Natural language processing for subjectivity analysis in personal narratives

Gustave Cortal

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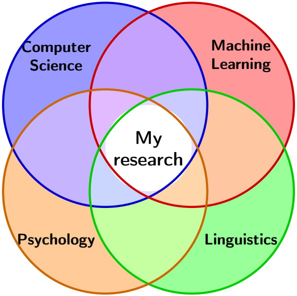
Introduction

Context



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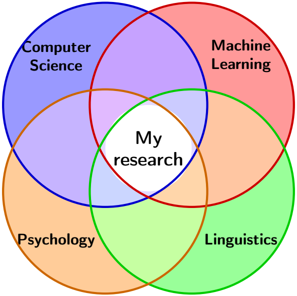

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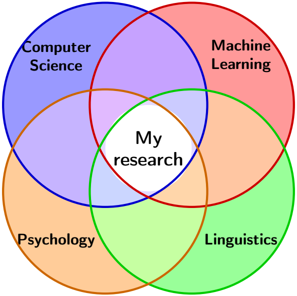

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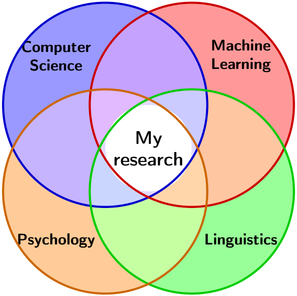

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- We focus on personal narratives (emotional narratives, dream reports)

Introduction

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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 *category*	"I love philosophy." → `joy`

Darwin (1872), Tomkins (1962), Ekman (1999), and Plutchik (2001)
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Constructivist theories	a continuous value with an *affective* meaning	"His voice soothes me." $\rightarrow$ `valence` (4/5), `arousal` (1/5)
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Appraisal theory	a continuous value with a *cognitive* 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 *semantic roles*	"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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(Micheli, 2013b; Etienne, Battistelli, and Lecorvé, 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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→ Emotion expression modes vary in interpretive difficulty
(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)

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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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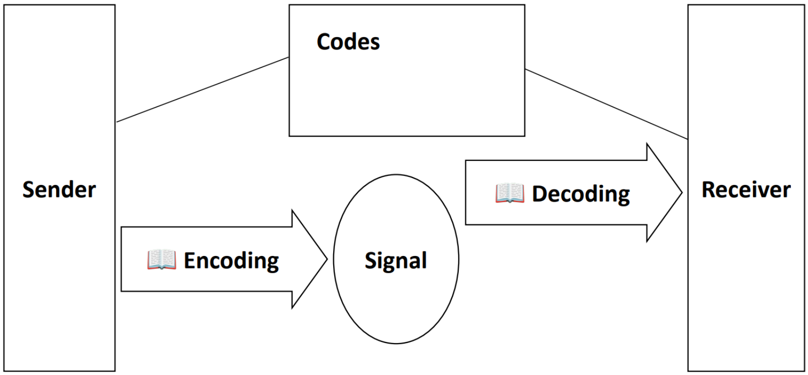

Figure: Dictionary analysis in cognitive pragmatics.

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

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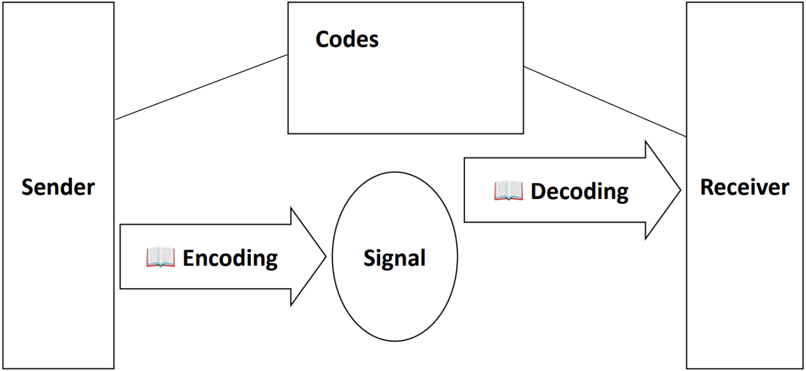

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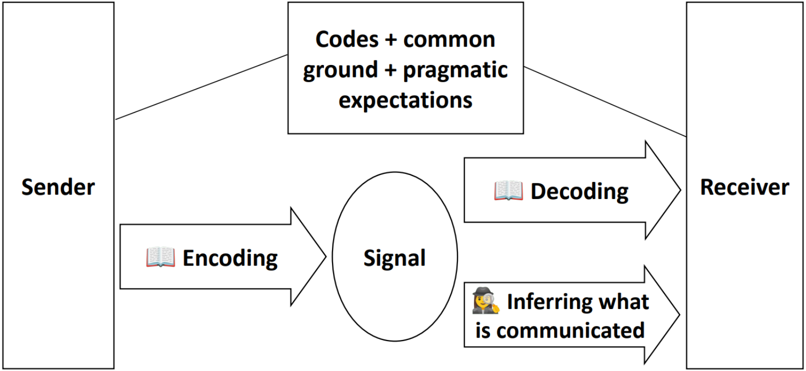

Figure: Detective analysis in cognitive pragmatics.

How to integrate psychological theories of emotion?

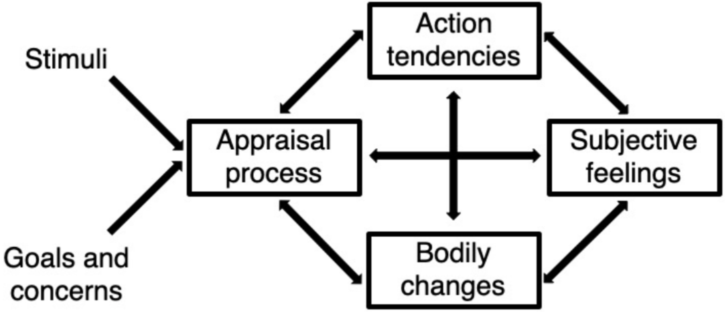

Figure: **The integrated framework for emotion theories** (Scherer, 2022b). Rectangles represents the components constituting an emotional episode, and arrows represent causation.

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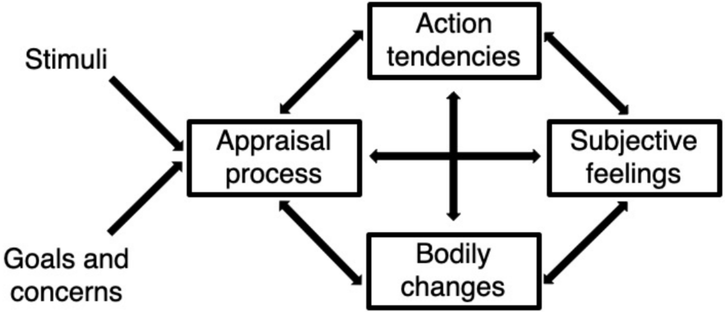

Figure: **The integrated framework for emotion theories** (Scherer, 2022b). Rectangles represents the components constituting an emotional episode, and arrows represent causation.

→ 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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→ 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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$\rightarrow$ How to automate the annotation process using language models?

Example of an annotated dream with HVdC

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

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

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

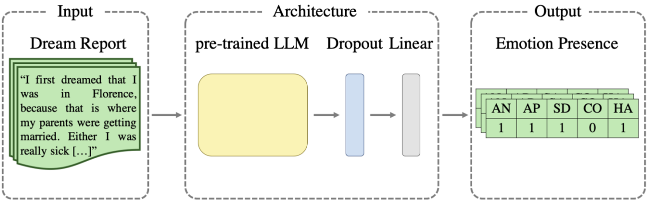

Figure: **Architecture for multi-label emotion detection** (Bertolini et al., 2023).

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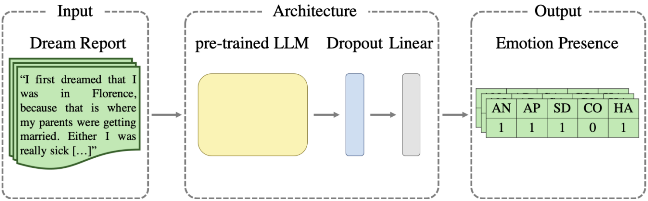

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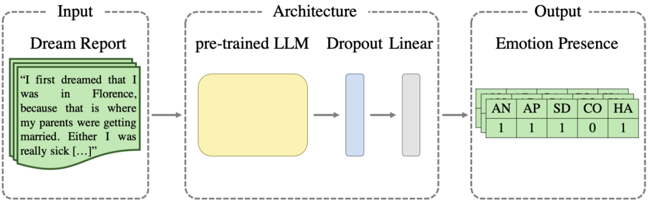

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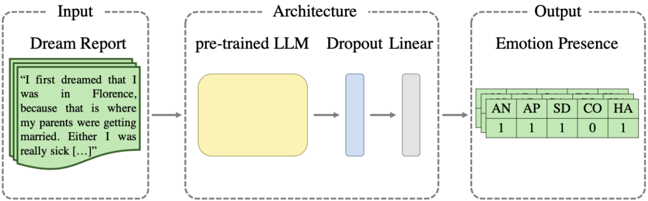

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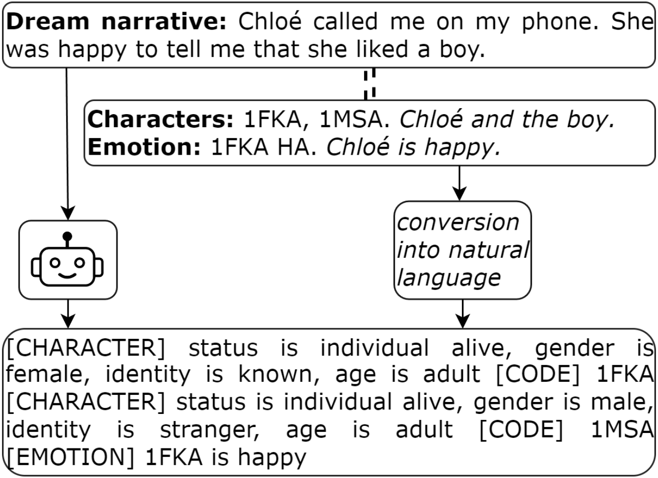
They use full context and compare predictions with gold annotations

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



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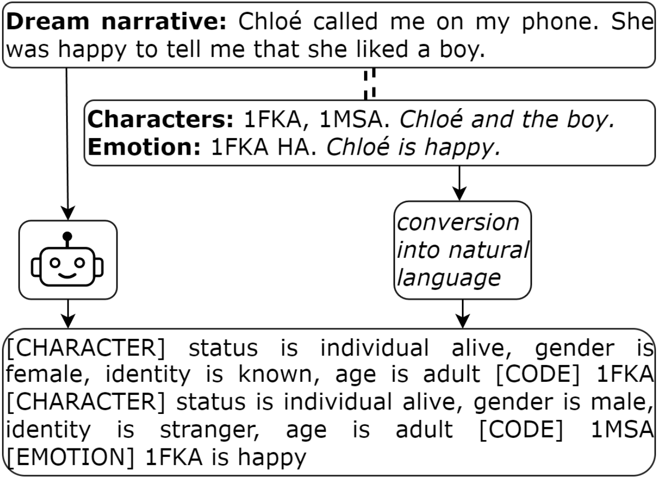

→ Our framework can be extended to include other HVdC categories

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
`Baseline`	82.9	78.0	76.2	86.2	64.7	75.1

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Baseline	82.9	78.0	76.2	86.2	64.7	75.1
$\texttt{No}_{\texttt{semantics}}$	71.4	56.5	61.0	90.5	41.8	75.8
$\texttt{No}_{\texttt{names}}$	80.7	74.3	74.2	84.0	60.9	73.0

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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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→ 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

callyope.com

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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- Thematic analysis studies how people construct meaning
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- Computational approaches offers time savings, can analyze a larger amount of data

Methodology

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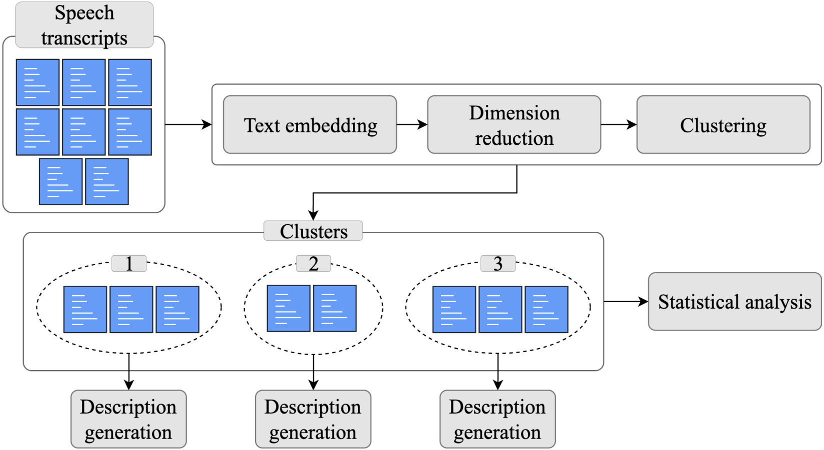
Open-ended questions involving last 24h, negative past event, positive future event, current feelings and sleep, etc.

Semantic clustering and description generation



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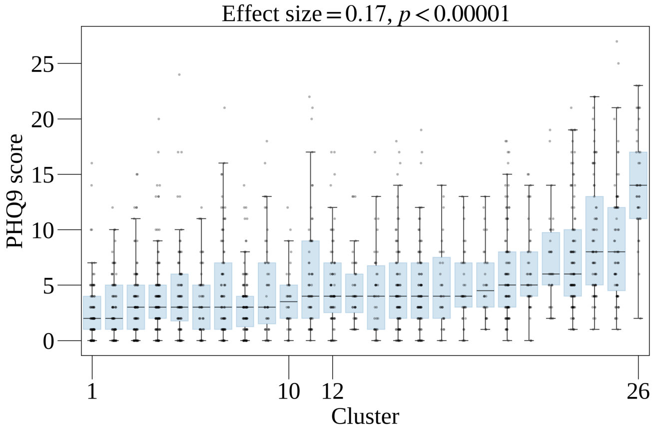
- Identified *risk* ("sleep disturbance") and *protective* ("physical activity") topics for depression, consistent with psychiatric literature

Distribution of depression scores across clusters

Current feelings and sleep (n=1786)



→ 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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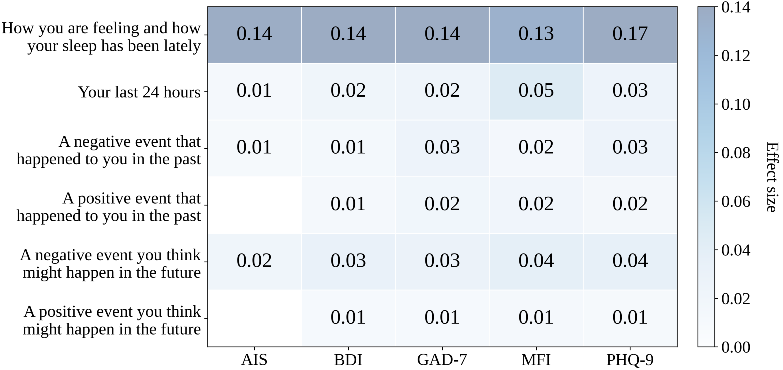
→ Clustering captures symptom severity and age-related circumstances

Effect size across questions and clinical scores



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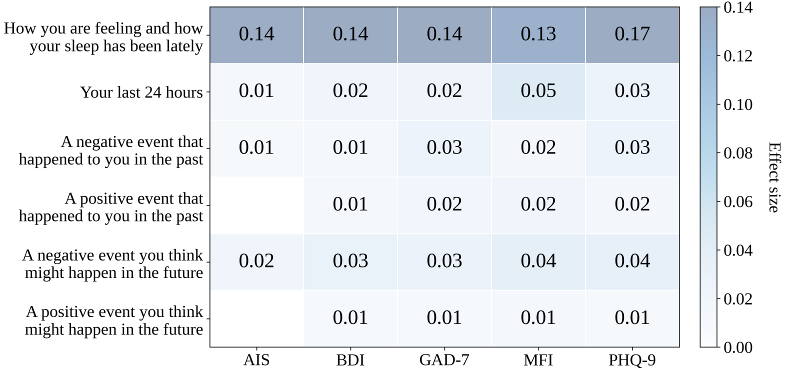
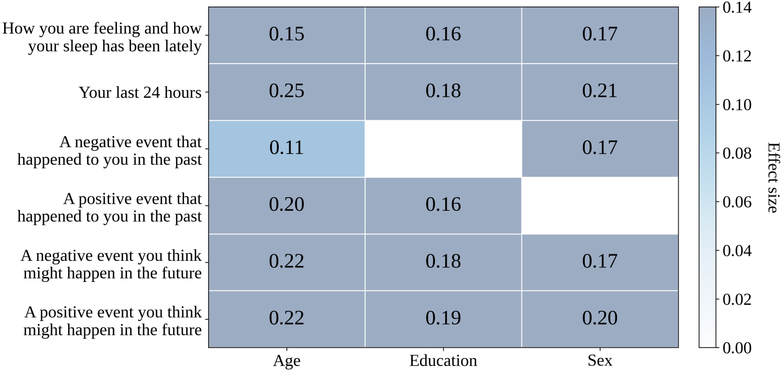


→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



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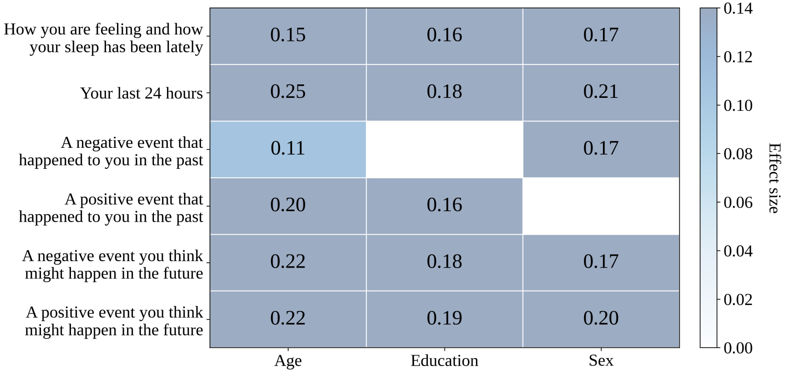

→ Nearly all questions discriminate sociodemographics

Risk and protective topics for depression

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→ We found topics consistent with psychiatric literature, aligned with labor-intensive qualitative research (Stanghellini et al., 2023)

Conclusion and 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 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**	F_1
Logistic Regression	84.9 (0.3)	84.3 (0.3)	84.4 (0.3)
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Table: Scores (± std) for emotion component classification.

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

$\rightarrow$ 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**	-

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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)

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

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?

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