Natural language processing for subjectivity analysis in personal narratives

Gustave Cortal

Introduction

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We first address the *content* by classifying elements of personal narratives (*e.g.*, characters and emotions). Then, we study the *form* through the concept of style

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- Automatic thematic analysis in mental health narratives

Definition of objectives using cognitive science

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

Definition of objectives and scope using cognitive science

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What are current limitations and interesting research directions?

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

Integrated framework for emotion theories

How to integrate psychological theories of emotion?

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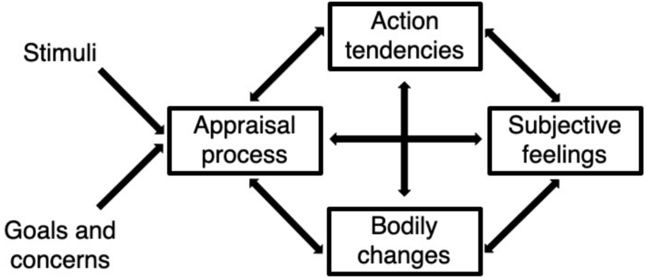

Figure: Emotional episodes are synchronized changes in four components (Scherer, 2022).

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→ Different emotion expression modes are more or less difficult to interpret

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

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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.

More than 1,000 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

Component	Logistic Regression Precision	Logistic Regression Recall	Logistic Regression F_1	CamemBERT Precision	CamemBERT Recall	CamemBERT 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
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→ Some components benefit from contextual understanding and world knowledge (*e.g.*, `behavior` and `thinking`)

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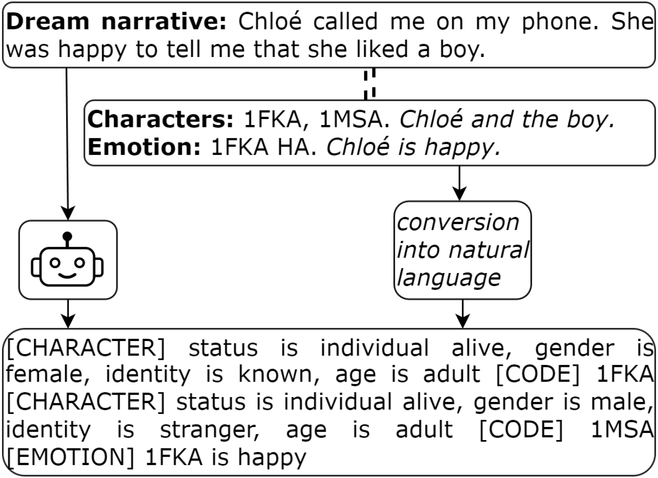
Character and emotion detection in dream narratives



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`: ** ($p < 0.01$), * ($p < 0.05$).

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→ Language models can effectively address character and emotion detection in dream narratives

Results

`StableBeluga`$_{\texttt{i}}$ 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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→ 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
Identity	known*	24.9	51.6	-26.7
	prominent	1.9	2.5	-0.6
	occupational*	22.4	8.0	14.4
	ethnic*	4.1	0.9	3.1
	unknown*	46.8	37.0	9.8
Gender	male*	56.2	43.0	13.1
	female*	24.1	33.1	-9.0
	joint	10.9	12.2	-1.3
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Table: Identity and gender proportions for the veteran (n=566 narratives) versus other dreamers. Δ shows the difference in percentage points. * indicates significant difference ($p < 0.05$).

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→ 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*.

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

Contributions

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3. A case study on dream narratives

Categorizing linguistic features

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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]$_{\text{Possessed}}$

Pipeline 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`

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4. We perform sequence analysis to identify patterns such as frequent substrings and representative sequences

Results on the war veteran

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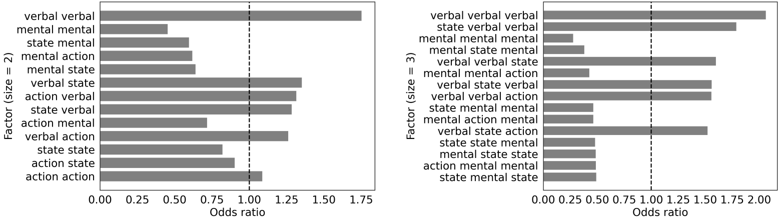

(a) Size 2. (b) Size 3.

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

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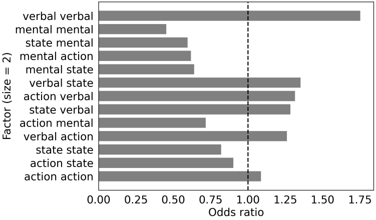

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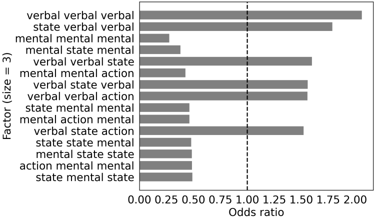

(b) Size 3.

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

We show a preference for the war veteran to remain in a verbal process, as indicated by substrings such as *verbal.verbal* and *verbal.verbal.verbal* with high odds ratios (respectively 2.00 and 1.75)

Results on the war veteran

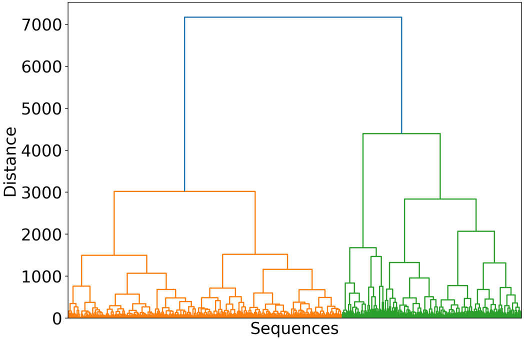

Figure: Dendrogram with Ward linkage and cosine similarity

Results on the war veteran

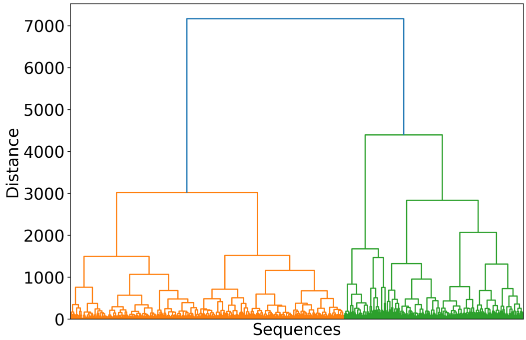

Figure: Dendrogram with Ward linkage and cosine similarity

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

Perspectives

- Authorship profiling

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- Style-conditioned narrative generation

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

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

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$\rightarrow$ We developed a multilingual pipeline that (a) clusters narratives from four cohorts, (b) generates natural-language descriptions for each cluster, and (c) links clusters to variation in clinical scores and sociodemographic factors

Data collection

We collect clinical scores and open-ended 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

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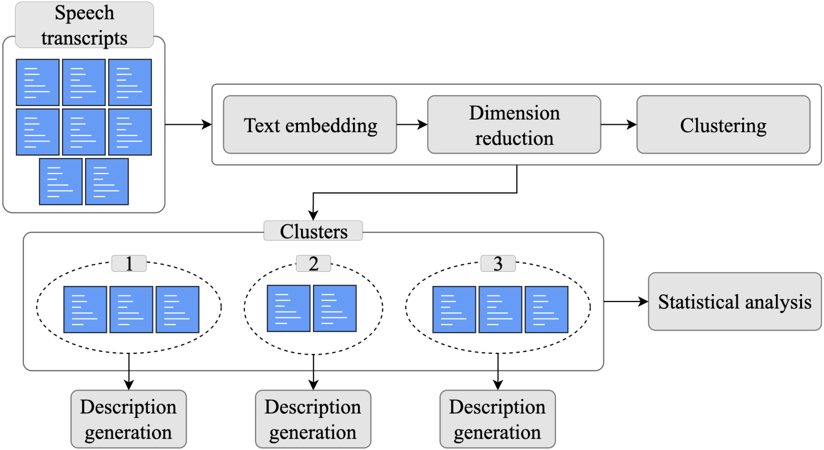
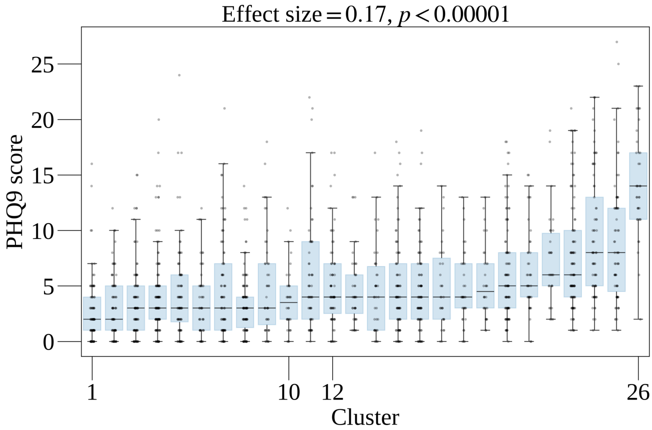
Open-ended questions: *Describe your last 24 hours / a negative event that happened to you in the past / a positive event that happened to you in the past / a negative event you think might happen in the future / a positive event you think might happen in the future / Describe how you are feeling at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



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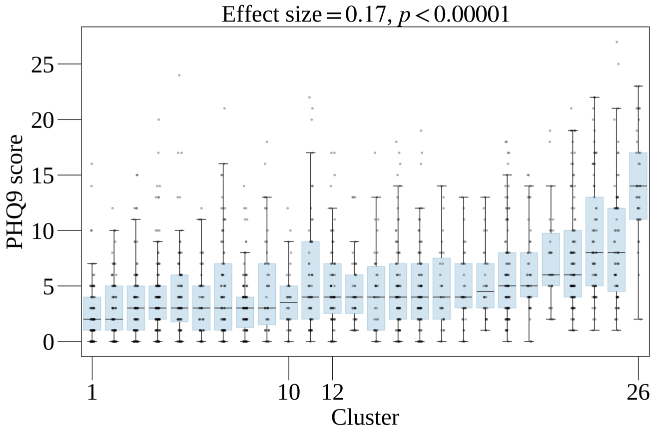

→ Depression scores vary significantly: cluster 26 highest (13.4±5.4), cluster 1 lowest (2.6±2.2)

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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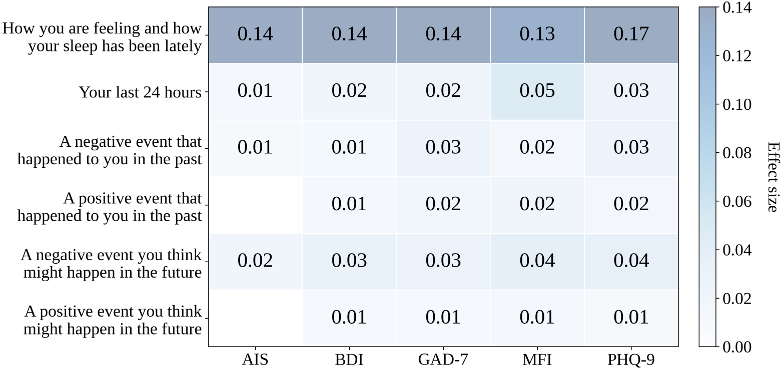
→ Clustering captures symptom severity and age-related circumstances

Effect size across questions and clinical scores



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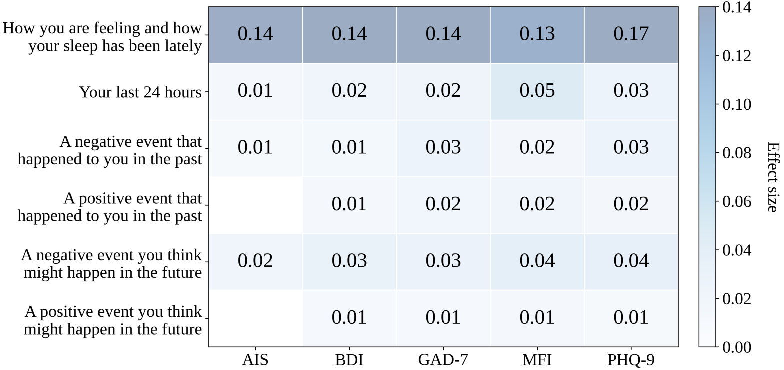
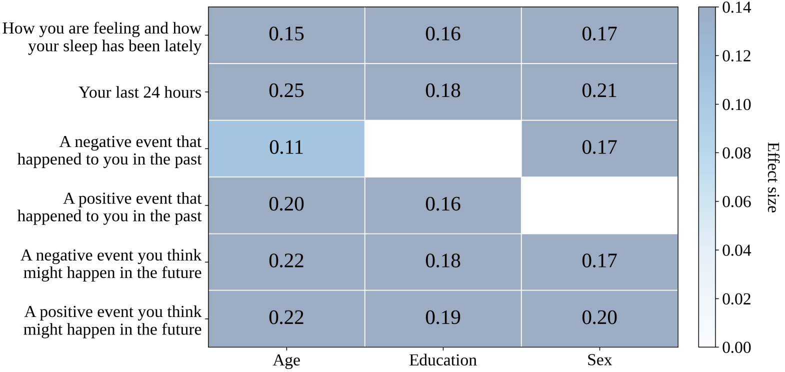


→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



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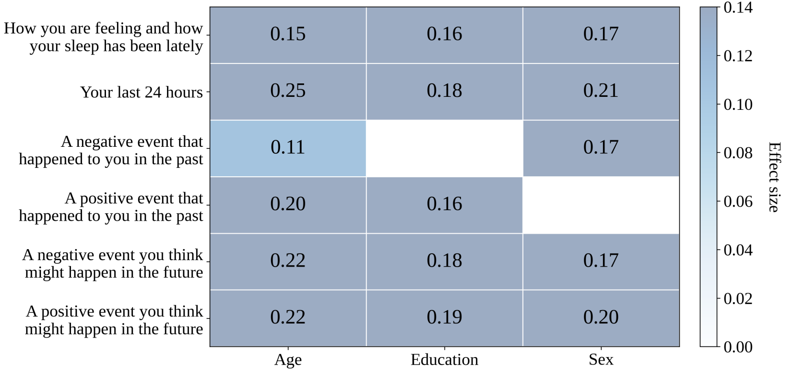

→ Nearly all questions discriminate sociodemographics

Conclusion

How to model subjective experience in personal narratives?

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- Definition of objectives and scope using cognitive science

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Appendix

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Oneirogen, a model for dream generation, and Dream-T5, a model for emotion and character prediction in 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 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

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Scherer, Klaus R. (2022). "Theory Convergence in Emotion Science Is Timely and Realistic". In: *Cognition and Emotion* 36.2, pp. 154–170. ISSN: 0269-9931. DOI: 10.1080/02699931.2021.1973378.