People Still Care About Facts: Twitter Users Engage More with Factual Discourse than Misinformation

Luiz Giovanini[*1], *Shlok Gilda*[*1], Mirela Silva[**1], Fabrício Ceschin[**2], Prakash Shrestha[1], Christopher Brant[1], Juliana Fernandes[1], Catia S. Silva[1], André Grégio[2], and Daniela Oliveira[1].

[1] University of Florida.

[2] Federal University of Paraná, Brazil.

[*] Authors have equal contribution.

[**] Authors have equal contribution.

The Big Question

How do Twitter users engage with COVID-19 misinformation and factual-information?

Research Questions

RQ1: Are COVID-19 misinformation tweets more engaging than COVID-19 factual tweets?

RQ2: Are general topic misinformation tweets more engaging than general topics factual tweets?

RQ3: Which features are most correlated with engagement in COVID-19 vs. general topics misinformation tweets?

RQ4: Which features are most correlated with engagement in COVID-19 vs. general topics factual tweets?

Data Collection

2.1M tweets.

Four primary datasets:

- COVID-19 misleading claims.
- COVID-19 factual claims.
- Misleading claims on general topics.
- Factual claims on general topics.

COVID-19 Twitter Data Sources

Source	Description	False	True
Shahi et al.	Fact-checked Coronavirus-related tweets	1345	41
Schroeder et al.	Tweets linking COVID-19 with 5G conspiracy theories	~58K	N/A
CoAID	News articles & social media posts with fake and factual claim labels	484	8092
Paka et al. (CTF)	Labeled and unlabeled tweets related to COVID-19	~17K	~18K
Muric et al.	Tweets related to anti-vaccine narratives for COVID-19	~1.8M	N/A

General Topics Twitter Data Sources

Source	Description	False	True
Mitra and Gilbert (CREDBANK)	Crowdsourced tweets related to real-world news events	N/A	~1.94M
Russian Troll Tweets Kaggle	Tweets from malicious accounts connected to Russia's Internet Research Agency	200K	N/A
Vo and Lee	Fact-checked tweets based on news articles from Snopes and Politifact	~59K	~14K
Jiang et al.	Tweets labeled across a spectrum of fact-check ratings	1264	231

Data Cleaning and Preparation

- **Discarded Tweets:** Removed duplicates, non-English, and text-less entries.
- **Collected Metadata:** Gathered details on tweets, authors, and engagement.

Data Cleaning and Preparation

	Factual		**Misinformation**	
	COVID-Related	*General Topics*	*COVID-Related*	*General Topics*
N	9,111 *(0.43%)*	1,243,913 *(58.84%)*	828,501 *(39.19%)*	32,243 *(1.52%)*
n_{strata}	4,814	4,448	4,533	4,147
μ	368.5	9,791.6	2,214.3	3,014.7
σ	7,157.9	73,305.6	10,051.9	28,727.4
Mean Rank	2407.5	2244.5	2267.0	2074.0

Descriptive statistics of our final four datasets based on the combined engagement metric.

Stratified Random Sampling

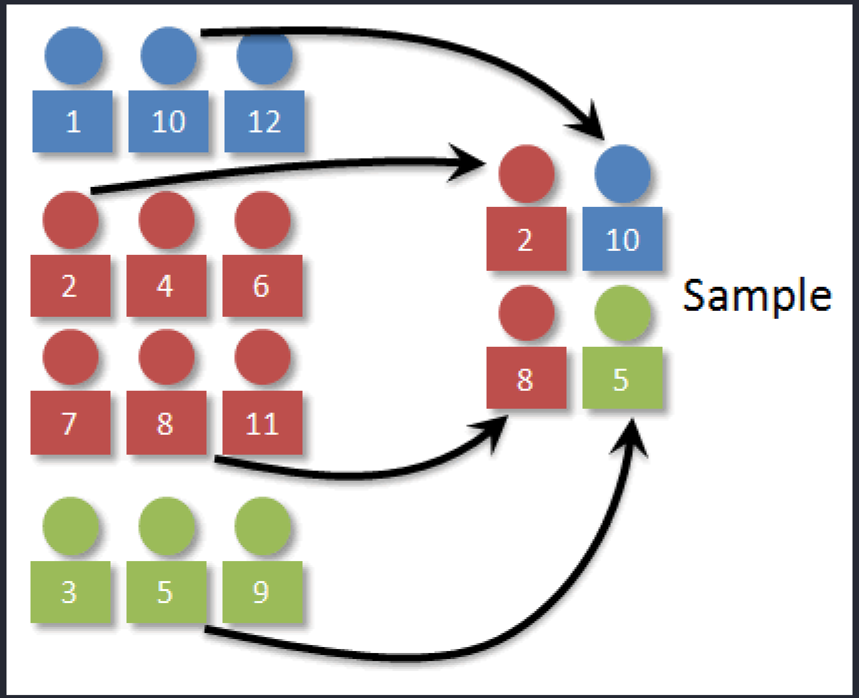
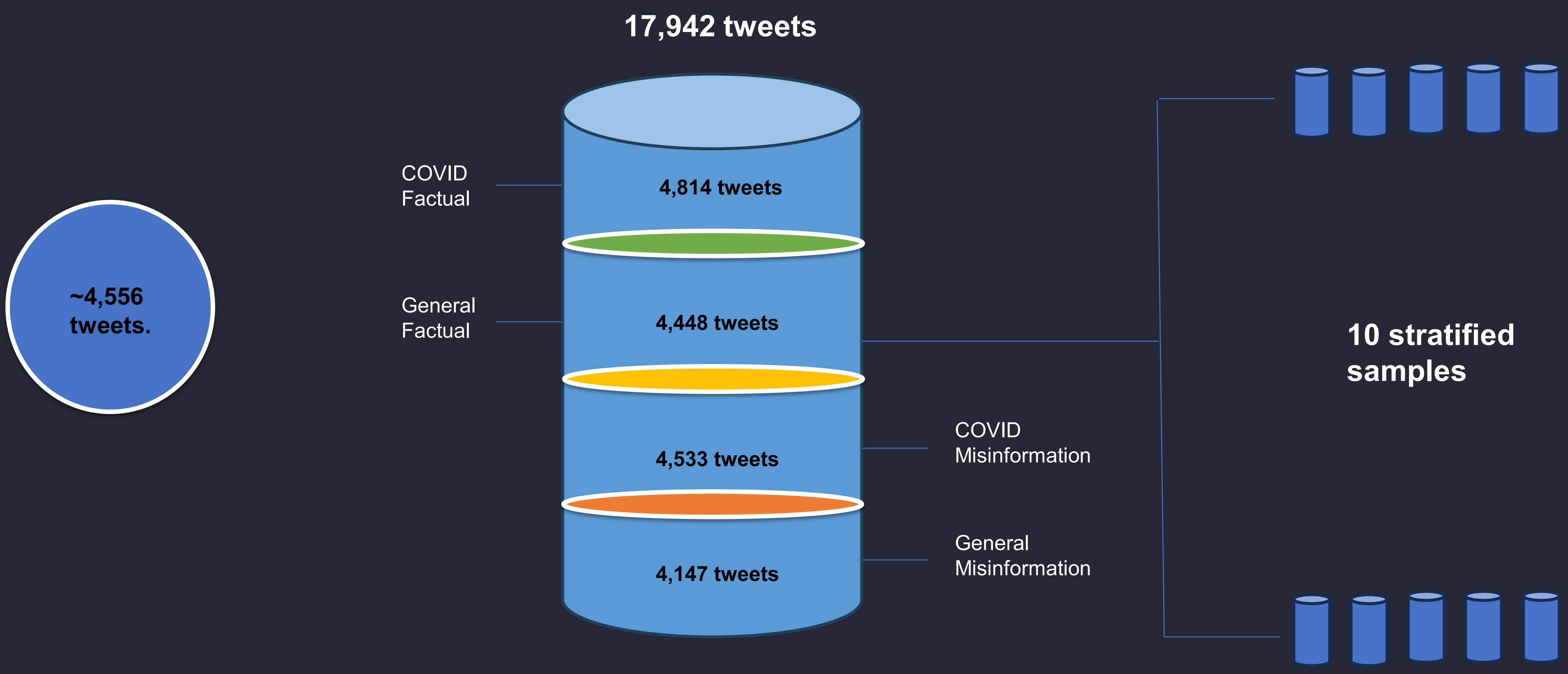
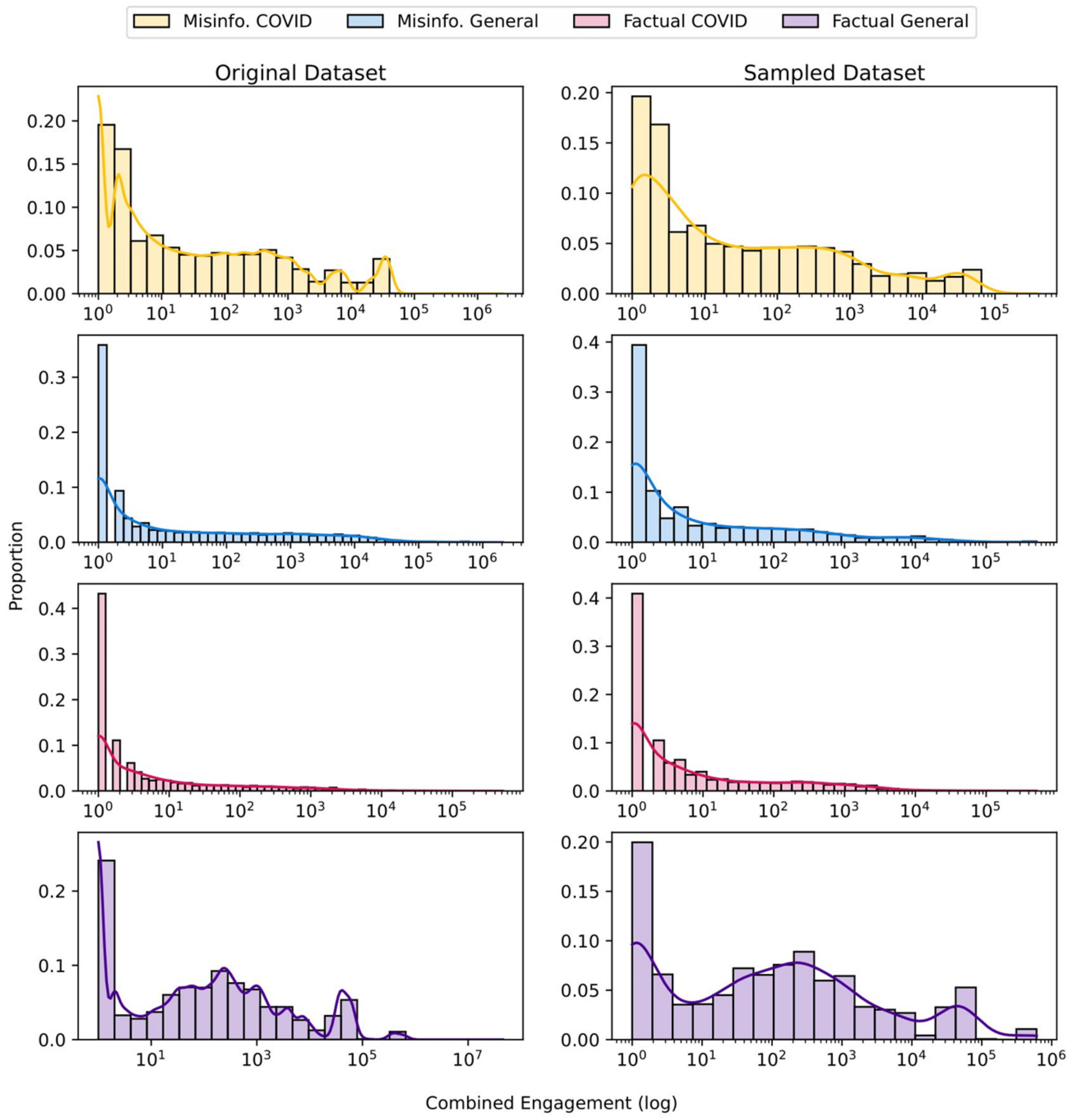


Image courtesy of elgin.edu

Stratified Random Sampling





Misinfo. COVID
Misinfo. General
Factual COVID
Factual General
Original Dataset
Sampled Dataset
Proportion
Combined Engagement (log)

Feature Extraction

Sociolinguistic Analysis

- Linguistic Inquiry and Word Count (LIWC) software.
- Emotional, cognitive, and structural components.

2

1

Tweet Metadata

- Text-based features.
- User-based features
- Network-based features.

3

Sentiment Analysis

- NLTK VADER

Tweet Metadata

# likes	# retweets
# combined engagement +	# hashtags
# links	# emojis

Tweet Metadata

User-related features

- # of followers.
- # of friends.
- # of lists.
- # of favorited tweets.
- # of tweets made by the user.
- verified (binary).
- presence of profile image.
- use of default profile image.
- use of default profile.
- whether geolocation is enabled.
- user has an extended profile.
- user has a background tile.

Sociolinguistic Analysis

Language Metrics

- Total number of words.
- Average number of words per sentence.
- Number of words containing more than six letters.
- Number of words found in the LIWC dictionary

Sociolinguistic Analysis

Linguistic Indicators

- Function words.
- Grammar characteristics.
- Affective words.
- Social words.
- Cognitive process.
- Core needs.
- Informal speech.

Sociolinguistic Analysis

Summary Variables

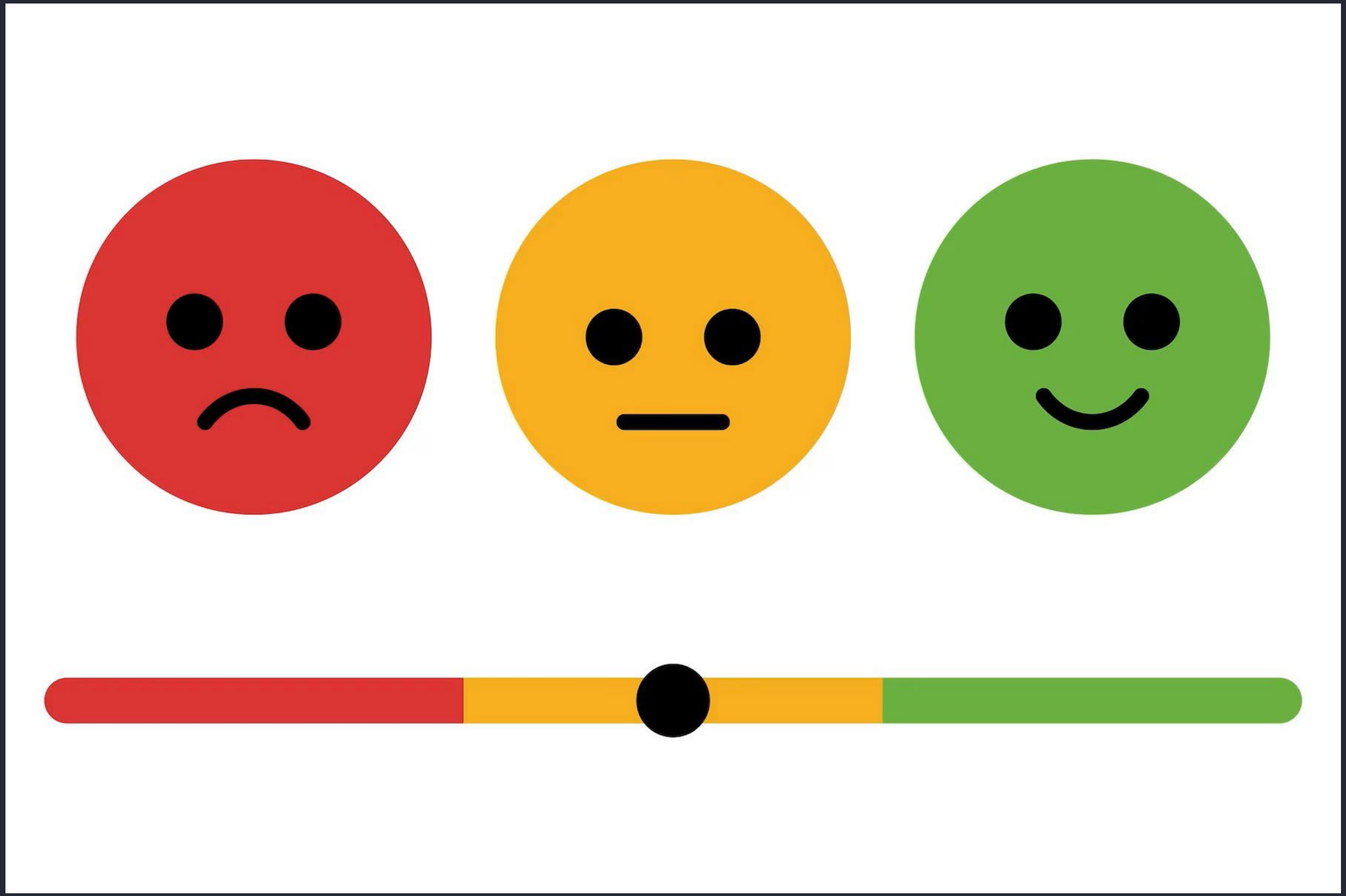
- Analytical Thinking.
- Clout.
- Authenticity.
- Emotional Tone.

Sociolinguistic Analysis

Moral Frames

- Care.
- Fairness.
- Loyalty.
- Authority.
- Sanctity.

Sentiment Analysis



Correlation Analysis

Pearson's correlation coefficient (*r*)

- Measure feature importance.
- *r* only captures linear relationships.

Fisher *z*-transformation

- Reduce bias.
- Estimate population correlation.

Alternating Conditional Expectations

- Feature's fixed point of Maximal Correlation.

Statistical Analyses - RQ1 and RQ2

Data	Measure	Measurement Statistics	
Combined Engagement (raw)	Shapiro-Wilk	Factual COVID-Related	$W = 0.7875^{***}$
		Misinformation General Topics	$W = 0.8946^{***}$
		Factual General Topics	$W = 0.9374^{***}$
		Misinformation General Topics	$W = 0.7969^{***}$
Combined Engagement (log-norm)	Levene	Factual vs. Misinformation COVID-Related	$W = 378.89^{***}$
		Factual vs. Misinformation General Topics	$W = 359.59^{***}$
	Two-Sample Kolmogorov-Smirnov	Factual vs. Misinformation COVID-Related	$K_2 = 0.2133^{***}$
		Factual vs. Misinformation General Topics	$K_2 = 0.3459^{***}$
	Mann-Whitney U	Factual vs. Misinformation COVID-Related	$U = 7,662,279^{***}$, $r = 0.35$
		Factual vs. Misinformation General Topics	$U = 5,725,193^{***}$, $r = 0.31$

*** Significant at $p < .001$

Summary results for statistical tests conducted on engagement metrics and bot/user account labels.

Findings – RQ1 and RQ2

Factual tweets were more engaging than misinformation tweets, regardless of their topic.

Statistical Analyses – RQ3

Feature Type	Feature	r_z	(MC) r_z
Misinformation: COVID-Related			
LIWC	Assent (Informal Speech)	0.26	0.75
	Colons (All Punctuation)	0.34	0.75
	Informal Speech	0.19	0.69
	Impersonal Pronouns	0.06	0.64
	Netspeak (Informal Speech)	0.26	0.73
	Quotation Marks (All Punctuation)	0.10	0.50
	Word Count	-0.10	0.51
Misinformation: General Topics			
User Metadata	Followers Count	0.28	0.73
	Listed Count	0.30	0.66
	User Verified	0.53	0.53

Summary of correlation analysis between the log normalized combined engagement metric and relevant features.

Statistical Analyses –RQ4

Feature Type	Feature	r_z	(MC) r_z
Factual: COVID-Related			
LIWC	Affective Processes	0.53	0.71
	All Punctuation	-0.05	0.58
	Assent (Informal Language)	0.65	0.74
	Clout	0.36	0.56
	Colon (Punctuation)	0.34	0.54
	Dictionary Words	0.13	0.56
	Past Focus	0.49	0.66
	Informal Speech	0.62	0.72
	Insight (Cognitive Processes)	0.32	0.68
	Male Referents (Social Words)	0.77	0.88
	Netspeak (Informal Language)	0.66	0.77
	Positive Emotion (Affect Words)	0.52	0.78
	Person Pronouns (Linguistic Dimensions)	0.31	0.56
	Question Marks (All Punctuation)	-0.31	0.53
	Reward (Drives)	0.33	0.67
	Sad (Affect Words)	0.48	0.65
	3rd Person Singular (Function Words)	0.81	0.91
	Words $>$ 6 Letters	-0.26	0.59
	Social Words	0.41	0.63
	Time (Relativity)	0.21	0.51
Sentiment	VADER Compound	0.19	0.66
Factual: General Topics			
LIWC	Assent (Informal Speech)	0.36	0.68
	Colons (All Punctuation)	0.20	0.52
	Informal Speech	0.29	0.62
	Netspeak (Informal Speech)	0.32	0.63
	Prepositions (Function Words)	0.02	0.54

Findings – RQ3

RQ3: Which features are most correlated with engagement in COVID-19 vs. general topics misinformation tweets?

COVID-19:

- Grammar (e.g., use of informal speech).

Factual:

- User metadata (e.g., verified user).

Findings – RQ4

RQ4: Which features are most correlated with engagement in COVID-19 vs. general topics factual tweets?

COVID-19:

- Grammar (e.g., use of netspeak).
- Emotion (both positive and negative).
- Writer's confidence.

Factual:

- Grammar (e.g., use of colons or prepositions).

Discussion

- General topic misinformation ➔ User metadata

Discussion

- Semantic content of tweet not relevant *(except for factual COVID-19 tweets)*.
- Factual COVID → Tweet syntax.
- General topic → Tweet syntax.

Discussion

- Factual COVID-19 → Sentiment.
  → Cognitive processing keywords.
- Misinformation COVID-19 → Clear, straightforward language.

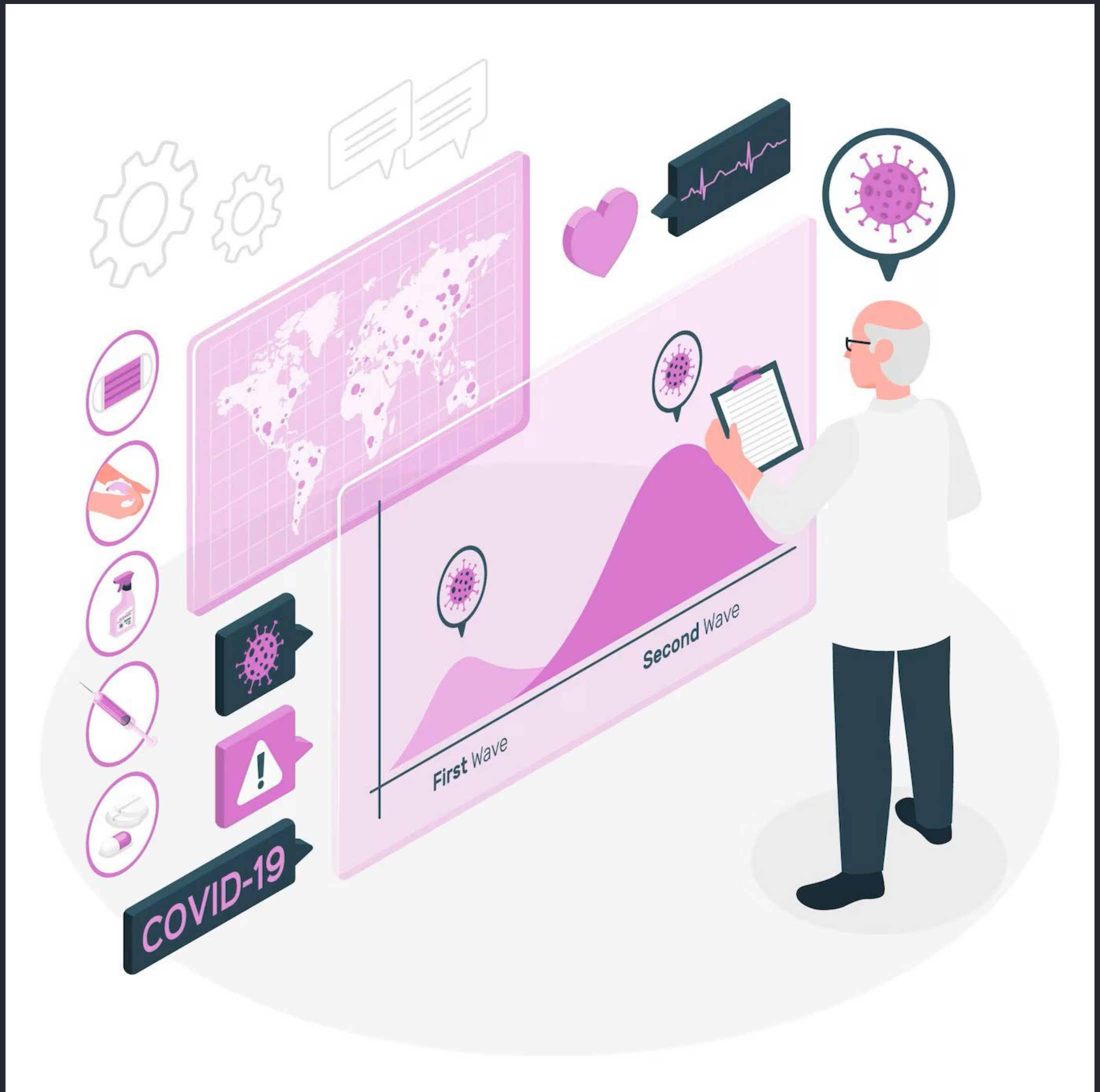
Discussion

- Factual tweets > Misinformation tweets
  (in terms of engagement)

Study Limitations & Future Work

Dataset Imbalance

- Highly imbalanced dataset.
- Findings may not apply to other contexts.
- Explore temporal trends in tweet data.



Study Limitations & Future Work

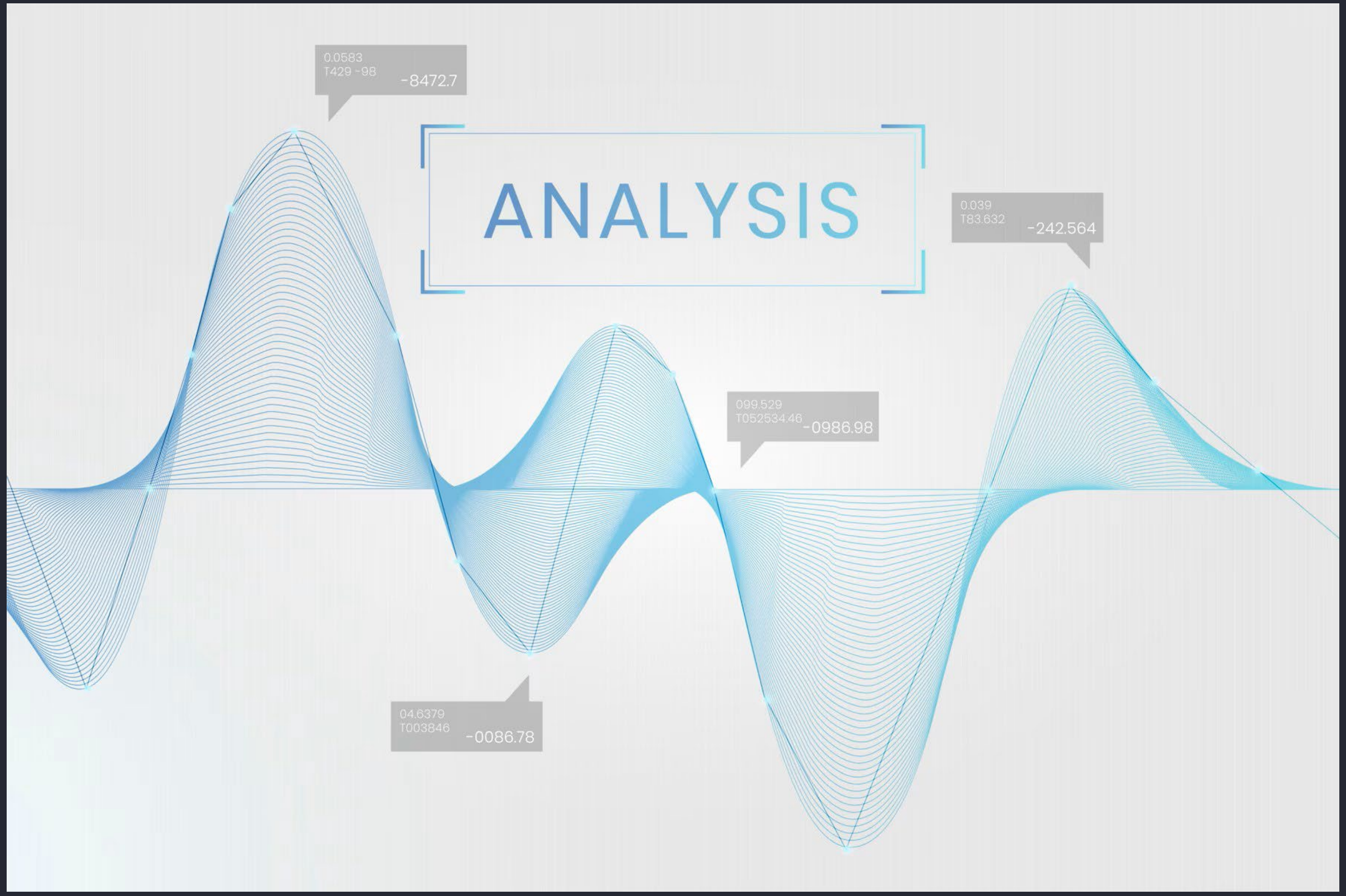
Feature Engineering

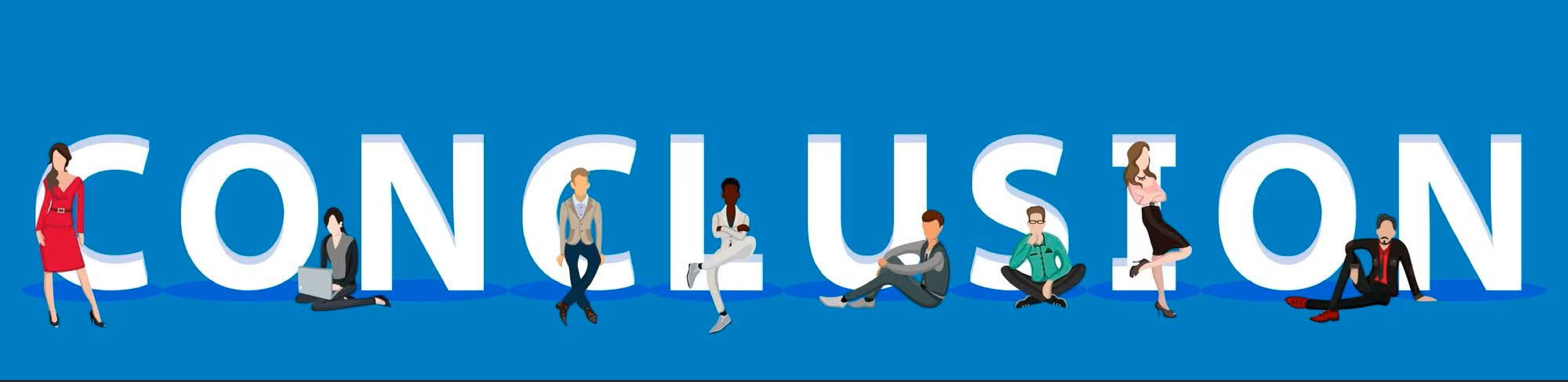
- Did not measure presence of images.
- Utilize automated feature extractors.

Study Limitations & Future Work

Classification Models

- Relied only on pairwise correlation.
- Study multivariate analyses.





- Dataset of 2.1M COVID-19 and non-COVID related tweets.

- Misinformation tweets less engaging than factual tweets.

- Tweet features correlating with engagement vary based on veracity.

Acknowledgements

We acknowledge our funding sources, collaborators, and others who contributed to the research. This work was supported by the National Science Foundation, the University of Florida Seed Fund, and by the Embry-Riddle Aeronautical University award.

Images courtesy of freepik.com.

People Still Care About Facts: Twitter Users Engage More with Factual Discourse than Misinformation

Luiz Giovanini: lfrancogiovanini@ufl.edu

Shlok Gilda: shlokgilda@ufl.edu

Mirela Silva: msilva1@ufl.edu

Fabrício Ceschin: fjocescin@inf.ufpr.br

Daniela Oliveria: daniela@ece.ufl.edu

Questions?

We welcome questions and further discussion.