Natural language processing for subjectivity analysis in personal narratives

Gustave Cortal

Thesis director: Alain Finkel
Co-advisors: Patrick PAROUBEK and Lina YE

Laboratoire Méthodes Formelles

école normale supérieure paris–saclay

université PARIS-SACLAY

Introduction

Context

- Natural language processing for psychology is underexplored

Context

- Natural language processing for psychology is underexplored
- We build on an existing subfield: emotion analysis

Context

- Natural language processing for psychology is underexplored
- We build on an existing subfield: emotion analysis
- We study subjectivity (involving first-person perspective, meaning-making processes, and experiential content)

Context

- Natural language processing for psychology is underexplored
- We build on an existing subfield: 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)

Context

- Natural language processing for psychology is underexplored
- We build on an existing subfield: 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)

Context

- Natural language processing for psychology is underexplored
- We build on an existing subfield: 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 (*e.g.*, characters and emotions). Then, we study the *form* through the concept of style

Introduction

How to model subjective experience in personal narratives?

Introduction

How to model subjective experience in personal narratives?

- Definition of objectives and scope using cognitive science

Introduction

How to model subjective experience in personal narratives?

- Definition of objectives and scope using cognitive science
- Construction of an emotion dataset

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

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

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
- Automatic thematic analysis in mental health narratives

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
- Automatic thematic analysis in mental health narratives

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
- Automatic thematic analysis in mental health 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*.

Psychological theories and emotion annotation schemes

What are current limitations and interesting research directions?

Psychological theories and emotion annotation schemes

What are current limitations and interesting research directions?

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

Limitations in emotion analysis

- Different emotion theories lead to divergences in how to annotate them in the text
- Some linguistic and cognitive science theories are not considered

Limitations in emotion analysis

- 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

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:

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")

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!")

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")

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

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

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

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

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

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

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

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

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

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?

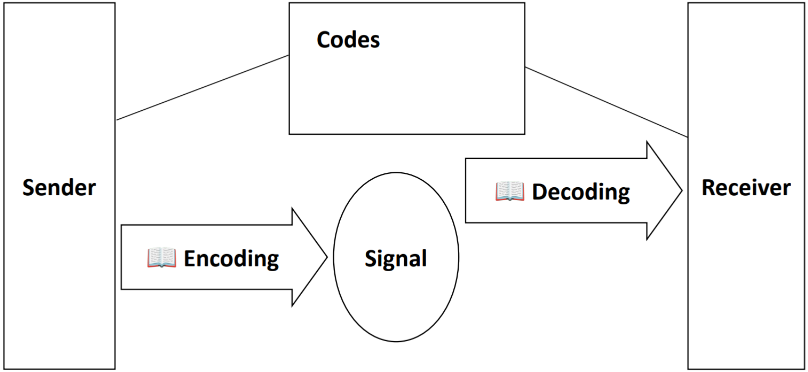


Figure: Dictionary analysis in cognitive pragmatics.

Codes underdetermine emotion meaning

Codes underdetermine emotion meaning

Let's take emotion expression modes as an example:

Codes underdetermine emotion meaning

Let's take emotion expression modes as an example:

- *Labeled*: "I am happy now" is explicit about the feeling but does not encode what the emotion is about

Codes underdetermine emotion meaning

Let's take emotion expression modes as an example:

- *Labeled*: "I am happy now" is explicit about the feeling but does not encode what the emotion is about
- *Displayed*: interjections ("Wow!", "Ah!", "Damn!") show affect yet leave valence and focus unclear

Codes underdetermine emotion meaning

Let's take emotion expression modes as an example:

- *Labeled*: "I am happy now" is explicit about the feeling but does not encode what the emotion is about
- *Displayed*: interjections ("Wow!", "Ah!", "Damn!") show affect yet leave valence and focus unclear
- *Suggested*: "The ship has black sails." can communicate any kind of emotion

Codes underdetermine emotion meaning

Let's take emotion expression modes as an example:

- *Labeled*: "I am happy now" is explicit about the feeling but does not encode what the emotion is about
- *Displayed*: interjections ("Wow!", "Ah!", "Damn!") show affect yet leave valence and focus unclear
- *Suggested*: "The ship has black sails." can communicate any kind of emotion

Codes underdetermine emotion meaning

Let's take emotion expression modes as an example:

- *Labeled*: "I am happy now" is explicit about the feeling but does not encode what the emotion is about
- *Displayed*: interjections ("Wow!", "Ah!", "Damn!") show affect yet leave valence and focus unclear
- *Suggested*: "The ship has black sails." can communicate any kind of emotion

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

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

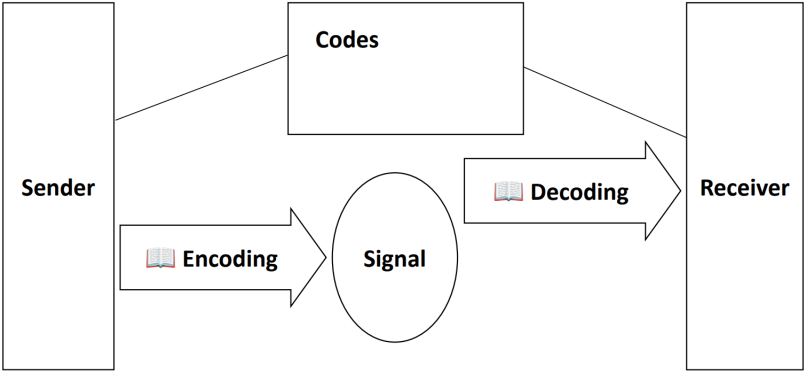


Figure: Dictionary analysis in cognitive pragmatics.

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

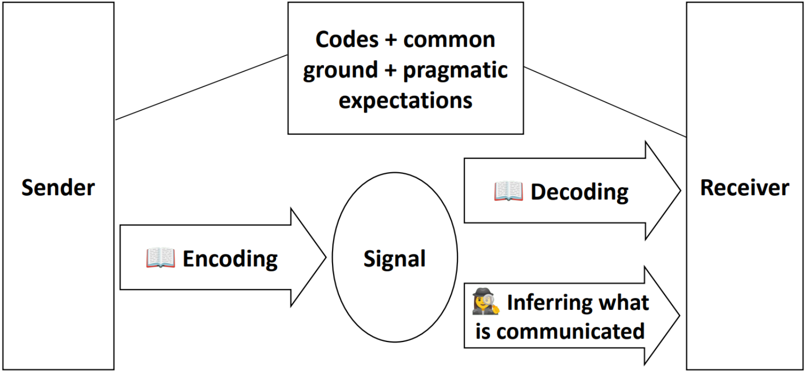


Figure: Detective analysis in cognitive pragmatics.

How to integrate psychological theories of emotion?

How to integrate psychological theories of emotion?

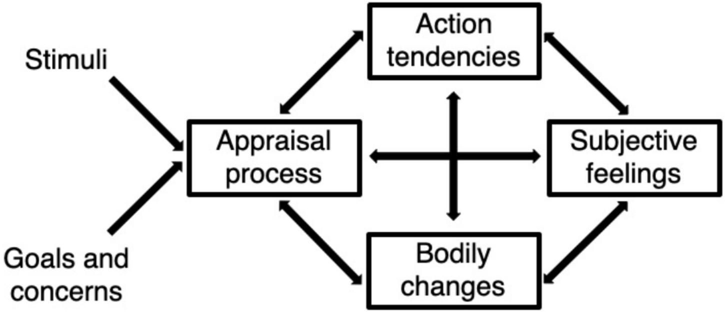


Figure: Integrated framework for emotion theories. Emotional episodes are synchronized changes in four components (Scherer, 2022).

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

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`)

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			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**
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

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

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

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
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

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

Quantitative analysis of dream narratives

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)

Quantitative analysis of dream narratives

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

Quantitative analysis of dream narratives

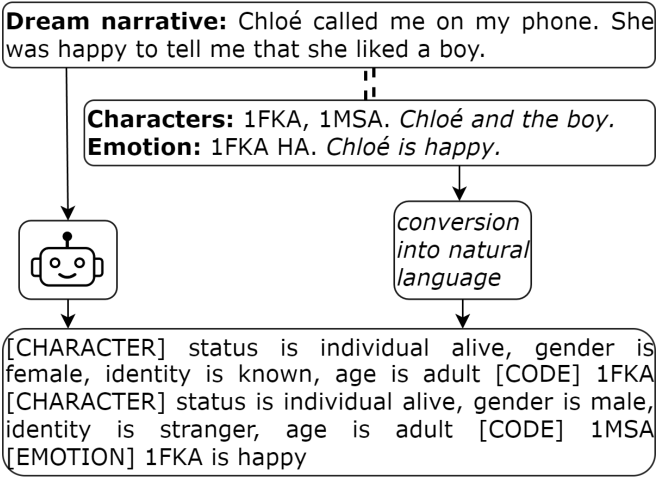
Need other datasets with narrative structure, emotional content, and available for research

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



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

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

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

Results

$\texttt{StableBeluga}_\texttt{i}$ 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
$\texttt{StableBeluga}_1$	43.95**	39.76**	31.25**	56.16**	15.65**	-
$\texttt{StableBeluga}_3$	52.44**	46.49**	38.46**	63.88**	21.06**	-
$\texttt{StableBeluga}_5$	55.89**	46.29**	42.61**	63.73**	24.86**	-

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

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)

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)

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

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. * indicates significant difference ($p < 0.05$).

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. * indicates significant difference ($p < 0.05$).

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

Oneirogen, a language model for dream generation

Oneirogen (0.5, 1.5, 7B), a language model for dream generation. It is based on Qwen2 and was trained on DreamBank

Oneirogen, a language model for dream generation

Oneirogen (0.5, 1.5, 7B), a language model for dream generation. It is based on Qwen2 and was trained on DreamBank

Oneirogen was used to produce The Android and The Machine, an English dataset composed of 10,000 real and 10,000 generated dreams

I'm in a building that seems to be a school or maybe a university. There is a lot of noise and activity, and everyone is very busy talking. It is very loud and unpleasant - too loud to talk to anyone easily. The walls are made out of some soft material that might be plastic foam.

I was at a shop. There were lots of people there and I lost Mom and Ezra. Later, we were in a car park. We went to get pizza's for dinner from the nearby pizza place but it was really late so they wouldn't serve us. [I think I was also walking around the shops earlier].

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?

How is subjective experience communicated in narratives?

We use narratives to express our representations of reality and make sense of the world (Bruner, 1990)

How is subjective experience communicated in narratives?

We use narratives to express our representations of reality and make sense of the world (Bruner, 1990)

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

How is subjective experience communicated in narratives?

We use narratives to express our representations of reality and make sense of the world (Bruner, 1990)

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

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

How is subjective experience communicated in narratives?

We use narratives to express our representations of reality and make sense of the world (Bruner, 1990)

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

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

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

How to give an operational definition of style?

How to give an operational definition of style?

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

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

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

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)

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

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)

What linguistic features encode subjective experience?

What linguistic features encode subjective experience?

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

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]$_{\text{Possessed}}$

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`

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

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`

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

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`

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

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`

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

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`

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

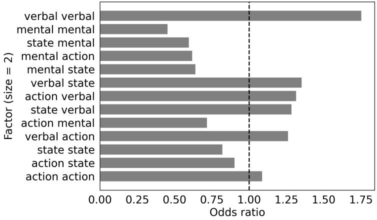
1. We first segment *"I wake in a dark room. I feel a cold wind. I tell myself to move."* into clauses
2. Identify features (*e.g.*, processes and participants) for each clause using in-context learning with large language models
3. Each narrative is mapped to a symbolic sequence using an alphabet based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

Results on the war veteran

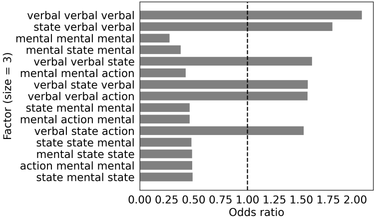
We compare the proportion of sequences containing a given substring

Results on the war veteran

We compare the proportion of sequences containing a given substring



(a) Size 2.

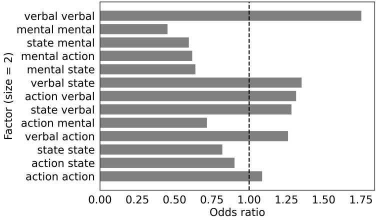


(b) Size 3.

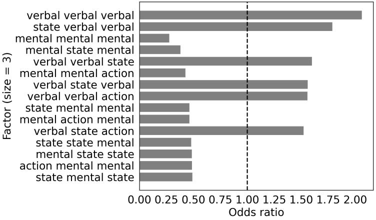
Figure: Top substring odds ratio between the veteran and the norm

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

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

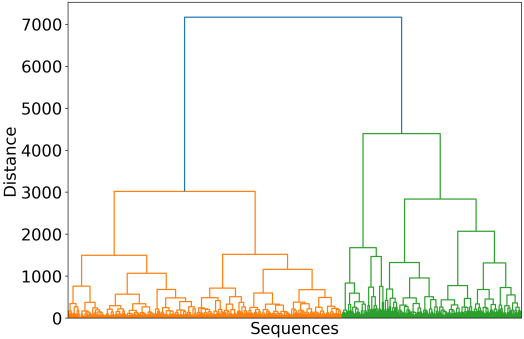


Figure: Dendrogram with Ward linkage and cosine similarity

Results on the war veteran

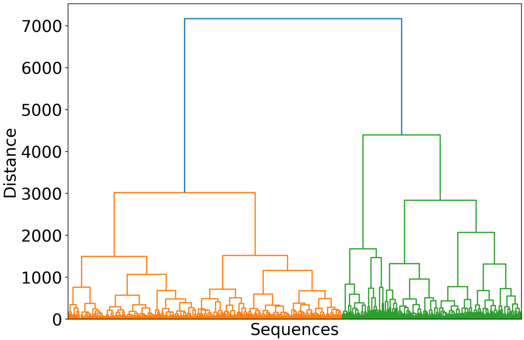


Figure: Dendrogram with Ward linkage and cosine similarity

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

Perspectives

- Authorship profiling

Perspectives

- Authorship profiling
- Style-conditioned narrative generation

Perspectives

- Authorship profiling
- 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

- Qualitative analysis of speech content is central to clinical practice

Introduction

- Qualitative analysis of speech content is central to clinical practice
- Thematic analysis studies how people construct meaning

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

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

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

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

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)

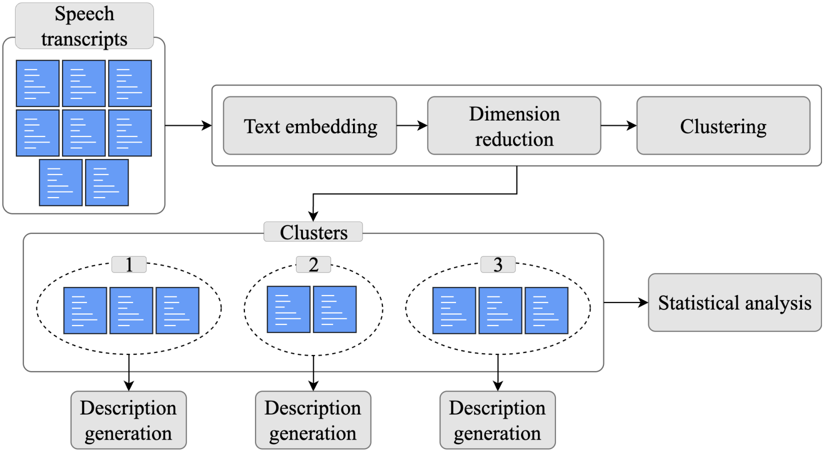
Data collection

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)

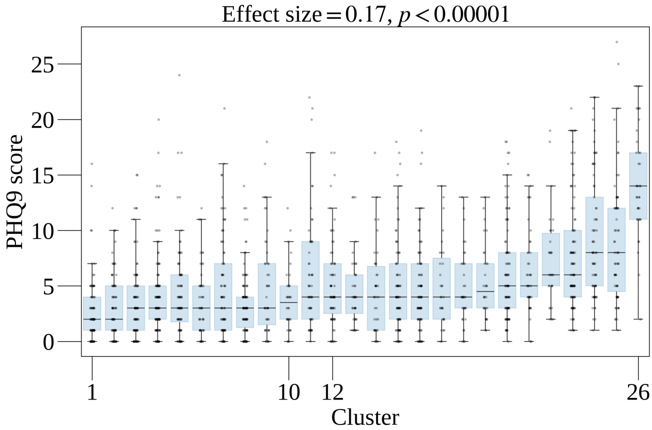
Open-ended questions: *Describe your last 24 hours / a negative event that happened to you in the past / a positive event that happened to you in the past / a negative event you think might happen in the future / a positive event you think might happen in the future / Describe how you are feeling at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

Pipeline for semantic clustering and description generation



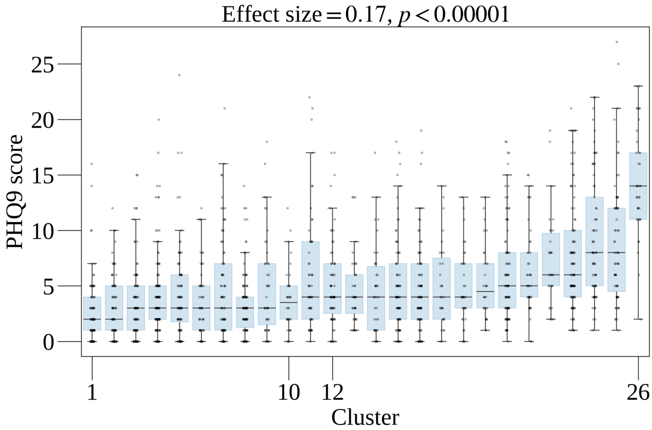
Distribution of depression scores across clusters

How you are feeling and how your sleep has been lately



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)

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)

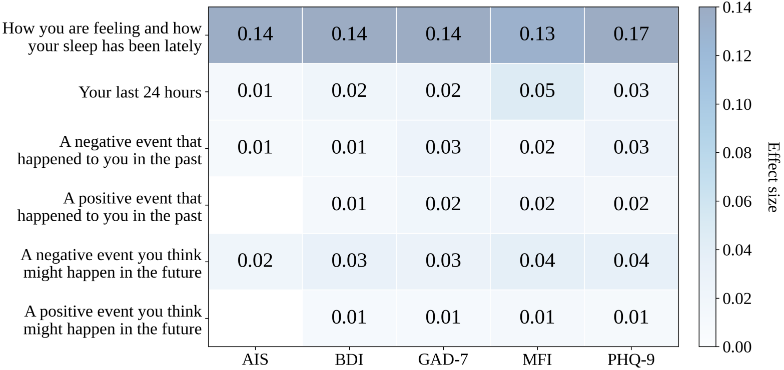
Cluster 10 description: The individuals express frequent nighttime urinary interruptions disrupting sleep, often attributed to age-related conditions like prostate issues or overactive bladder, alongside mixed reports of physical well-being, mental resilience, and lifestyle factors such as retirement 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)

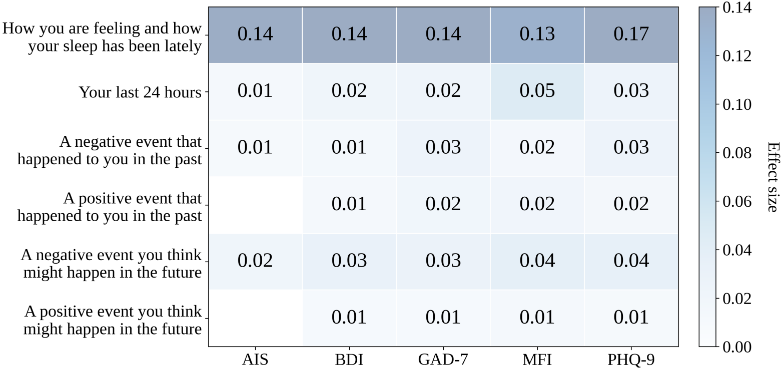
Cluster 26 description: The individuals express sleep disturbances characterized by insomnia, frequent awakenings, and restless sleep, alongside pervasive anxiety, emotional instability, and self-esteem issues, which collectively contribute to persistent fatigue, impaired daily functioning, and a diminished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

→ Clustering captures symptom severity and age-related circumstances

Effect size across questions and clinical scores

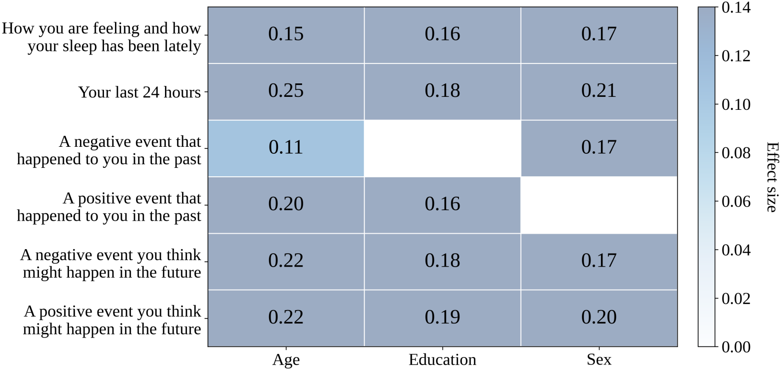


Effect size across questions and clinical scores

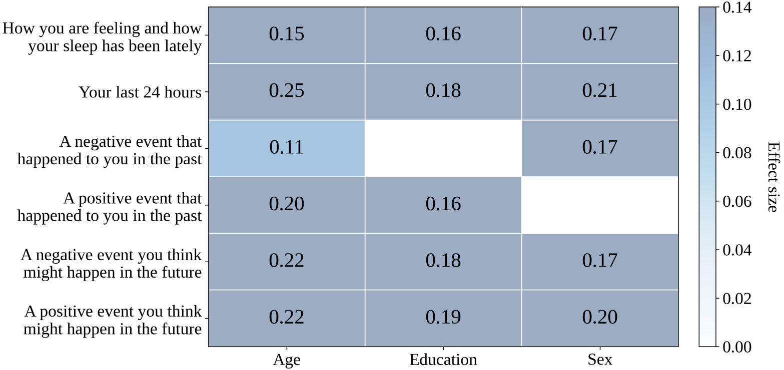


→ Certain questions better discriminate clinical scores

Effect size across questions and sociodemographics



Effect size across questions and sociodemographics



→ Nearly all questions discriminate sociodemographics

Conclusion and perspectives

Conclusion

How to model subjective experience in personal narratives?

Conclusion

How to model subjective experience in personal narratives?

- Definition of objectives and scope using cognitive science

Conclusion

How to model subjective experience in personal narratives?

- Definition of objectives and scope using cognitive science
- Construction of an emotion dataset

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

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

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
- Automatic thematic analysis in mental health narratives

Perspectives

- Emotion analysis for mental health (empathic support, cognitive distortions, theory of mind)

Perspectives

- Emotion analysis for mental health (empathic support, cognitive distortions, theory of mind)
- Psychology of language models (sycophancy, thought operations)

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)

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)

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)

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

Post-training for psychology

Piaget (0.6, 1.7, 4, 8B), a model for psychological reasoning

Post-training for psychology

Piaget (0.6, 1.7, 4, 8B), a model for psychological reasoning

Domain filtering on open reasoning traces from Dolphin R1 and General Reasoning

Post-training for psychology

Piaget (0.6, 1.7, 4, 8B), a model for psychological reasoning

Domain filtering on open reasoning traces from Dolphin R1 and General Reasoning

Prompts were embedded, clustered with k-means ($k = 20\,000$) and majority-voted for domain labels using Qwen3-1.7B

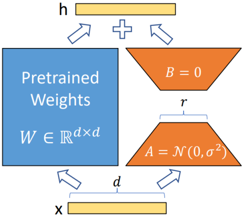
Post-training for psychology

Piaget (0.6, 1.7, 4, 8B), a model for psychological reasoning

Domain filtering on open reasoning traces from Dolphin R1 and General Reasoning

Prompts were embedded, clustered with k-means ($k = 20\,000$) and majority-voted for domain labels using Qwen3-1.7B

Clusters tagged psychology or philosophy were retained for LoRA finetuning based on Qwen3



Post-training for psychology

Beck (0.6, 1.7, 4, 8B), a model aligned with psychotherapeutic preferences

Post-training for psychology

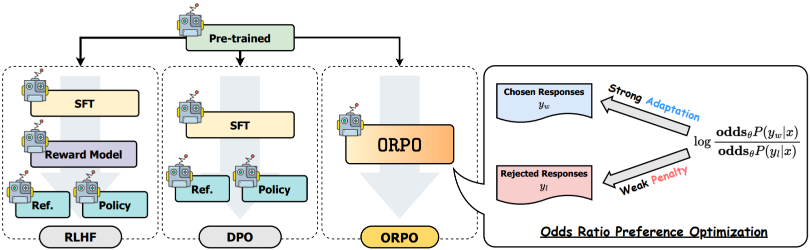
Beck (0.6, 1.7, 4, 8B), a model aligned with psychotherapeutic preferences

Beck is based on Piaget and was finetuned on psychotherapeutic preferences from PsychoCounsel-Preference using preference optimization (ORPO) and LoRA

Post-training for psychology

Beck (0.6, 1.7, 4, 8B), a model aligned with psychotherapeutic preferences

Beck is based on Piaget and was finetuned on psychotherapeutic preferences from PsychoCounsel-Preference using preference optimization (ORPO) and LoRA



How does it compare to other language models?

User prompt

Anxiety often strikes when I'm faced with making decisions. The fear of making the wrong choice or disappointing others paralyzes me, leaving me stuck in indecision. I want to learn how to trust myself and make confident choices.

Qwen3-8B

It's completely natural to feel anxious when facing important decisions, especially when you're worried about making the wrong choice or letting others down. This internal conflict can create a sense of overwhelm that makes it hard to move forward. Learning to trust yourself is a powerful step toward overcoming this challenge. Start by reflecting on past decisions—what worked, what didn't, and what you learned from them. Over time, you'll begin to recognize your own values, strengths, and patterns of thinking.

Practicing self-compassion is also key; remind yourself that no decision is perfect and that growth comes from experience, not perfection [...]

Beck-8B

It sounds like you're dealing with a lot of pressure regarding decision-making and it's causing you significant distress. This is quite common for many people, as we all have moments where choosing can feel overwhelming. Let's explore what might be contributing to these feelings so that we can work on building your confidence in decision-making.

Firstly, consider what specific fears arise when you think about making a decision. Is there a particular aspect of the choice that triggers anxiety? Sometimes identifying just one component can help in breaking down the process.

Also, think about past decisions that went well, even if they don't seem big at first [...]

Appendix

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

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

References

References I

Bonard, Constant 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.

Bruner, Jerome (1990). *Acts of Meaning*. Acts of Meaning. Cambridge, MA, US: Harvard University Press. ISBN: 978-0-674-00360-6.

Cortal, Gustave (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.

References II

Cortal, Gustave 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.

Cortal, Gustave, 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.

Domhoff, G. William and Adam Schneider (2008). "Studying Dream Content Using the Archive and Search Engine on DreamBank.Net". In: *Consciousness and Cognition* 17.4, pp. 1238–1247. ISSN: 10538100. DOI: 10.1016/j.concog.2008.06.010.

References III

Halliday, M.A.K. et al. (2014). *An Introduction to Functional Grammar*. 0th ed. Routledge. ISBN: 978-1-4441-1908-4. DOI: 10.4324/9780203783771.

Micheli, Raphaël (2013). "Esquisse d'une typologie des différents modes de sémiotisation verbale de l'émotion". In: *Semen. Revue de sémio-linguistique des textes et discours* 35. ISSN: 0761-2990. DOI: 10.4000/semen.9795.

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.