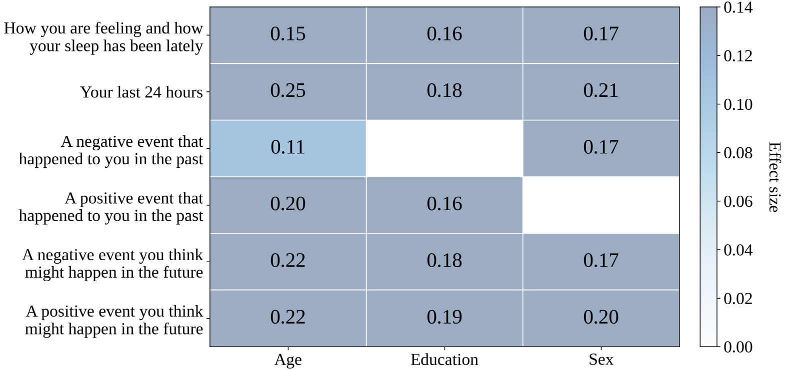
Effect size across questions and clinical scores

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



→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



→ Nearly all questions discriminate sociodemographics

Perspectives

- Emotion analysis for mental health (empathic support, cognitive distortions, theory of mind)
- Psychology of language models (sycophancy, thought operations)
- Post-training for psychology (preferences and reasoning data)

Selected research papers

[noframenumbering]

Constant Bonard and Gustave Cortal (2024). "Improving Language Models for Emotion Analysis: Insights from Cognitive Science". In: *Proceedings of the Workshop on Cognitive Modeling and Computational Linguistics*. Ed. by Tatsuki Kuribayashi et al. Bangkok, Thailand: Association for Computational Linguistics, pp. 264–277. DOI: 10.18653/v1/2024.cmcl-1.23

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

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**	$\boldsymbol{F_1}$
Logistic Regression	84.9 (0.3)	84.3 (0.3)	84.4 (0.3)
CamemBERT	**93.2**	**93.0**	**93.1**

Table: Scores ($\pm$ std) for emotion component classification.

$\rightarrow$ Models can be used to automatically classify unstructured narratives

Demographics

	General Population n=1809	Androids n=116	MODMA n=52	VOCES n=90
Demographics				
Language	French	Italian	Chinese	Spanish
Age	***	*n.s.*	*n.s.*	***
Mean (SD)	37.8 (18.2)	37.4 (12.0)	31.3 (9.2)	38.6 (14.9)
Range	18–91	19–71	18–52	21–76
Sex, n (%)	*n.s.*	*n.s.*	*n.s.*	*n.s.*
Female	1187 (66.2)	84 (72.4)	16 (30.8)	39 (43.3)
Male	595 (33.2)	32 (27.6)	36 (69.2)	48 (53.3)
Other	11 (0.6)	0 (0.0)	0 (0.0)	3 (3.3)
Education, n (%)	*n.s.*	*n.s.*	*n.s.*	*n.s.*
No diploma	52 (2.9)	11 (9.5)	7 (13.5)	-
Secondary	291 (16.2)	37 (31.9)	8 (15.4)	-
Higher short	213 (11.9)	52 (44.8)	0 (0.0)	-
Higher long	1236 (69.0)	16 (13.8)	37 (71.2)	-

Clinical evaluation

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

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