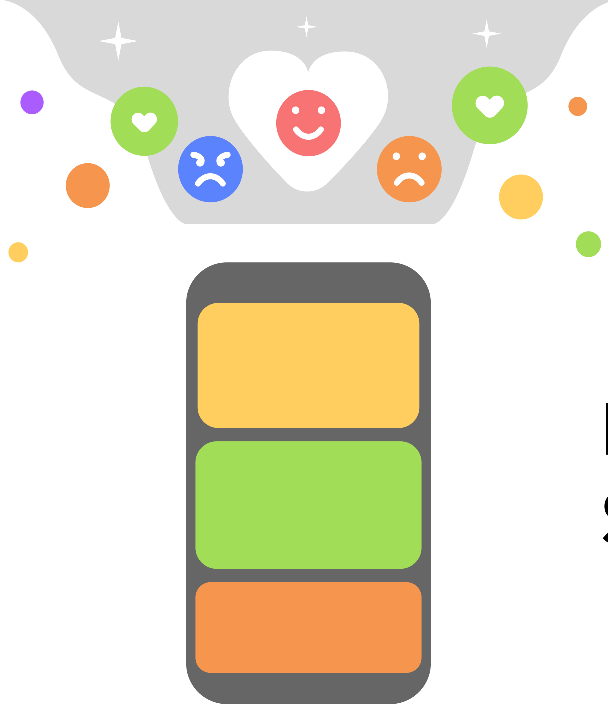
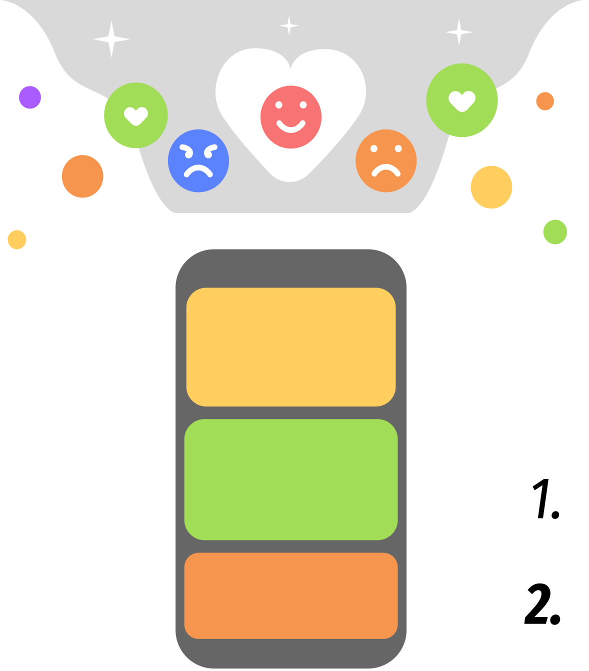


Predict Emotional Experience of Users on Social Media via Emotional Impact



1. *Predict Emotional Impacts?*
2. ***Study 1: Emotional Impacts != Expressed Emotions***
3. *Study 2: Predict Emotional Impacts in Field*
4. *Next Steps*

RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES

Experimental evidence of massive-scale emotional contagion through social networks

Adam D. I. Kramer, Jamie E. Guillory, and Jeffrey T. Hancock Authors Info & Affiliations

RESEARCH-ARTICLE | PUBLIC ACCESS

Anyone Can Become a Troll: Causes of Trolling Behavior in Online Discussions

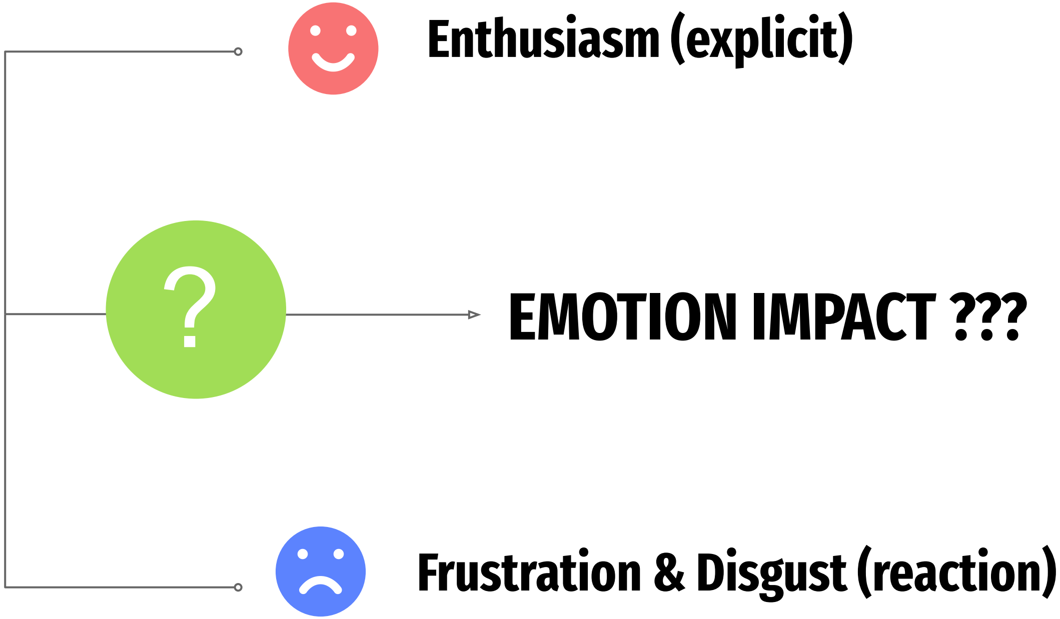
Authors: Justin Cheng, Michael Bernstein, Cristian Danescu-Niculescu-Mizil, Jure Leskovec | Authors Info & Claims

CSCW '17: Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing
Pages 1217 - 1230 • https://doi.org/10.1145/2998181.2998213

Expressed Emotion != Emotional Impact

@elonmusk:

I love all my kids so much."



“Neutral” sentences can have emotional impact implied via sentence-level comprehension.

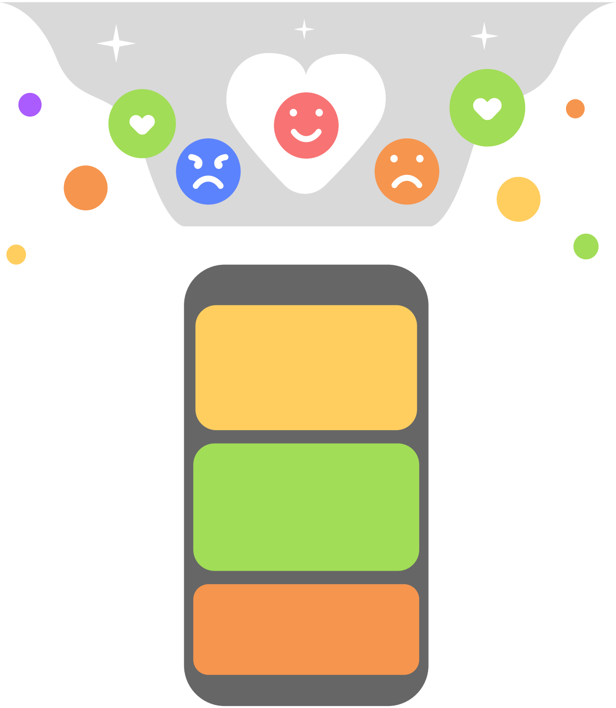
“The boy fell asleep and never woke up again. ” 💀 😢

vs.

“The boy stood up and grabbed his bag.” 🚶 😐

Lai, V. T., Willems, R. M., & Hagoort, P. (2015). Feel between the lines: implied emotion in sentence comprehension. *Journal of Cognitive Neuroscience*, *27*(8), 1528-1541.

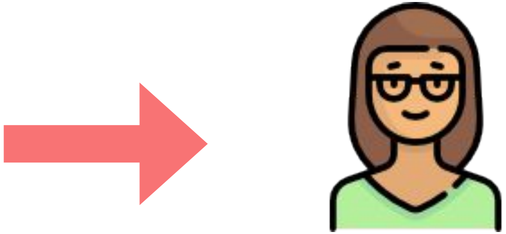
"I love CURIS SOOOO MUCH. Best Summer ever. Y'all should do CURIS. "



"I love CURIS SOOOO MUCH. Best Summer ever. Y'all should do CURIS. "

Expressed emotions

- *Happiness*
- *Satisfaction*



"I love CURIS SOOOO MUCH. Best Summer ever. Y'all should do CURIS. "

Expressed emotions

- *Happiness*
- *Satisfaction*

*Charlotte's friend who was **rejected from** CURIS and is currently **stressed** about getting more research experience.*

"I love CURIS SOOOO MUCH. Best Summer ever. Y'all should do CURIS. "

Emotional Impacts

- *Not necessarily Happy?*

Expressed emotions

- *Happiness*
- *Satisfaction* ☺

Emotional Experience

- 😢 *"I'm missing out!"*

*Charlotte's friend who was **rejected from** CURIS and is currently **stressed** about getting more research experience.*

"I love CURIS SOOOO MUCH. Best Summer ever. Y'all should do CURIS. "

Emotional Impacts

- *Not necessarily Happy?*

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☺

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Emotional Impacts

- *Not necessarily Happy?*

Expressed emotions

- *Happiness*
- *Satisfaction*

"I'm missing out!"

*Charlotte's friend who was **rejected from** CURIS and is currently **stressed** about getting more research experience.*

Existing NLP Emotion Analysis literature focus primarily on the goal of identifying specific emotions expressed by the author of a particular utterance or set of utterances

Vader, LIWC, SentiStrength, EmoLLM, etc.

🤔 ***BUT we care more about actual Emotional Impacts ??***

Emotional Experience

- 😢 *"I'm missing out!"*

How can we directly predict Emotional Experience of users on social media via Emotional Impacts?

Existing NLP Emotion Analysis literature focus primarily on the goal of identifying specific emotions expressed by the author of a particular utterance or set of utterances

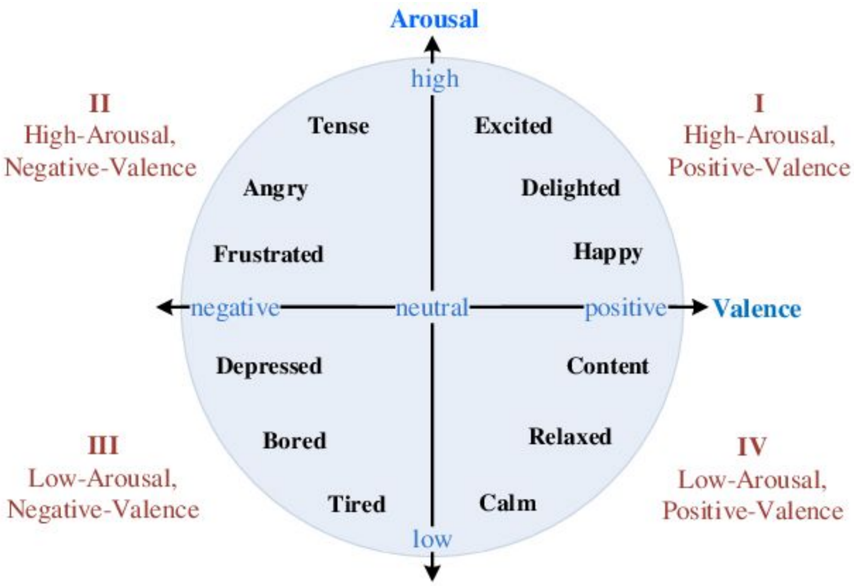
Vader, LIWC, SentiStrength, EmoLLM, etc.

Study 1: Emotional Impact != Expressed Emotion

Study 2: Predict Emotional Experience in Field

How can we directly predict Emotional Experience of users on social media via Emotional Impacts?

Arousal Valence Circumplex Model -> we drew 12 affects



High Arousal, Positive Valence:

- Excited, Enthusiastic, Happy

High Arousal, Negative Valence:

- Angry, Fearful, Nervous

Low Arousal, Positive Valence:

- Calm, Relaxed, Satisfied

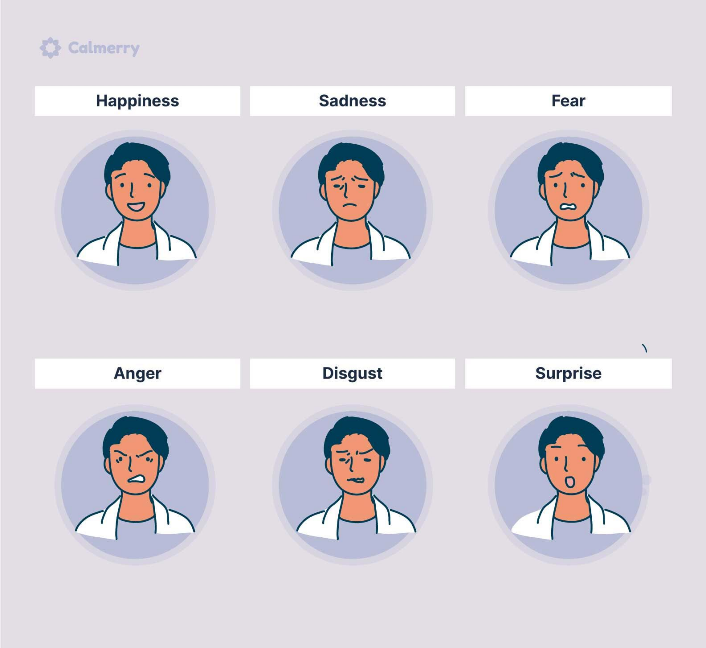
Low Arousal, Negative Valence:

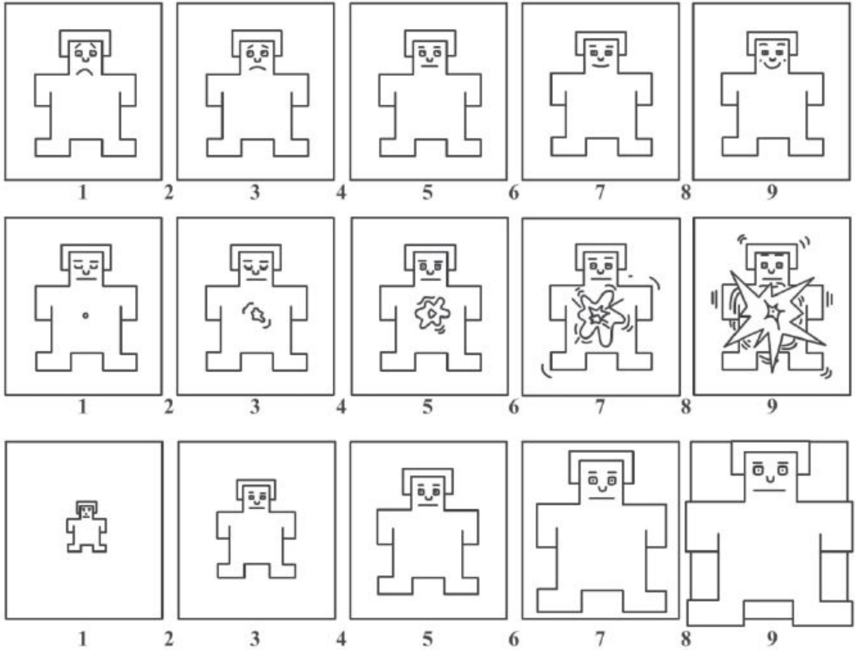
- Sad, Bored, Lonely

With intensity varying from 1 (none) - 5 (extremely).

Watson & Tellegen (1985), Barrett & Russell (1999)

+ Ekman’s Basic Emotions, VAD Model





➡️ 14 categorical emotions + 3 dimensions

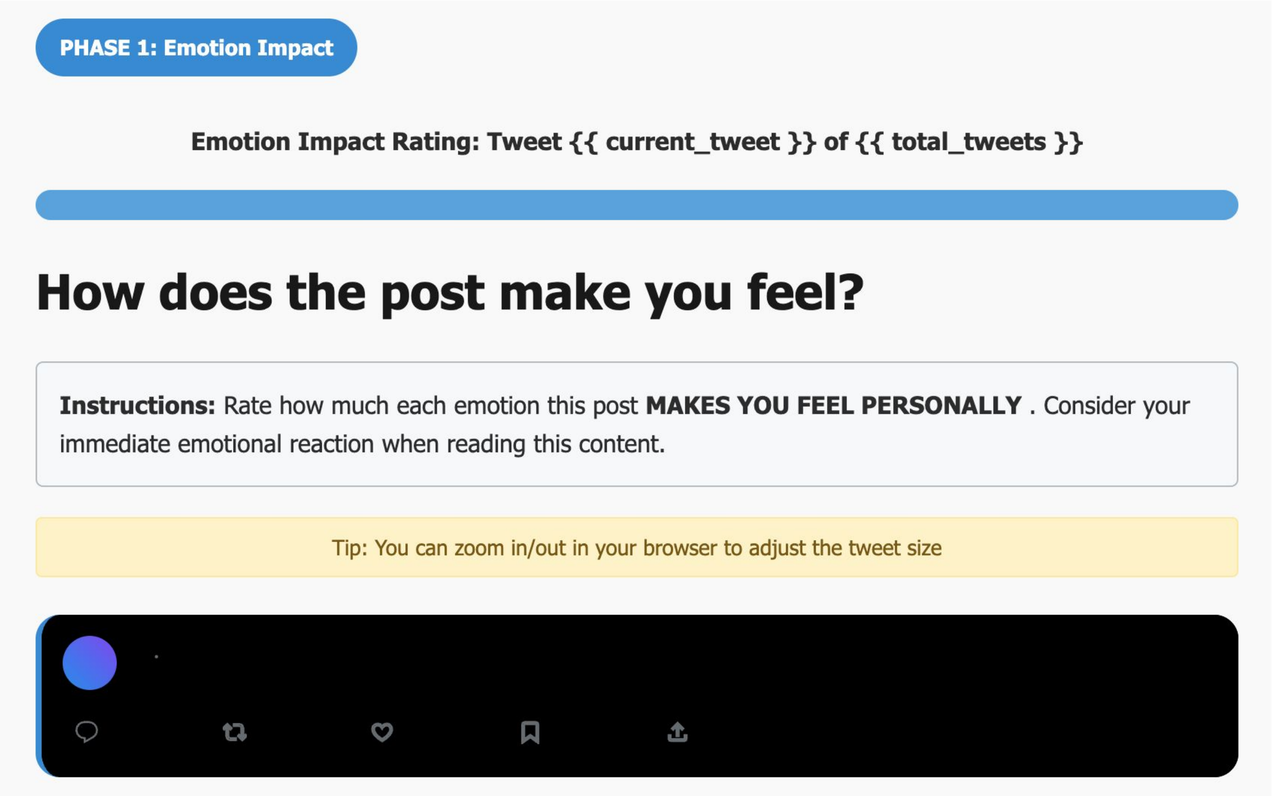
Study 1. Emotional Impact vs. Expressed Emotions（N=200）

😢 *“I’m missing out!”*

☺️ *“CURIS is great!”*

Emotional Impact → Expressed Emotions → If (emotional impact != expressed emotion): Ask: WHY?

Emotional Impact



Expressed Emotions

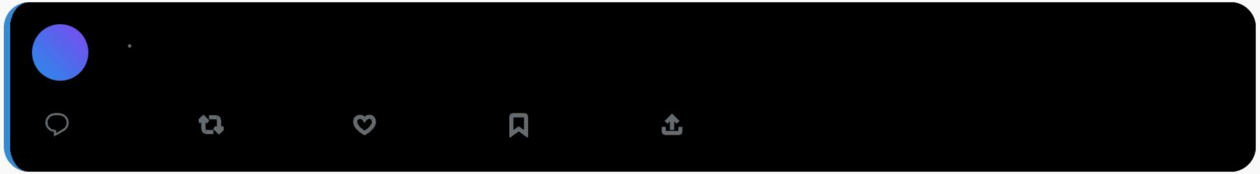
PHASE 2: Explicit Emotion

Explicit Emotion Rating: Tweet {{ current_tweet }} of {{ total_tweets }}

What emotions does this post explicitly express?

Instructions: Rate what emotions this post **directly expresses** , regardless of how it makes you feel personally. **Focus on the content.**

Tip: You can zoom in/out in your browser to adjust the tweet size



Categorical Emotions

Emotion	Emotional Impact TO YOU	Emotion in the POST CONTENT	Difference
Happy	2	5	-3
Sad	3	1	+2
Excited	1	5	-4
Satisfied	2	5	-3

Overall Emotion Tone

Dimension	Emotional Impact TO YOU	Emotion in the POST CONTENT	Difference
Negative vs. Positive	3	8	-5

Summary of Rating Differences

Emotions: You felt less happy, excited, and satisfied when reading this post, while also feeling somewhat sad - even though the post clearly expresses joy and excitement.

Emotional tone: The post had a negative impact on you (rating: 3) despite expressing very positive emotions (rating: 8).

Reasons for Differences

Emotion Impacts != Expressed Emotions

Wilcoxon Signed-Rank Test Results

Emotion	W-statistic	p-value	Median Diff	Effect Size	N	Significant
Nervous	22868.5	0.4760	0.000	0.954	1000	No
Sad	30523.0	0.9176	0.000	0.939	1000	No
Happy	50843.0	0.0000	0.000	0.898	1000	Yes***
Calm	55309.0	0.0000	1.000	0.889	1000	Yes***
Excited	39643.0	0.0000	-1.000	0.921	1000	Yes***
Angry	21673.0	0.0000	0.000	0.957	1000	Yes***
Relaxed	56111.0	0.0000	0.000	0.888	1000	Yes***
Fearful	13740.5	0.0239	0.000	0.973	1000	Yes*
Enthusiastic	37294.0	0.0000	-1.000	0.925	1000	Yes***
Satisfied	51017.0	0.0000	0.000	0.898	1000	Yes***
Bored	13511.0	0.0000	0.000	0.973	1000	Yes***
Lonely	5175.0	0.0812	0.000	0.990	1000	No
Disgusted	25383.5	0.0023	0.000	0.949	1000	Yes**
Surprised	81983.0	0.7752	0.000	0.836	1000	No
Valence	115191.0	0.0417	0.000	0.770	1000	Yes*
Arousal	73334.0	0.0000	-1.000	0.853	1000	Yes***
Dominance	79872.0	0.0000	-1.000	0.840	1000	Yes***

Most emotions showed statistically significant differences in Impact vs. Expressed Ratings

Happy, Calm, Excited, Angry, Relaxed, Enthusiastic, Satisfied, Bored, Disgusted, Arousal, Dominance all showed very high

Wilcoxon Signed-Rank Test Results

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Impact > Expressed

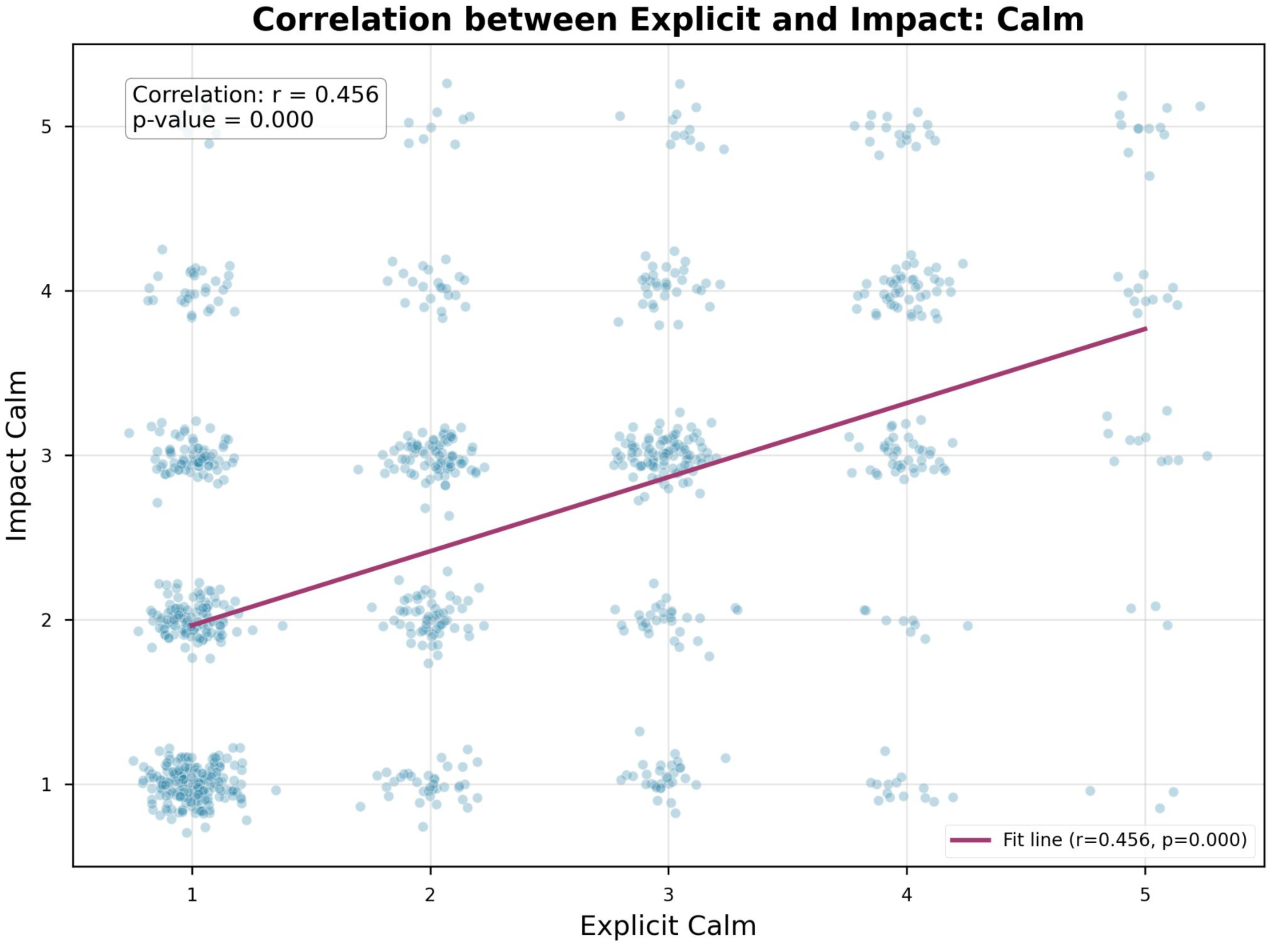
Impact > Expressed &&

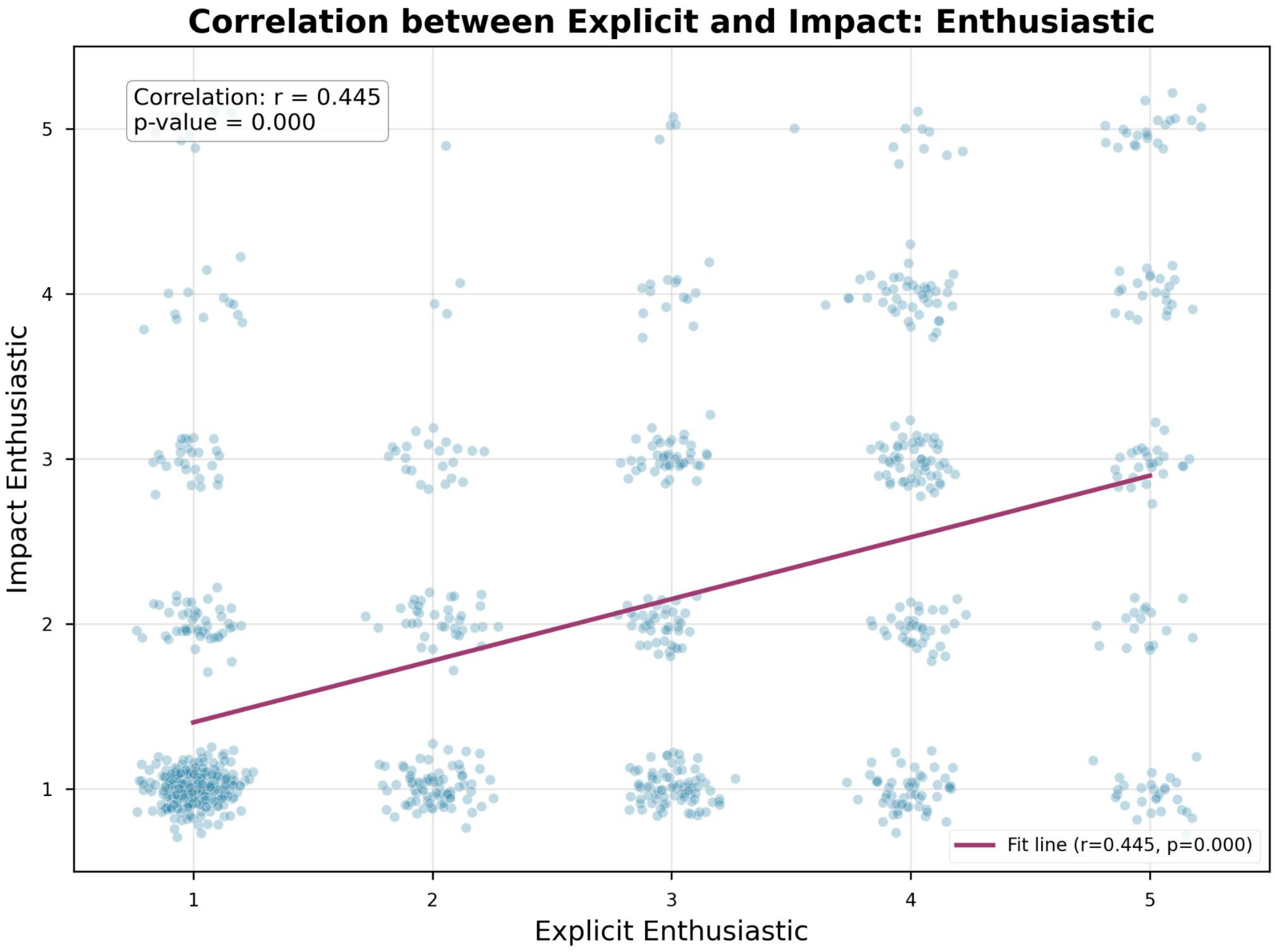
Impact < Expressed

Impact < Expressed

Impact > Expressed

Generally, people feel more calm than the level of calmness expressed in posts.





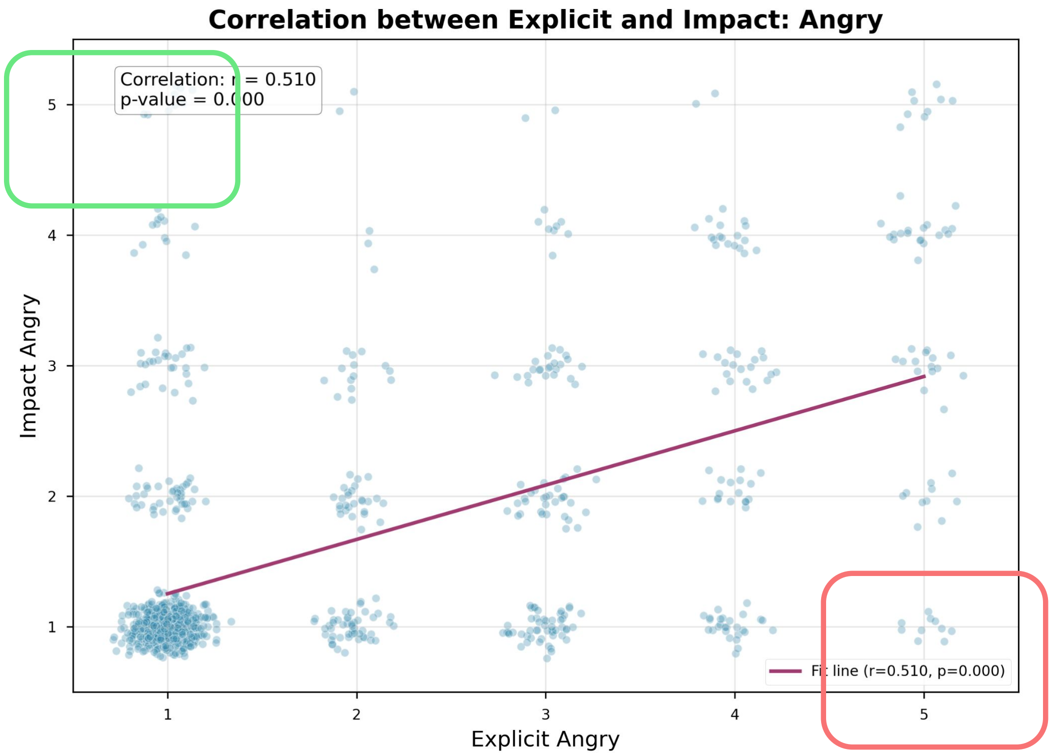
Impact < Expressed

Generally, people feel less enthusiastic than the level of enthusiasm expressed in posts.

Impact > Expressed && Impact < Expressed

Impact < Expressed

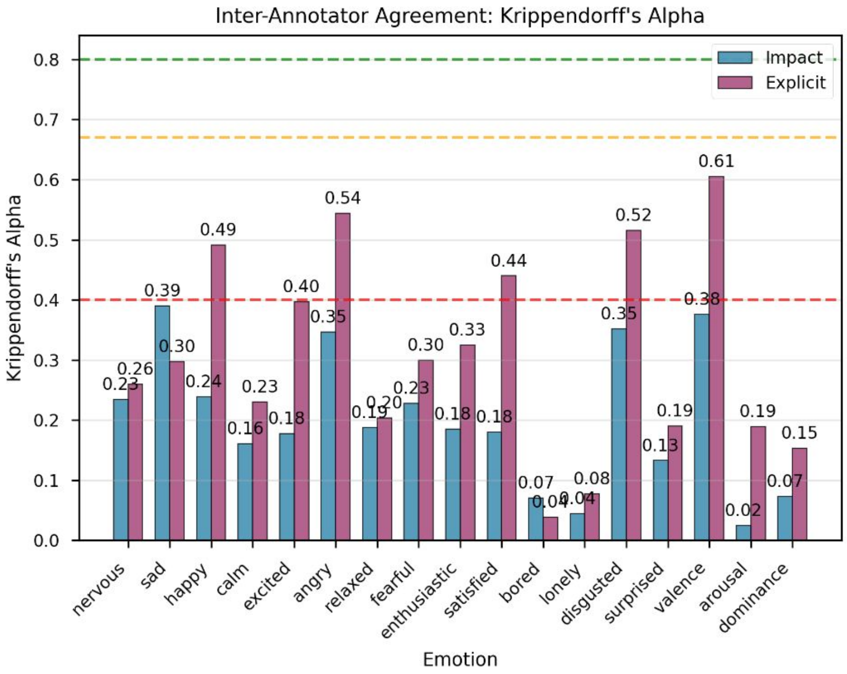
“I **absolutely do not support Trump**, but the person who posted **seemed eager and happy** to know what other supporters were out there."

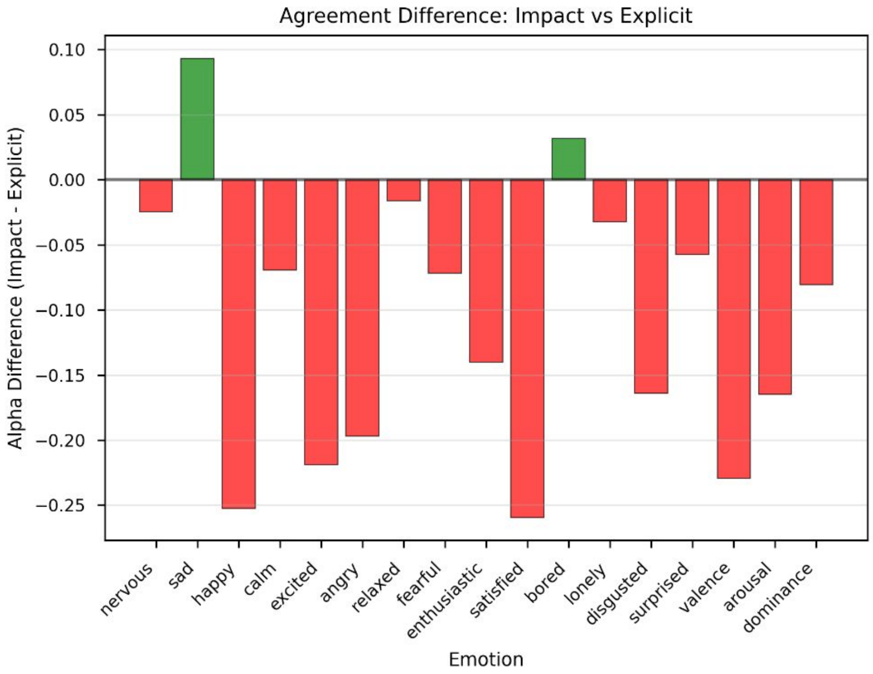


Impact < Expressed

“This person is angry about a game **I don't care about.** This post **doesnt resonate** with me at all.”

Annotators agree more in Expressed Emotion, than Emotional Impact





Similar Expressed Emotion -> Different Emotional Impact

Study 2. Predict Emotional Impacts in Field (N=1232)

* AAPA = expressions of anti-democratic attitudes and partisan animosity

Pre-Study

10-day Exposure

Track Tweet Viewing
Random Inline Surveys

How much do you feel the following emotion?

- Nervous
- Sad
- Happy

…… (12 emotions)

Inline-Survey

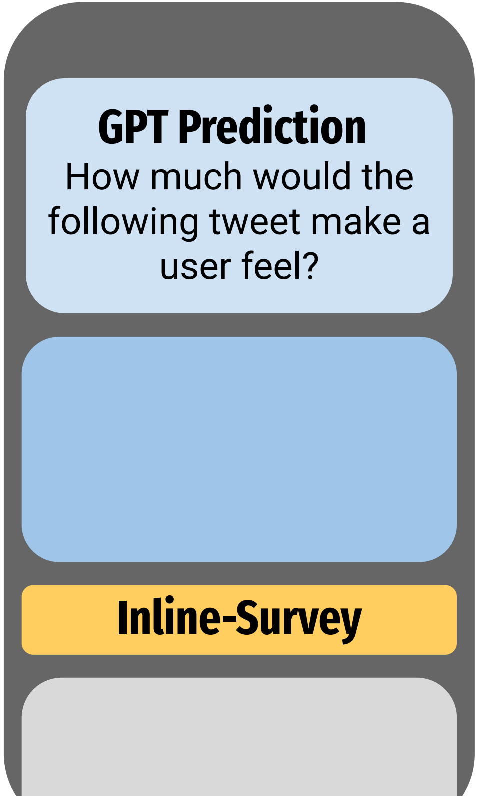
How much do you feel the following emotions right now?

- Angry
- Calm

…… (4 emotions)

Piccardi et al. (2024).

GPT Prediction of Emotional Impact is generated for each tweet viewed by participants.



After Pre-processing
456k unique tweets viewed by the users

- 1232 participants
16k inline surveys

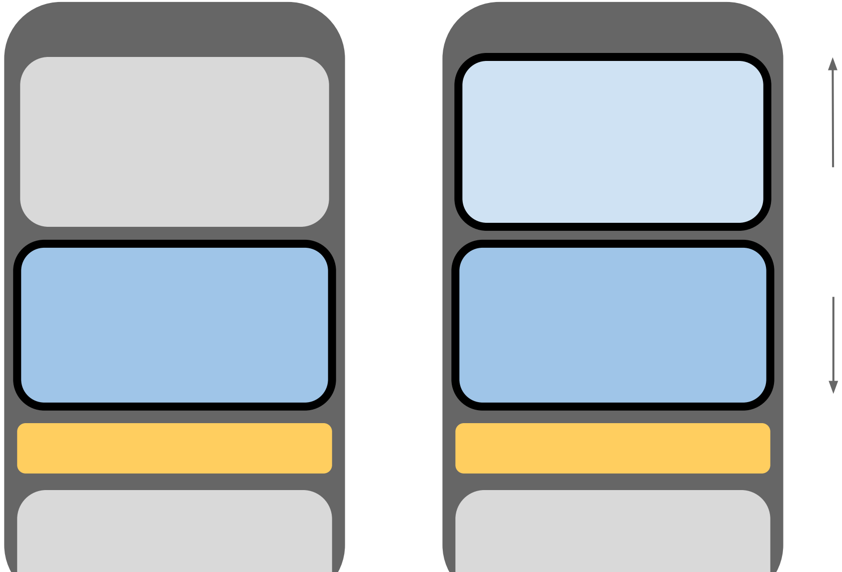
On average, each participant received
13 inline surveys -> Emotional Experience

Measure Prediction of Emotional Impact of tweet viewing over time.

Immediate Impact

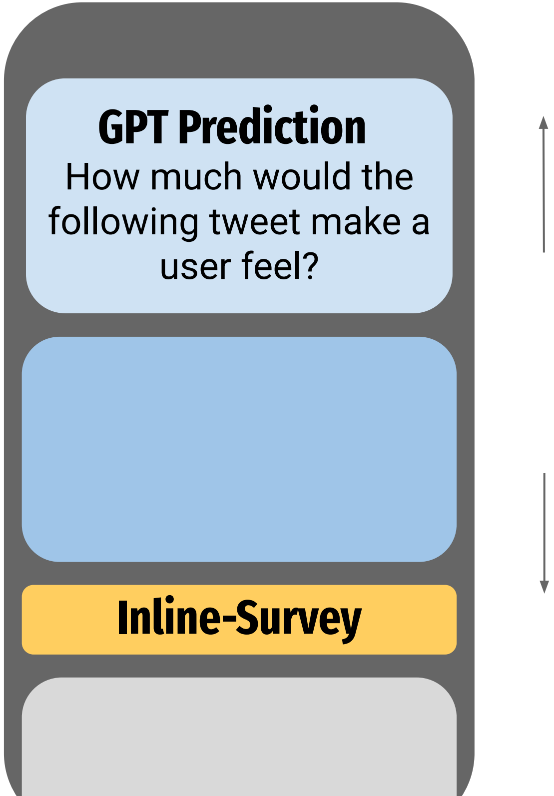
Aggregation of Emotion Predictions

Emotional Impacts of the tweet the user viewed **right before the inline survey.**



Emotional impacts of all tweet the user viewed **n hour before the inline survey**.

Aggregation of Impact



Time: 1 hour

Aggregation Method:
- Average
- Maximum
- Exponential Decay

Incorporated the affect definitions into a structured prompt.

<Input Post>

With all the things that users can see.

GPT Response in JSON:

- **Sad: 3** (Moderately)
- **Happy: 2** (Slightly)
- **Excited: 2** (Slightly)
- **Enthusiastic: 2** (Slightly)
- **Lonely: 2** (Slightly)

Ask GPT to act like a classifier -> **expressed emotions** / **emotional impacts**

Validating GPT as an annotator.

Model	Overall MAE	Std Dev	Emotion MAE	Dimension MAE
Human Baseline	0.718	0.722	0.614	1.201
gpt-5	0.745	0.595	0.648	1.201
gpt-5-mini	0.806	0.652	0.710	1.252
gpt-5-nano	0.828	0.664	0.730	1.288
gpt-4.1	0.752	0.595	0.624	1.348
gpt-4.1-mini	0.690	0.584	0.626	0.986
gpt-4.1-nano	0.855	0.683	0.753	1.328
gpt-4.1-CP	0.735	0.612	0.652	1.120
gpt-4.1-mini-CP	0.710	0.581	0.625	1.108
gpt-4.1-CP-UP	0.694	0.588	0.600	1.129
gpt-4.1-mini-CP-UP	0.687	0.576	0.604	1.076

emotional impacts

Model	Overall MAE	Std Dev	Emotion MAE	Dimension MAE
Human Baseline	0.686	0.721	0.582	1.172
gpt-5	0.677	0.591	0.612	0.984
gpt-5-mini	0.660	0.592	0.584	1.014
gpt-5-nano	0.703	0.615	0.624	1.070
gpt-4.1	0.611	0.541	0.532	0.979
gpt-4.1-mini	0.560	0.513	0.506	0.811
gpt-4.1-nano	0.697	0.634	0.581	1.242
gpt-4.1-CP	0.592	0.534	0.527	0.896
gpt-4.1-mini-CP	0.536	0.496	0.467	0.861
gpt-4.1-CP-UP	0.594	0.531	0.533	0.877
gpt-4.1-mini-CP-UP	0.554	0.514	0.482	0.887

expressed emotions

GPT's MAE is below the MAE of human baseline.

Prompts.

You are a common social media user. *Your task is to report the emotional impacts of a tweet to you. Rate how much this post makes you feel each emotion.*

How does the post make you feel?
…..

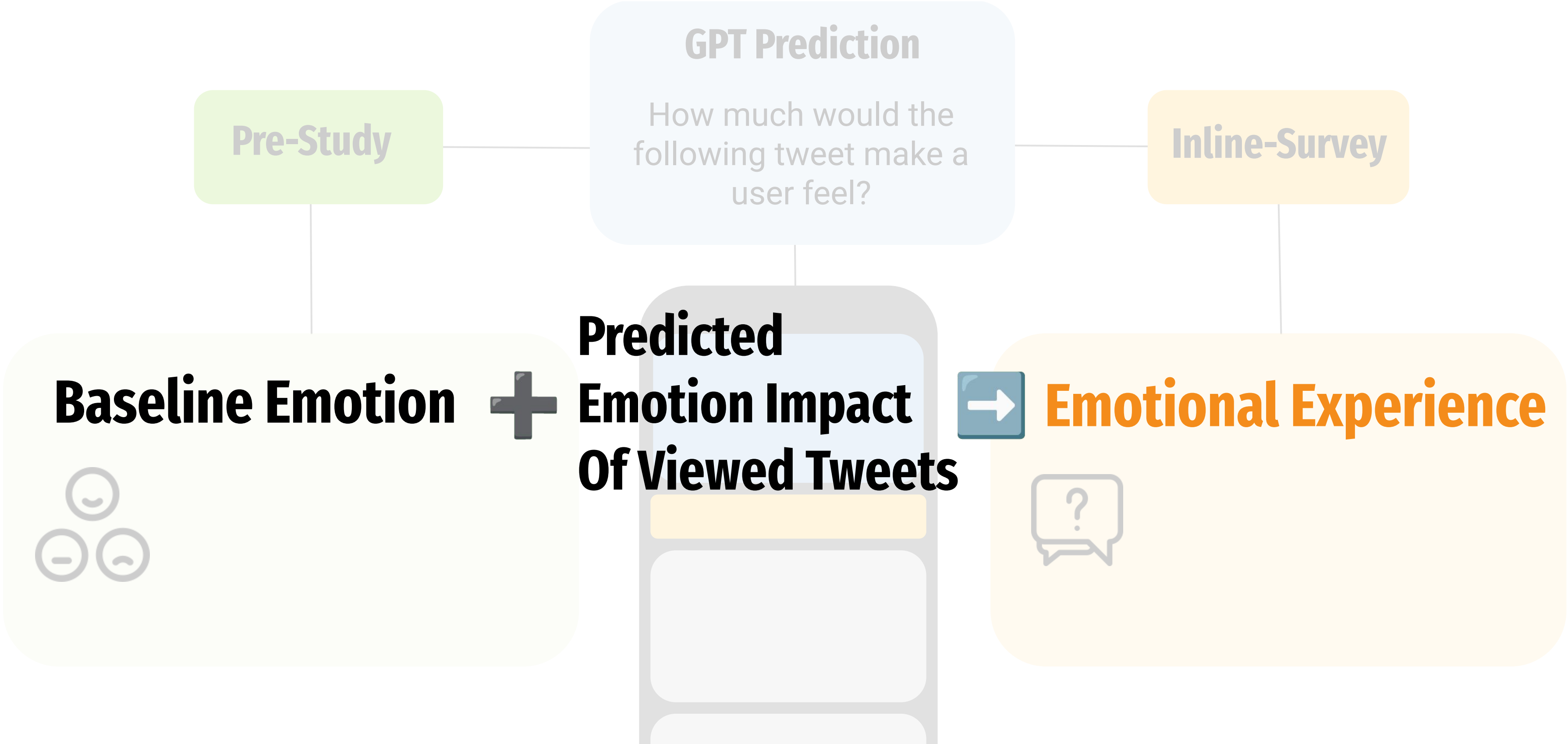
emotional impacts

*You are an **expert in emotion analysis on social media**. Your task is to analyze the emotions expressed in a tweet. Rate what emotions this post directly expresses, regardless of how it makes you feel personally. Focus on the content itself.*

How much of the following emotions does this post explicitly express?
…..

expressed emotions

Can we predict users' emotional experience with ...



Emotional Impact -> Emotional Experience

	angry	excited	sad	calm
Age	0.89.	1.047	-1.136*	2.499***
Gender (Female)	-2.718**	-1.613	-0.72	-1.155
Ladder Score	-0.701	5.638***	-2.56***	3.537***
Baseline Angry	6.358***	nan	nan	nan
Impact Angry	1.149***	nan	nan	nan
Group Var	0.819***	1.272***	1.006***	1.109***
Baseline Excited	nan	11.354***	nan	nan
Impact Excited	nan	0.631**	nan	nan
Baseline Sad	nan	nan	6.821***	nan
Impact Sad	nan	nan	0.704**	nan
Baseline Calm	nan	nan	nan	9.392***
Impact Calm	nan	nan	nan	1.003***

	angry	excited	sad	calm
Age	0.903.	1.051	-1.129*	2.515***
Female	-2.734**	-1.663	-0.703	-1.172
Ladder Score	-0.695	5.638***	-2.565***	3.535***
Baseline Angry	6.381***	nan	nan	nan
Impact HAN	1.556***	nan	nan	nan
Group Var	0.819***	1.273***	1.006***	1.109***
Baseline Excited	nan	11.346***	nan	nan
Impact HAP	nan	0.76***	nan	nan
Baseline Sad	nan	nan	6.822***	nan
Impact LAN	nan	nan	1.326**	nan
Baseline Calm	nan	nan	nan	9.39***
Impact LAP	nan	nan	nan	1.221***

Expressed Emotions -> Emotional Experience

	angry	excited	sad	calm
Age	0.924.	1.027	-1.127*	2.496***
Female	-2.741**	-1.617	-0.699	-1.126
Ladder Score	-0.705	5.646***	-2.575***	3.545***
Baseline Angry	6.348***	nan	nan	nan
Explicit Angry	1.108***	nan	nan	nan
Group Var	0.818***	1.274***	1.008***	1.107***
Baseline Excited	nan	11.363***	nan	nan
Explicit Excited	nan	0.259	nan	nan
Baseline Sad	nan	nan	6.825***	nan
Explicit Sad	nan	nan	0.287	nan
Baseline Calm	nan	nan	nan	9.404***
Explicit Calm	nan	nan	nan	0.873***

END OF Actual RESULTS

Some More Preliminary Results

Which is what we need to convert to Actual RESULTS

Study 2. Predict Emotional Impacts in Field (N=1232)

10-day Exposure

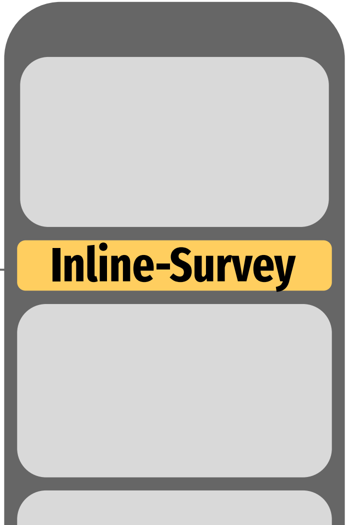
Track Tweet Viewing
Random Inline Surveys

Post-Study

How much do you feel the following emotions right now?

- Angry
- Calm

…… (4 emotions)



How much do you feel the following emotion?

- Nervous
- Sad
- Happy

…… (12 emotions)

Piccardi et al. (2024).

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.097***	0.001	0.022	0.022	-0.008	-0.029	0.039	-0.046	0.050	0.030	-0.079**	-0.064**	0.029	-0.057**	0.028	-0.048**
binary_female	0.005	-0.046	-0.005	-0.032	0.004	-0.050	0.010	-0.009	0.008	0.049	0.005	-0.087	0.019	-0.020	0.022	-0.043
var_ladder	-0.045**	-0.073***	0.078***	0.037*	0.082***	-0.052***	0.046**	-0.012	0.067***	0.090***	-0.060***	-0.060***	0.062***	-0.032**	0.049***	-0.060***
var_pre_survey_nervous	0.486***															
average_predicted_nervous	0.239***															
var_pre_survey_sad		0.455***														
average_predicted_sad		0.296*														
var_pre_survey_happy			0.602***													
average_predicted_happy			0.165***													
var_pre_survey_calm				0.467***												
average_predicted_calm				0.116												
var_pre_survey_excited					0.571***											
average_predicted_excited					0.258**											
var_pre_survey_angry						0.489***										
average_predicted_angry						0.338***										
var_pre_survey_relaxed							0.539***									
average_predicted_relaxed							-0.093***									
var_pre_survey_fearful								0.457***								
average_predicted_fearful								0.372***								
var_pre_survey_enthusiastic									0.607***							
average_predicted_enthusiastic									0.295***							
var_pre_survey_satisfied										0.563***						
average_predicted_satisfied										0.169***						
var_pre_survey_bored											0.474***					
average_predicted_bored											1.575					
var_pre_survey_lonely												0.481***				
average_predicted_lonely												1.108***				
var_pre_survey_HAP													0.620***			
average_predicted_HAP													0.207***			
var_pre_survey_HAN														0.488***		
average_predicted_HAN														0.419***		
var_pre_survey_LAP															0.534***	
average_predicted_LAP															0.156***	
var_pre_survey_LAN																0.413***
average_predicted_LAN																0.114

[All data]

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.097***	0.001	0.022	0.022	-0.008	-0.029	0.039	-0.046	0.050	0.030	-0.079**	-0.064**	0.029	-0.057**	0.028	-0.048**
binary_female	0.005	-0.046	-0.005	-0.032	0.004	-0.050	0.010	-0.009	0.008	0.049	0.005	-0.087	0.019	-0.020	0.022	-0.043
var_ladder	-0.045**	-0.073***	0.078***	0.037*	0.082***	-0.052***	0.046**	-0.012	0.067***	0.090***	-0.060***	-0.060***	0.062***	-0.032**	0.049***	-0.060***
var_pre_survey_nervous	0.486***															
average_predicted_nervous	0.239***															
var_pre_survey_sad		0.455***														
average_predicted_sad		0.296*														
var_pre_survey_happy			0.602***													
average_predicted_happy			0.165***													
var_pre_survey_calm				0.467***												
average_predicted_calm				0.116												
var_pre_survey_excited					0.571***											
average_predicted_excited					0.258**											
var_pre_survey_angry						0.489***										
average_predicted_angry						0.338***										
var_pre_survey_relaxed							0.539***									
average_predicted_relaxed							-0.093***									
var_pre_survey_fearful								0.457***								
average_predicted_fearful								0.372***								
var_pre_survey_enthusiastic									0.607***							
average_predicted_enthusiastic									0.295***							
var_pre_survey_satisfied										0.563***						
average_predicted_satisfied										0.169***						
var_pre_survey_bored											0.474***					
average_predicted_bored											1.575					
var_pre_survey_lonely												0.481***				
average_predicted_lonely												1.108***				
var_pre_survey_HAP													0.620***			
average_predicted_HAP													0.207***			
var_pre_survey_HAN														0.488***		
average_predicted_HAN														0.419***		
var_pre_survey_LAP															0.534***	
average_predicted_LAP															0.156***	
var_pre_survey_LAN																0.413***
average_predicted_LAN																0.114

Only calm, bored, LAN are non-significant

So we can predict emotional experience in Long Term too.

[All data]

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.141*	-0.030	0.006	0.001	0.003	-0.004	0.069	-0.063	0.031	0.033	-0.131*	-0.091	0.020	-0.069*	0.033	-0.076*
binary_female	-0.039	-0.097	0.025	-0.135	0.049	-0.083	-0.069	0.041	0.026	0.019	-0.069	-0.084	0.048	-0.014	-0.067	-0.083
var_ladder	0.020	-0.057	0.106**	0.029	0.116***	-0.050	0.053	-0.010	0.108**	0.091**	-0.065	-0.036	0.096***	-0.009	0.052	-0.046*
var_pre_survey_nervous	0.569***															
average_predicted_nervous	-0.095															
var_pre_survey_sad		0.398***														
average_predicted_sad		0.287														
var_pre_survey_happy			0.591***													
average_predicted_happy			0.365***													
var_pre_survey_calm				0.415***												
average_predicted_calm				0.266												
var_pre_survey_excited					0.541***											
average_predicted_excited					0.427*											
var_pre_survey_angry						0.539***										
average_predicted_angry						0.125										
var_pre_survey_relaxed							0.562***									
average_predicted_relaxed							0.310***									
var_pre_survey_fearful								0.511***								
average_predicted_fearful								0.369								
var_pre_survey_enthusiastic									0.594***							
average_predicted_enthusiastic									0.533***							
var_pre_survey_satisfied										0.576***						
average_predicted_satisfied										0.456***						
var_pre_survey_bored											0.394***					
average_predicted_bored											0.374					
var_pre_survey_lonely												0.571***				
average_predicted_lonely												1.393***				
var_pre_survey_HAP													0.588***			
average_predicted_HAP													0.446***			
var_pre_survey_HAN														0.541***		
average_predicted_HAN														0.238		
var_pre_survey_LAP															0.533***	
average_predicted_LAP															0.558*	
var_pre_survey_LAN																0.419***
average_predicted_LAN																0.859*

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.141*	-0.030	0.006	0.001	0.003	-0.004	0.069	-0.063	0.031	0.033	-0.131*	-0.091	0.020	-0.069*	0.033	-0.076*
binary_female	-0.039	-0.097	0.025	-0.135	0.049	-0.083	-0.069	0.041	0.026	0.019	-0.069	-0.084	0.048	-0.014	-0.067	-0.083
var_ladder	0.020	-0.057	0.106**	0.029	0.116***	-0.050	0.053	-0.010	0.108**	0.091**	-0.065	-0.036	0.096***	-0.009	0.052	-0.046*
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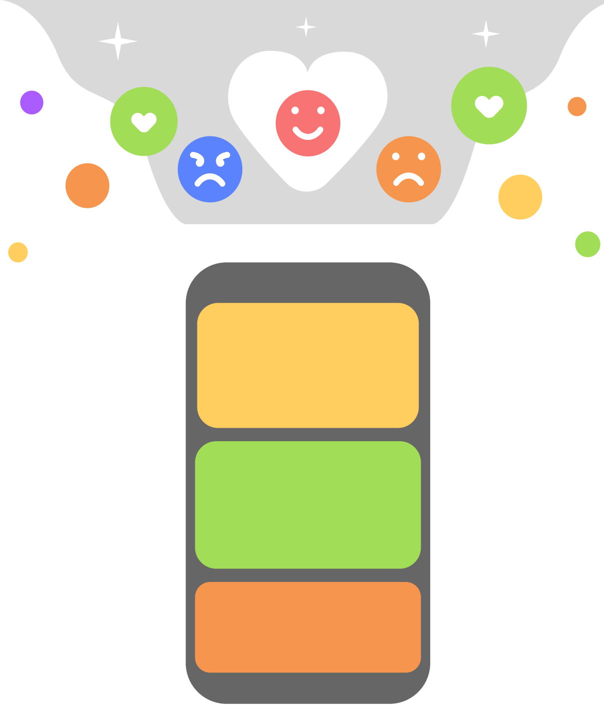
average_predicted_LAP															0.558*	
var_pre_survey_LAN																0.419***
average_predicted_LAN																0.859*

Positive Emotions + lonely(?)



Next Steps

Study 1

- ***More Qualitative Analysis on what leads to the difference between expressed emotion and emotional impacts***

Study 2

- ***Regression results on Aggregated Impacts***
- ***Post Study***
- ***Other Metrics -> not just regressions***

Existing NLP literature focus primarily on the goal of identifying specific emotions expressed by the author of a particular utteranc

SentiStrength

The text 'omg congrats! I wish my chi paper was accepted too so we can have fun in Japan together...'
has positive strength **4** and negative strength **-1**

LIWC

Positive Tone	11.11	5.93
Negative Tone	0.00	2.34

Vader

{'neg': 0.0, 'neu': 0.549, 'pos': 0.451, 'compound': 0.8885}

but ignore the implied emotions.

Thelwall, M. (2016). Tausczik, Y. R., & Pennebaker, J. W. (2010). Hutto, C., & Gilbert, E. (2014, May).

LLM presents potentials as emotion predictor that captures the impact of implied emotions to the viewers.

The Poster (who has their paper rejected):

"omg congrats
I wish my CHI paper was
accepted too so we can
have fun in Japan
together…"

The Viewer (who has their paper accepted)

might feel:

- **Happy** (due to the congratulations)
- **Guilty or sympathetic** (because their friend is feeling down)
- **Bittersweet** (if they also wish their friend could join them)

Studying implied emotions on Social Media is important because:

- Emotions on Social Media can be transferred to others via **emotional contagion.**
- Negative Emotions can lead to **undesirable behaviors** such as trolling.

Experimental evidence of massive-scale emotional contagion through social networks

Adam D. I. Kramer, Jamie E. Guillory, and Jeffrey T. Hancock Authors Info & Affiliations

Edited by Susan T. Fiske, Princeton University, Princeton, NJ, and approved March 25, 2014 (received for review October 23, 2013)

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Anyone Can Become a Troll: Causes of Trolling Behavior in Online Discussions

Justin Cheng[1], Michael Bernstein[1], Cristian Danescu-Niculescu-Mizil[2], Jure Leskovec[1]
[1]Stanford University, [2]Cornell University
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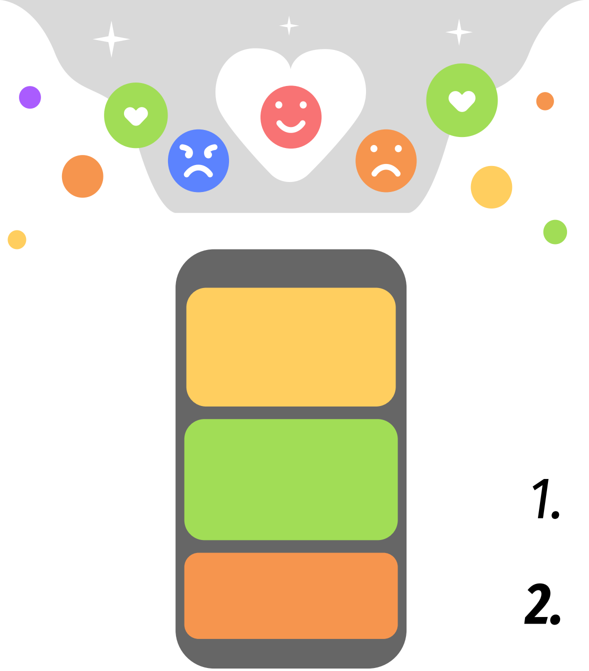
While Previous work has focused on expressed emotions,

We wonder:

- How does implied emotions impact users on social media?
- Would implied emotions lead to stronger and more lasting impacts?

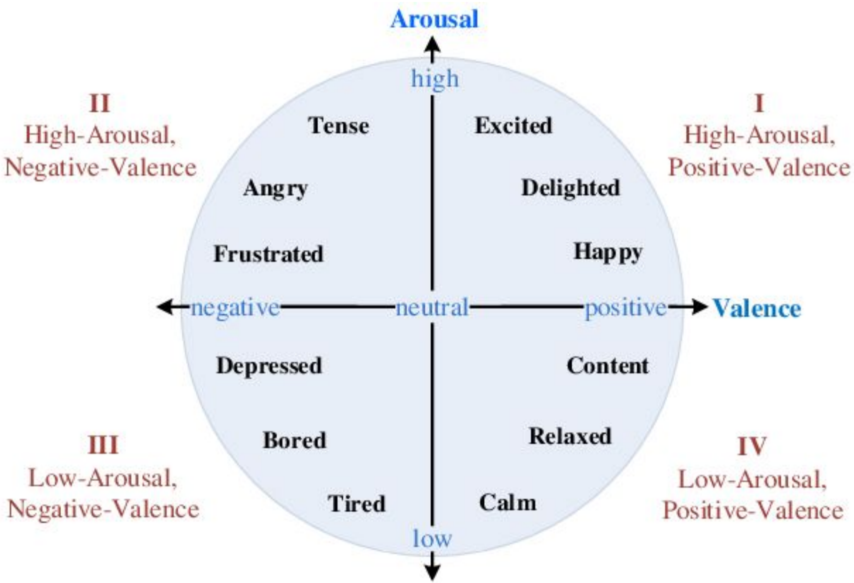
We hypothesize that implied emotions

- complement the expressed emotion to provide **prediction of users' emotion experience.**
  => better awareness of emotion impact
  => enhancement in feed ranking algorithm based on emotion



1. *Predict Emotional Impacts?*
2. ***Study 1: Emotional Impacts != Expressed Emotions***
3. *Study 2: Predict Emotional Impacts in Field*
4. *Next Steps*

Drawing from the Arousal Valence Theory, we defined 15 affects for LLM to predict on.



High Arousal, Positive Valence:

- Excited, Enthusiastic, Happy

High Arousal, Negative Valence:

- Angry, Fearful, Nervous, (Aroused)

Low Arousal, Positive Valence:

- Calm, Relaxed, Satisfied, (Still)

Low Arousal, Negative Valence:

- Sad, Bored, Lonely, (Tired)

With intensity varying from 1 (none) - 5 (extremely).

Watson & Tellegen (1985), Barrett & Russell (1999)

Incorporated the affect definitions into a structured prompt.

“omg congrats
I wish my CHI paper
was accepted too so
we can have fun in
Japan together…”

GPT Response in JSON:

- **Sad: 3** (Moderately)
- **Happy: 2** (Slightly)
- **Excited: 2** (Slightly)
- **Enthusiastic: 2** (Slightly)
- **Lonely: 2** (Slightly)

Our overall goal is to study implied vs expressed
But we start by ask GPT to predict **emotional impacts in general**
Later we will distinguish them.

Study 2. Predict Emotional Impacts in Field (N=

* AAPA = expressions of anti-democratic attitudes and partisan animosity

Pre-Study

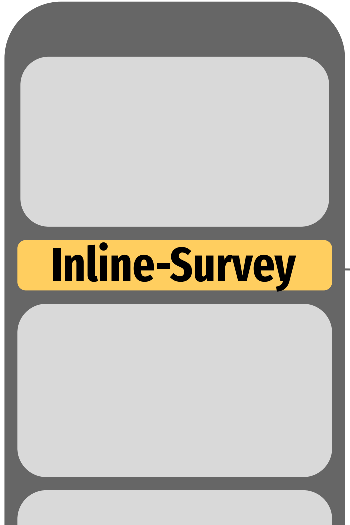
10-day Exposure

Track Tweet Viewing
Random Inline Surveys

How much do you feel the following emotion?

- Nervous
- Sad
- Happy

……



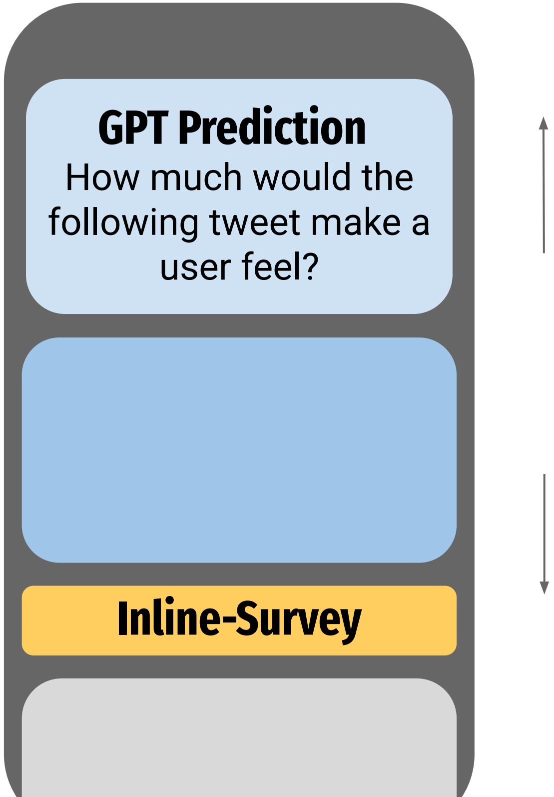
How much do you feel the following emotions right now?

- Angry
- Calm

……

Piccardi et al. (2024).

Aggregation of Impact



Time: 1 hour

Aggregation Method:

- Average
- Maximum
- Exponential Decay

Simple Correlation between User report (angry, etc.) **and GPT prediction** (predicted_{emotion})

	1 tweet Before	1-hour Average	1-hour Max	1-hour Exponential
Angry and predicted_angry	0.118	0.177	0.107	0.159
Sad and predicted_sad	0.039	0.081	0.058	0.047
Excited and predicted_excited	0.060	0.123	0.030	0.060
Calm and predicted_calm	0.037	0.005	-0.009	0.008

Individual differences in emotional experience
Everyone has a different baseline level of emotions, so we want to control for that.

Can we predict users' emotional experience with ...

Pre-Study

GPT Prediction

How much would the following tweet make a user feel?

Inline-Survey

Baseline Emotion ➕ **Predicted Emotion Impact Of Viewed Tweets** ➡️ **Emotional Experience**

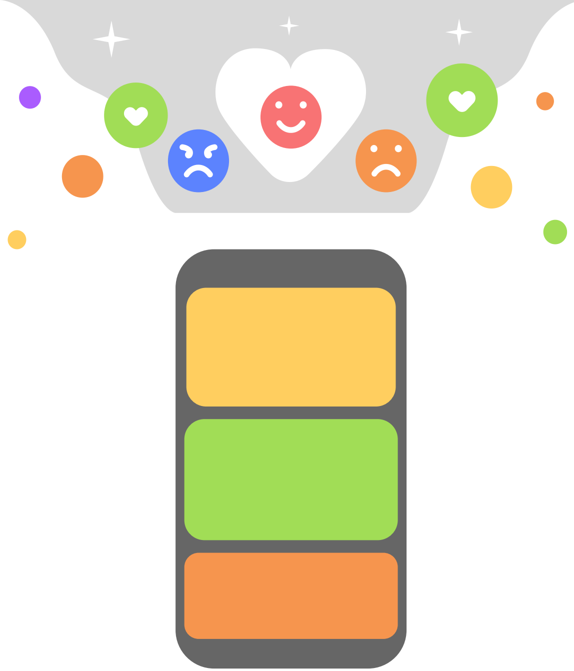
Linear Mixed Effect Regression Model:

Baseline Emotion ➕ **Emotion Impact Of Viewed Tweet** ➡️ **Emotional Experience**

(gender + age + ladder)

pre_survey_{emotion(s)}

➕ predicted_emotion ~ Inline_survey_emotion



1. *Implied vs Expressed Emotions*
2. *Predict Emotion Impact w/ LLM*
3. ***Analysis & Evaluation***
4. *Next Step & Future Direction*

1-hour Average of gpt prediction is a strong predictor of users' emotional experience.

	Anrgy		Excited		Sad		Calm	
Control/Indep. Variable	Coefficient	Stf. Err.	Coefficient	Stf. Err.	Coefficient	Stf. Err.	Coefficient	Stf. Err.
var_age	0.662	0.500	1.317	0.632	-1.025	0.533	2.401***	0.591
binary_female	-2.667**	1.014	-1.865	1.279	-0.702	1.093	-0.984	1.211
var_ladder	-0.445	0.291	3.178***	0.371	-1.445***	0.315	2.006***	0.346
var_pre_survey_angry	6.047***	0.501						
var_pre_survey_excited			11.316***	0.648				
var_pre_survey_sad					6.796***	0.545		
var_pre_survey_calm							9.347***	0.580
predicted_angry	**3.705*** **	0.375						
predicted_excited			**4.453*** **	0.516				
predicted_sad					**3.707*** **	0.597		
predicted_calm							1.054	1.151

(*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$)

⬆️ Linear Mixed Effects Model Results; each variable Standardized

For different emotions,
Gender and Social Status play different roles in the prediction.

	Anrgy		Excited		Sad		Calm	
Control/Indep. Variable	**Coefficient**	**Stf. Err.**	**Coefficient**	**Stf. Err.**	**Coefficient**	**Stf. Err.**	**Coefficient**	**Stf. Err.**
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predicted_calm							1.054	1.151

(*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$)

The coefficient of GPT prediction from aggregation methods.

	1 tweet Before	1-hour Average	1-hour Max	1-hour Exponential
Angry ~ predicted_angry	1.163***	3.705***	1.676***	1.097***
Sad ~ predicted_sad	0.698***	3.707***	0.804***	0.528***
Excited ~ predicted_excited	0.598**	4.453***	0.745*	0.528***
Calm ~ predicted_calm	0.942	1.054	-0.629**	-0.184

(*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$)

Align with previous psychology research: **high arousal negative** content influence the users more than the other three affect types on US social media.

Hsu et al. (2021)

We validate the GPT prediction with crowdsourced annotations.

GPT Prediction

Prompt

⬇️

Structured Output

How would the following tweet make a user feel?

Crowdsourced Annotation

7 annotators

⬇️

Aggregated Prediction

100 tweets are annotated across 35 annotators. Randomly assigned 20 to each annotator.

How do you think most users on X would feel after reading this post?

“ Our intern decided to join our weekly Monday meeting and tell the entire team that he’s been drinking since 10 am ”

Emotion	Definition	1 (Not at all)	2 (Slightly)	3 (Moderately)	4 (Strongly)	5 (Extremely)
Nervous	Restless tension, anxiety, apprehension.	○	○	○	○	○
Sad	Affected with grief or unhappiness.	○	○	○	○	○
Happy	Enjoyable feelings from positive experiences.	○	○	○	○	○
Calm	Quiet, tranquil, undisturbed.	○	○	○	○	○
	Heightened state of energy					

Agreements between GPT annotations and averaged-human annotations.

	Correlation (Average of Human) to GPT	Kappa (Average of Human) to GPT
Nervous	0.480	0.214
Sad	0.643	0.185
Happy	0.584	0.047
Calm	0.412	0.063
Excited	0.528	0.117
Aroused	0.317	0.050
Angry	0.760	0.208
Relaxed	0.311	0.050
Fearful	0.637	0.194
Enthusiastic	0.476	0.059
Still	0.164	0.030
Satisfied	0.346	0.202
Bored	0.276	0.002
Lonley	0.413	0.110
Tired	0.054	0.011

- **HAN** has highest agreement between human and gpt annotations.

	Correlation (Average of Human) to GPT	Kappa (Average of Human) to GPT
HAP	0.593	0.091
HAN	0.774	0.297
LAP	0.453	0.113
LAN	0.451	0.092

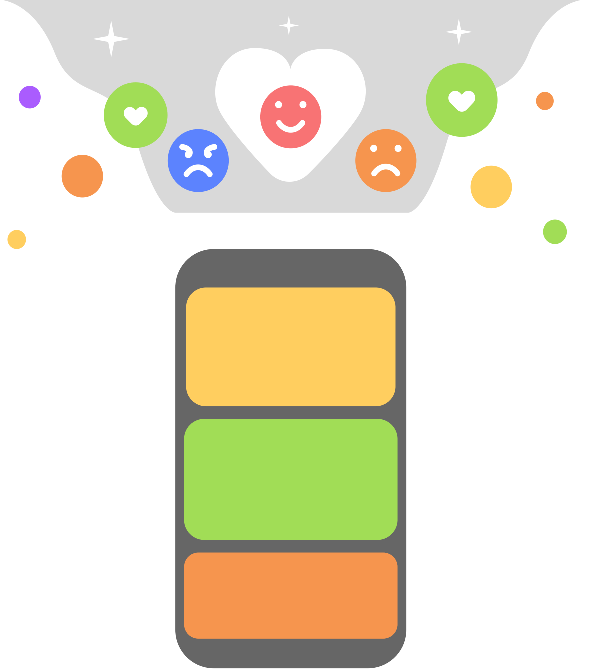
The challenge of crowdsourcing annotations

"In other words, the Democrats are insane."

Annotator	Political Affiliation	Nervous	Sad	Happy	Calm	Angry	Relaxed	Fearful	Enthusiastic
1	independent	1	3	2	1	5	1	5	5
2	don't affiliate	3	2	2	1	4	1	2	2
3	independent	3	1	1	1	3	1	2	1
4	**democrat**	4	4	2	1	4	1	3	3
5	**democrat**	1	1	1	1	3	1	1	1
6	don't affiliate	2	1	4	4	3	3	4	5
7	**democrat**	2	2	1	1	5	1	2	3

People have different identities and affiliations.
Even within same political group, baseline emotions could be different.

Information about the poster & viewer could be essential.



1. *Implied vs Expressed Emotions*
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Distinguish implied emotions from expressed emotions and see whether they have different impacts.

- More holistic view on emotion contagion.
- Understand and predict impacts on users behaviors.
- Insights for feed design.

Experimental evidence of massive-scale emotional contagion through social networks

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Embedding Democratic Values into Social Media AIs via Societal Objective Functions

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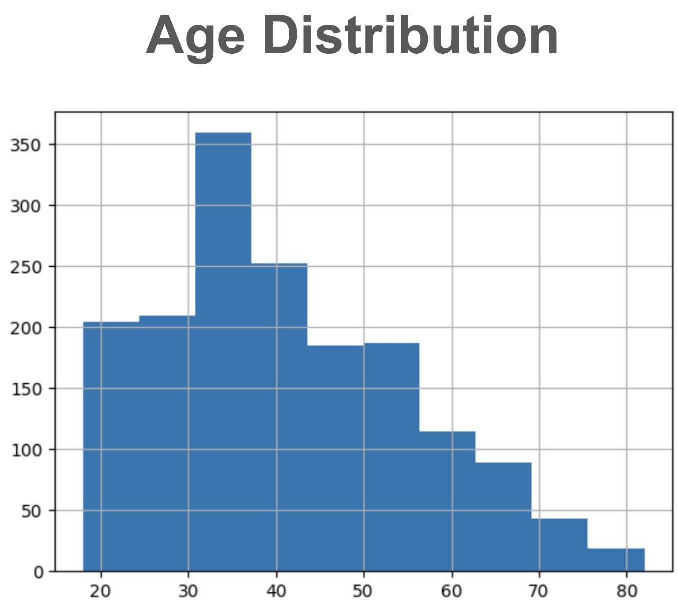
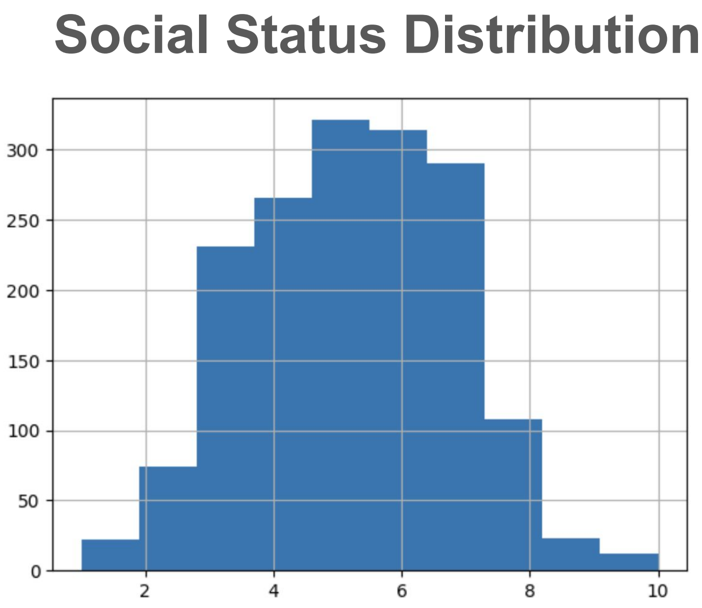
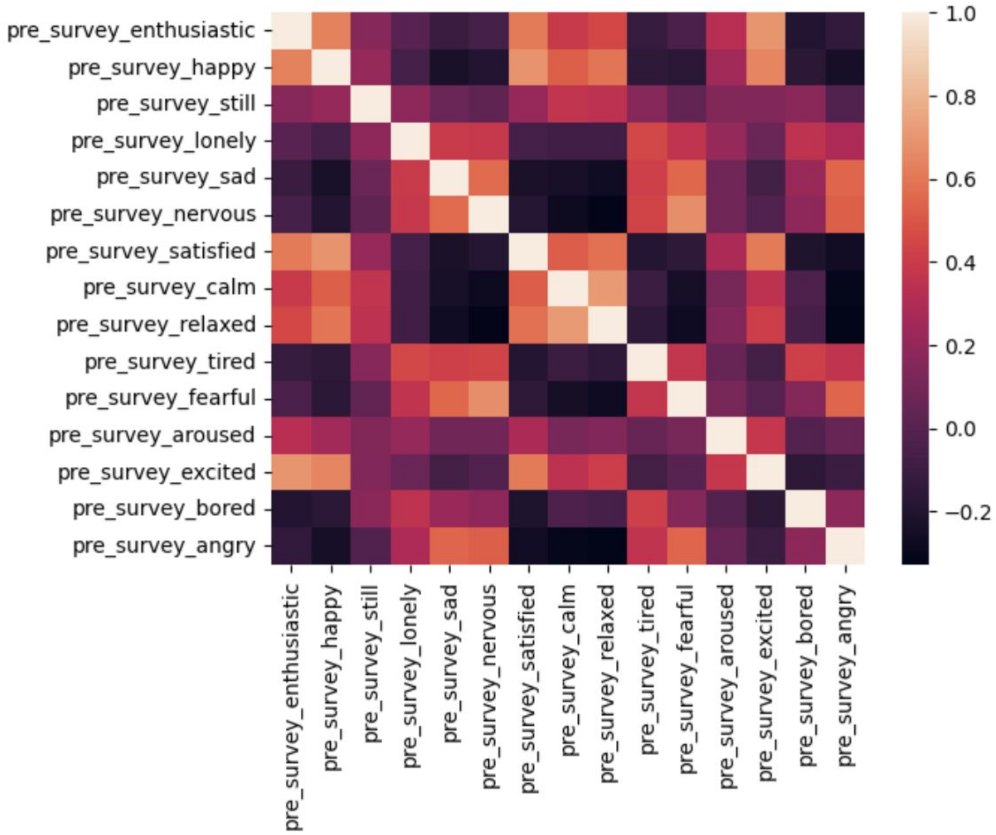
Participants' age and ladder (social status) distribution





Gender Distribution - 828 male, 805 female, 29 other

Correlation of pre_survey emotions.



GPT Prompt

{Definitions of Emotions}

As an expert annotator specializing in emotions in social media content, your job is to predict what emotions and feelings the input tweet would make a user feel.

Given the definitions of emotions above, evaluate if the input tweet and image would make the user feel the following emotions: Nervous, Sad, Happy, Calm, Excited, Aroused, Angry, Relaxed, Fearful, Enthusiastic, Still, Satisfied, Bored, Lonely, Tired.

Rate the intensity of each emotion with the following categories:
1: Not at all — the tweet would not evoke this emotion in the user.
2: Slightly — the tweet would evoke this emotion only slightly.
3: Moderately — the tweet would evoke this emotion to a moderate degree.
4: Strongly — the tweet would evoke this emotion strongly.
5: Extremely — the tweet would evoke this emotion very strongly.

If the tweet would make the user feel that emotion, assign a 2 - 5 to the emotion category depending on the intensity; if the tweet would not make the user feel such emotion, assign a 1.
Also, provide a brief explanation for each of your answers that is not 1.

Input tweet: {tweet_text}

Example input: I'm passionate about indie app development because I've been able to take months off at a time for my health and have no impact on my income 🩷 Example output: {{ "Nervous": 1, "Sad": 1, "Happy": 5, "Calm": 1, "Excited": 4, "Aroused": 2, "Angry": 1, "Relaxed": 1, "Fearful": 1, "Enthusiastic": 3, "Still": 1, "Satisfied": 1, "Bored": 1, "Lonely": 1, "Tired": 1, "explanation": "The tweet is likely to make a user feel extremely happy due to the use of the word "passionate" and the heart emoji 🩷. Although the tweet conveys an enthusiastic tone, it would probably make the user feel moderately enthusiastic, as they might not be interested in app development or fully empathetic toward the author of the tweet. " }} """

GPT vs. Inline_survey -> Correlation (tb.1) Regression Results (tb.2)

Correlation Results ⬇️

all / I_C	1-hour Average	1-hour Max	1-hour Exponential	1 tweet Before
Angry and predicted_angry	0.177 / 0.185	0.107 / 0.103	0.159 / 0.156	0.118 / 0.112
Sad and predicted_sad	0.081 / 0.091	0.058 / 0.072	0.047 / 0.054	0.039 / 0.028
Excited and predicted_excited	0.123 / 0.114	0.03 / -0.008	0.06 / 0.061	0.06 / 0.048
Calm and predicted_calm	0.005 / 0.009	-0.009 / 0	0.008 / -0.006	0.037 / 0.014

all / I_C	1-hour Average	1-hour Max	1-hour Exponential	1 tweet Before
Angry ~ predicted_angry	3.705*** / 2.904***	1.676*** / 0.872*	1.097*** / 0.913***	1.163*** / 0.668*
Sad ~ predicted_sad	3.707*** / 3.276***	0.804*** / 0.699*	0.528*** / 0.573	0.698*** / 0.15
Excited ~ predicted_excited	4.453*** / 2.979***	0.745* / 0.119	0.528*** / 0.383	0.598** / 0.393
Calm ~ predicted_calm	1.054 / 1.428	-0.629** / - 0.20	-0.184 / 0.134	0.942 / 0.949

Regression Results ⬆️

Human Annotation #2

1. Correlation:
   Average of 7 Human vs. GPT

2. Cohen's Kappa:
   Average of 7 Human vs. GPT

🤔 What is a good way to compute agreement between human vs. agreement of human vs. LLM?

	Correlation	Cohen_Kappa
Nervous	0.487	0.113
Sad	0.628	0.208
Happy	0.674	0.148
Calm	0.34	0.14
Excited	0.562	0.167
Angry	0.798	0.236
Relaxed	0.39	0.177
Fearful	0.604	0.248
Enthusiastic	0.585	0.091
Satisfied	0.514	0.254
Bored	0.345	-0.0
Lonely	0.39	0.217
HAP	0.657	0.186
HAN	0.777	0.322
LAP	0.502	0.232
LAN	0.585	0.146

Post-Survey

1. Correlation
   Average of all gpt predictions of emotional impacts of all tweets user viewed vs. Post survey

2. Regression
   Post survey ~ Pre survey + User Demographics + Gpt Predictions

Correlation: Average_gpt_predict_emotion vs. Post_survey_emotion

	All Data	Control Group
nervous	-0.008	-0.118
sad	0.052	0.013
happy	0.108	0.109
calm	0.01	-0.041
excited	0.143	0.148
angry	0.193	0.07
relaxed	-0.007	-0.017
fearful	0.046	0.015
enthusiastic	0.109	0.17
satisfied	0.058	0.07
bored	0.105	0.095
lonely	0.106	0.069
HAP	0.124	0.149
HAN	0.115	-0.003
LAP	0.03	0.01
LAN	0.045	0.034

Low as expected 🤔

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.097***	0.001	0.022	0.022	-0.008	-0.029	0.039	-0.046	0.050	0.030	-0.079**	-0.064**	0.029	-0.057**	0.028	-0.048**
binary_female	0.005	-0.046	-0.005	-0.032	0.004	-0.050	0.010	-0.009	0.008	0.049	0.005	-0.087	0.019	-0.020	0.022	-0.043
var_ladder	-0.045**	-0.073***	0.078***	0.037*	0.082***	-0.052***	0.046**	-0.012	0.067***	0.090***	-0.060***	-0.060***	0.062***	-0.032**	0.049***	-0.060***
var_pre_survey_nervous	0.486***															
average_predicted_nervous	0.239***															
var_pre_survey_sad		0.455***														
average_predicted_sad		0.296*														
var_pre_survey_happy			0.602***													
average_predicted_happy			0.165***													
var_pre_survey_calm				0.467***												
average_predicted_calm				0.116												
var_pre_survey_excited					0.571***											
average_predicted_excited					0.258**											
var_pre_survey_angry						0.489***										
average_predicted_angry						0.338***										
var_pre_survey_relaxed							0.539***									
average_predicted_relaxed							-0.093***									
var_pre_survey_fearful								0.457***								
average_predicted_fearful								0.372***								
var_pre_survey_enthusiastic									0.607***							
average_predicted_enthusiastic									0.295***							
var_pre_survey_satisfied										0.563***						
average_predicted_satisfied										0.169***						
var_pre_survey_bored											0.474***					
average_predicted_bored											1.575					
var_pre_survey_lonely												0.481***				
average_predicted_lonely												1.108***				
var_pre_survey_HAP													0.620***			
average_predicted_HAP													0.207***			
var_pre_survey_HAN														0.488***		
average_predicted_HAN														0.419***		
var_pre_survey_LAP															0.534***	
average_predicted_LAP															0.156***	
var_pre_survey_LAN																0.413***
average_predicted_LAN																0.114

[All data]

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.097***	0.001	0.022	0.022	-0.008	-0.029	0.039	-0.046	0.050	0.030	-0.079**	-0.064**	0.029	-0.057**	0.028	-0.048**
binary_female	0.005	-0.046	-0.005	-0.032	0.004	-0.050	0.010	-0.009	0.008	0.049	0.005	-0.087	0.019	-0.020	0.022	-0.043
var_ladder	-0.045**	-0.073***	0.078***	0.037*	0.082***	-0.052***	0.046**	-0.012	0.067***	0.090***	-0.060***	-0.060***	0.062***	-0.032**	0.049***	-0.060***
var_pre_survey_nervous	0.486***															
average_predicted_nervous	0.239***															
var_pre_survey_sad		0.455***														
average_predicted_sad		0.296*														
var_pre_survey_happy			0.602***													
average_predicted_happy			0.165***													
var_pre_survey_calm				0.467***												
average_predicted_calm				0.116												
var_pre_survey_excited					0.571***											
average_predicted_excited					0.258**											
var_pre_survey_angry						0.489***										
average_predicted_angry						0.338***										
var_pre_survey_relaxed							0.539***									
average_predicted_relaxed							-0.093***									
var_pre_survey_fearful								0.457***								
average_predicted_fearful								0.372***								
var_pre_survey_enthusiastic									0.607***							
average_predicted_enthusiastic									0.295***							
var_pre_survey_satisfied										0.563***						
average_predicted_satisfied										0.169***						
var_pre_survey_bored											0.474***					
average_predicted_bored											1.575					
var_pre_survey_lonely												0.481***				
average_predicted_lonely												1.108***				
var_pre_survey_HAP													0.620***			
average_predicted_HAP													0.207***			
var_pre_survey_HAN														0.488***		
average_predicted_HAN														0.419***		
var_pre_survey_LAP															0.534***	
average_predicted_LAP															0.156***	
var_pre_survey_LAN																0.413***
average_predicted_LAN																0.114

Only calm, bored, LAN are non-significant

[All data]

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.141*	-0.030	0.006	0.001	0.003	-0.004	0.069	-0.063	0.031	0.033	-0.131*	-0.091	0.020	-0.069*	0.033	-0.076*
binary_female	-0.039	-0.097	0.025	-0.135	0.049	-0.083	-0.069	0.041	0.026	0.019	-0.069	-0.084	0.048	-0.014	-0.067	-0.083
var_ladder	0.020	-0.057	0.106**	0.029	0.116***	-0.050	0.053	-0.010	0.108**	0.091**	-0.065	-0.036	0.096***	-0.009	0.052	-0.046*
var_pre_survey_nervous	0.569***															
average_predicted_nervous	-0.095															
var_pre_survey_sad		0.398***														
average_predicted_sad		0.287														
var_pre_survey_happy			0.591***													
average_predicted_happy			0.365***													
var_pre_survey_calm				0.415***												
average_predicted_calm				0.266												
var_pre_survey_excited					0.541***											
average_predicted_excited					0.427*											
var_pre_survey_angry						0.539***										
average_predicted_angry						0.125										
var_pre_survey_relaxed							0.562***									
average_predicted_relaxed							0.310***									
var_pre_survey_fearful								0.511***								
average_predicted_fearful								0.369								
var_pre_survey_enthusiastic									0.594***							
average_predicted_enthusiastic									0.533***							
var_pre_survey_satisfied										0.576***						
average_predicted_satisfied										0.456***						
var_pre_survey_bored											0.394***					
average_predicted_bored											0.374					
var_pre_survey_lonely												0.571***				
average_predicted_lonely												1.393***				
var_pre_survey_HAP													0.588***			
average_predicted_HAP													0.446***			
var_pre_survey_HAN														0.541***		
average_predicted_HAN														0.238		
var_pre_survey_LAP															0.533***	
average_predicted_LAP															0.558*	
var_pre_survey_LAN																0.419***
average_predicted_LAN																0.859*

	nervous	sad	happy	calm	excited	angry	relaxed	fearful	enthusiastic	satisfied	bored	lonely	HAP	HAN	LAP	LAN
var_age	-0.141*	-0.030	0.006	0.001	0.003	-0.004	0.069	-0.063	0.031	0.033	-0.131*	-0.091	0.020	-0.069*	0.033	-0.076*
binary_female	-0.039	-0.097	0.025	-0.135	0.049	-0.083	-0.069	0.041	0.026	0.019	-0.069	-0.084	0.048	-0.014	-0.067	-0.083
var_ladder	0.020	-0.057	0.106**	0.029	0.116***	-0.050	0.053	-0.010	0.108**	0.091**	-0.065	-0.036	0.096***	-0.009	0.052	-0.046*
var_pre_survey_nervous	0.569***															
average_predicted_nervous	-0.095															
var_pre_survey_sad		0.398***														
average_predicted_sad		0.287														
var_pre_survey_happy			0.591***													
average_predicted_happy			0.365***													
var_pre_survey_calm				0.415***												
average_predicted_calm				0.266												
var_pre_survey_excited					0.541***											
average_predicted_excited					0.427*											
var_pre_survey_angry						0.539***										
average_predicted_angry						0.125										
var_pre_survey_relaxed							0.562***									
average_predicted_relaxed							0.310***									
var_pre_survey_fearful								0.511***								
average_predicted_fearful								0.369								
var_pre_survey_enthusiastic									0.594***							
average_predicted_enthusiastic									0.533***							
var_pre_survey_satisfied										0.576***						
average_predicted_satisfied										0.456***						
var_pre_survey_bored											0.394***					
average_predicted_bored											0.374					
var_pre_survey_lonely												0.571***				
average_predicted_lonely												1.393***				
var_pre_survey_HAP													0.588***			
average_predicted_HAP													0.446***			
var_pre_survey_HAN														0.541***		
average_predicted_HAN														0.238		
var_pre_survey_LAP															0.533***	
average_predicted_LAP															0.558*	
var_pre_survey_LAN																0.419***
average_predicted_LAN																0.859*

Positive Emotions + lonely(?)

1 Hour Average - Angry

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	13.074	1.951	6.701	0.000	9.250	16.898
var_age	0.548	0.943	0.581	0.561	-1.301	2.397
binary_female	-1.296	1.899	-0.682	0.495	-5.018	2.426
var_ladder	0.568	0.567	1.003	0.316	-0.542	1.679
var_pre_survey_angry	7.555	0.988	7.650	0.000	5.620	9.491
predicted_angry_1hourAverage	2.904	0.716	4.057	0.000	1.501	4.307
Group Var	158.066	1.254				

1 Hour Average - Excited

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	26.947	3.416	7.888	0.000	20.251	33.643
var_age	0.656	1.344	0.488	0.626	-1.979	3.291
binary_female	-5.356	2.704	-1.981	0.048	-10.656	-0.057
var_ladder	4.090	0.813	5.033	0.000	2.497	5.683
var_pre_survey_excited	10.108	1.401	7.215	0.000	7.363	12.854
predicted_excited_1hourAverage	2.979	0.916	3.250	0.001	1.183	4.775
Group Var	376.799	2.605				

1 Hour Average - Sad

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	15.846	2.076	7.631	0.000	11.776	19.916
var_age	-1.105	1.042	-1.060	0.289	-3.148	0.939
binary_female	0.073	2.138	0.034	0.973	-4.119	4.264
var_ladder	-1.054	0.652	-1.617	0.106	-2.331	0.223
var_pre_survey_sad	7.918	1.127	7.028	0.000	5.709	10.126
predicted_sad_1hourAverage	3.276	1.062	3.085	0.002	1.195	5.358
Group Var	216.242	1.698				

1 Hour Average - Calm

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	59.718	3.087	19.348	0.000	53.669	65.768
var_age	2.810	1.221	2.301	0.021	0.417	5.203
binary_female	-4.149	2.503	-1.657	0.097	-9.055	0.758
var_ladder	1.622	0.744	2.181	0.029	0.164	3.079
var_pre_survey_calm	7.734	1.172	6.598	0.000	5.437	10.032
predicted_calm_1hourAverage	1.428	2.181	0.655	0.513	-2.847	5.702
Group Var	307.891	1.950				

1 Hour Max

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	15.426	1.929	7.998	0.000	11.645	19.206
var_age	0.818	0.957	0.855	0.393	-1.058	2.695
binary_female	-1.620	1.932	-0.839	0.402	-5.407	2.166
var_ladder	0.653	0.577	1.133	0.257	-0.477	1.784
var_pre_survey_angry	7.622	1.006	7.575	0.000	5.650	9.594
predicted_angry_1hourMax	0.872	0.342	2.550	0.011	0.202	1.542
Group Var	165.925	1.296				

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	18.138	1.746	10.385	0.000	14.715	21.561
var_age	-1.093	1.047	-1.044	0.297	-3.144	0.959
binary_female	0.147	2.147	0.068	0.946	-4.061	4.355
var_ladder	-1.084	0.654	-1.656	0.098	-2.367	0.199
var_pre_survey_sad	7.892	1.131	6.975	0.000	5.675	10.110
predicted_sad_1hourMax	0.699	0.295	2.368	0.018	0.120	1.278
Group Var	218.427	1.711				

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	35.821	3.484	10.283	0.000	28.993	42.649
var_age	0.499	1.348	0.371	0.711	-2.142	3.141
binary_female	-5.136	2.711	-1.894	0.058	-10.449	0.178
var_ladder	4.101	0.815	5.031	0.000	2.504	5.699
var_pre_survey_excited	10.135	1.405	7.213	0.000	7.381	12.889
predicted_excited_1hourMax	0.119	0.645	0.184	0.854	-1.145	1.383
Group Var	379.072	2.611				

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	61.455	1.948	31.540	0.000	57.636	65.274
var_age	2.819	1.222	2.306	0.021	0.423	5.215
binary_female	-4.049	2.503	-1.618	0.106	-8.954	0.857
var_ladder	1.611	0.744	2.164	0.030	0.152	3.070
var_pre_survey_calm	7.718	1.173	6.578	0.000	5.418	10.017
predicted_calm_1hourMax	-0.020	0.423	-0.048	0.962	-0.850	0.809
Group Var	308.650	1.954				

Pilot Study

- 10 Posts (5 randomly selected; 5 hand-picked)
- Annotation Task design
  - Page 1 - Annotation Task 1: How does the post make you feel? (And Why?)
    - Purpose: To gather general emotional impact
  - Page 2 - Question: What are the explicit emotions to you? What are the implied emotions to you?
    - Purpose: To gather views on implied/explicit emotions
  - Page 3 - Annotation Task 2: Given our definition of explicit and implied emotions, what are the explicit and implied emotions in the post? (And Why?)
    - Purpose: To compare with GPT, and construct better prompts

- Ideal outcome:
  - Comparing implied vs. explicit vs. general, we obtain an understanding of how people understand the segment of emotions.
  - We would obtain examples for LLM prompts in prediction tasks.
  - People's different reasoning would show us the importance of individualized predictions.

Pilot Study

10 people
(from the lab)

5 tweets
(randomly assigned)

21 min (±5 min)
(mean time)

General Annotations -> Definitions -> Implied vs. Explicit Annotations

Hypotheses

- HP1: The human annotations for explicit would be more consistent than that for implied.
- HP2: Some posts would have explicit emotions similar to the implied, while others could have completely different directions.
- HP3: Explanations will inform the topic influences of the implied / explicit emotion impact.
- HP4: Randomly picked examples and hand-picked examples would have similar outcome (-> we should randomly pick everything)
- HP5: We could construct general impact based on some combination of explicit and implied

HP1: The human annotations for explicit would be more consistent than that for implied.

- Explicit emotions MAE: 0.431
- Implied emotions MAE: 0.555
- General emotions MAE: 0.542

t-statistic: -2.092

p-value: 0.046

Largest Implied vs Explicit differences:

1. **fearful: 0.392**
2. **nervous: 0.320**
3. **angry: 0.208**
4. **pos: 0.128**
5. **enthusiastic: 0.120**

Explicit emotional expressions show significantly higher inter-annotator agreement compared to implied emotional expressions. ✅

HP4

The random selected group still has differences, but not significant.

```
Explicit emotions MAE: 0.481
Implied emotions MAE: 0.621
General emotions MAE: 0.621
```

HP2: Some posts would have explicit emotions similar to the implied, while others could have completely different directions.

- vec(general)
- vec(implied)
- vec(explicit)

🤔*Is it that people are not good in distinguishing??*

Calculated their cosine similarity.
Mean Explicit-Implied Similarity: 0.920 ± 0.068
Mean Explicit-General Similarity: 0.873 ± 0.091
Mean Implied-General Similarity: 0.874 ± 0.097

tweet_id	mean	std	range	min	max
tweet-1812935594181599415	0.8810	0.1108	0.2675	0.7325	1.0000
tweet-1821127975812645307	0.8530	0.1017	0.2634	0.6957	0.9591
tweet-1818707499983552696	0.9527	0.0732	0.1754	0.8246	1.0000
tweet-1819754323808543221	0.9263	0.0629	0.1357	0.8515	0.9872
tweet-1813344694317007274	0.9259	0.0590	0.1394	0.8528	0.9922
tweet-1813038230952108245	0.9375	0.0553	0.1418	0.8582	1.0000
tweet-1819507152765309432	0.9309	0.0517	0.1294	0.8608	0.9902
tweet-1813311911544390106	0.9519	0.0492	0.1282	0.8718	1.0000
tweet-1818325135897821318	0.9163	0.0445	0.1215	0.8583	0.9798
tweet-1820140601062330622	0.9247	0.0223	0.0593	0.8964	0.9557

Explicit, Implied, General are mostly in similar directions 🤔

My name is Matt Couch, and I'm voting for President Trump and Senator J.D. Vance on November 5, 2024 If you're also voting for Trump/Vance, I want to follow you!!! Comment below if I'm not following you! Love Y'all!

Today, we found a little dog left by the road near our house. Later, this poor pup found a spot behind our house and curled up to sleep. Seeing this lonely and scared dog broke our hearts 😍 We knew we had to

Individual Differences in Emotion Perception

“My name is Matt Couch, and I'm voting for President Trump and Senator J.D. Vance on November 5, 2024 If you're also voting for Trump/Vance, I want to follow you!!! Comment below if I'm not following you!   Love Y'all!”

	General	Implied vs. Explicit
	P1:“i hate trump supporters”	P1: “For explicit emotion, this person seems to be very outwardly supporting trump very excitedly. However, for implicit emotion, they seem very insecure about themselves.”
	P8: “Although I don't necessarily agree with their choice in candidates, I don't think feel too negatively over this individual simply wanting to get a community or followers.”	P8: “The user does not mention any specific emotions, so I rated the explicit emotions a bit low. For the implicit emotions, I mainly rated these high on enthusiastic and excited.”
	P5: “i can feel the passion through the words and 3 consecutive exclamation marks”	P5: “i cannot tell the difference”

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P1, P8 rated based on the author’s point of view.

P5 can’t tell the difference between implied and explicit.

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P1, P8 rated based on the author's point of view.

P5 can't tell the difference between implied and explicit.

🤔Learnings:
- Perspective taking in annotation.
- People are bad at distinguishing explicit vs. implied.

5/10 of the participants have somehow consistent ideas with what we are proposing:

“ Explicit emotions are directly stated through words, implied emotions are inferred from context/tone. (P10, P9, P4, P8, P7)”

The main remaining problem is **perspective-taking and the modality**.
Need to make sure they understand it is reader-perspective and only focusing on the text.

Unexpected Result: P9: “I feel slightly lonely because I don't understand it."

-> Meta understanding: If a tweet has high engagement and people seem to all understand it, what does it mean for people who still don’t understand?

Next Steps

✅

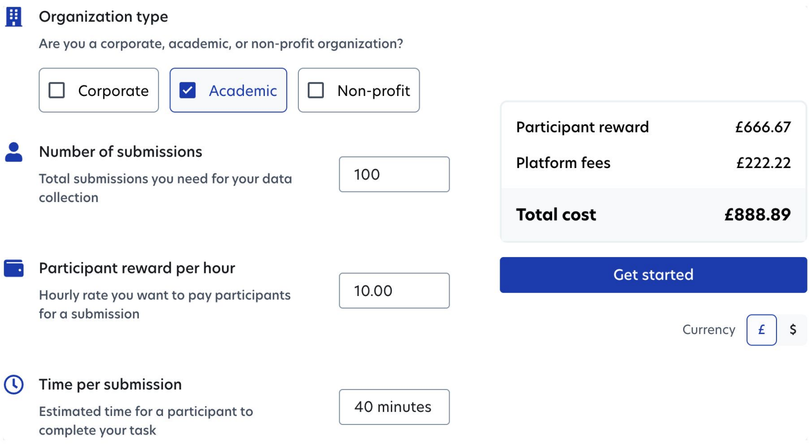
- Implied / explicit divide generally make sense.
- The explanation format yields very comprehensive / nuanced responses.

🤔

- Need more specification on perspective, modality.
- Annotation task design choices.

Things to confirm:

- $880 left for prolific
- 10 tweets per person
    - 40 minutes.



We use the Dataset gathered in the AAPA study.

Pre-Study

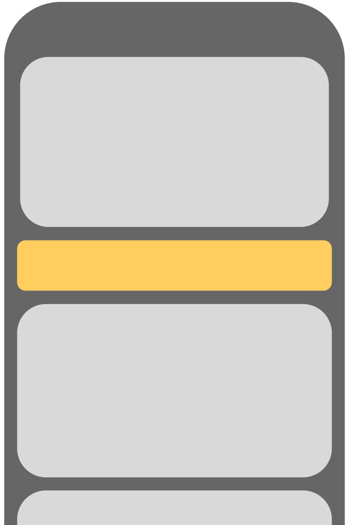
10-day Exposure

Track Tweet
Inline Surveys

How much do you feel the following emotion?

- Nervous
- Sad
- Happy

……



Inline-Survey

How much do you feel the following emotions right now?

- Angry
- Calm

……

Emotional Intelligence Infographics

3

Types of Motivation

Jupiter is a gas giant named after the Roman god of the skies and lightning

Extrinsic

Neptune is the farthest planet from the Sun

Intrinsic

Despite being red, Mars is a cold place

Addiction

Pluto is considered a dwarf planet

Emotional Intelligence Infographics

Social Skills Learning Benefits

Positive behavior

Good grades

Conduct problems

Emotional distress

-10 %

Mercury

Mercury is the closest planet to the Sun

11 %

Mars

Despite being red, Mars is a cold place

Emotional Intelligence Infographics

01

Self-motivation

Mercury is the closest planet to the Sun

02

Perseverance

Neptune is the farthest planet from the Sun

03

Self-control

Jupiter is a gas giant and the biggest planet

04

Empathy

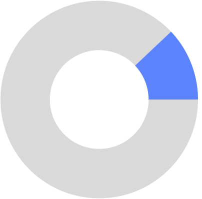
Despite being red, Mars is a cold place

Emotional Intelligence Infographics

30 %
Self-Awareness
It is the closest planet to the Sun

20 %
Empathy
Jupiter is the biggest planet

40 %
Self-Regulation
Despite being red, Mars is cold



10 %
Social Skills
Venus has a nice name, but is hot

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