Optimising public health communication: an analysis of type, sentiment and source of COVID-19 tweets

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Abstract

Background: Social media can be used to quickly disseminate focused public health messages, increasing message reach and interaction with the public. Social media can also be an indicator of people's emotions and concerns. Social media data text mining can be used for disease forecasting and understanding public awareness of health-related concerns. Limited studies explore the impact of type, sentiment and source of tweets on engagement.

Objective: To determine the association between message type, user (source) and sentiment of Covid-19 twitter posts and public engagement.

Methods: 867,485 tweets were extracted from 1 Jan 2020 to 31 Mar 2022 from Ireland and the UK. A four-step analytical process was undertaken, encompassing sentiment analysis, bio-classification, message classification and statistical analysis. Manual coding and machine learning coding models were used to categorise sentiment, user category and message type for every tweet. A zero-inflated negative binomial model was applied to explore the most engaging content mix.

Results: Our analysis resulted in 12 user categories, 6 messages categories and 3 sentiment classes. Personal stories and positive messages have the most engagement, even though not for every user group; known persons and influencers have the most engagement with humorous tweets. Health professionals receive more engagement with advocacy, personal stories/statements and humour based tweets. Health Institutes observe higher engagement with advocacy, personal stories/statements and tweets with a positive sentiment. This study suggests the optimum mix of message type and sentiment that each user category should use to get more engagement.

Conclusions: Our study provides valuable guidance for social media based public health campaigns for developing messages for maximum engagement

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Original Manuscript

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Keywords: Public health communication, COVID-19, health messaging, social media, public health, Twitter, social marketing, infoveillance, intervention planning, pandemic

Methods

Data Collection:

Data was extracted from twitter using a python script to communicate with Twitter Rest API using the “Search” endpoint. The “query” parameter was used to filter the results based on the “has:geo” tag, the “place_country:UK”/ “place_country:IE” tag (for Ireland and UK), and “lang:en” tag (for English). The ”start_time” and “end_time” parameters were used to filter the posts from 1 Jan 2020 to 31 Mar 2022.

A basic search was conducted with phrases such as coronavirus, SARS-CoV-2, and COVID-19 on Twitter. Using an iterative method, keywords were added and removed in order to find the most suitable for the data search. The final list of 10 keywords for data extraction included COVID-19, pandemic, SARS-CoV-2, coronavirus, SARS-CoV-2 virus, social distancing, self-isolation, self-quarantine, quarantine and new variant. The total number of tweets extracted totalled 867,485.

Data Analysis:

Due to the extensive volume of data, a systematic approach was adopted using a four-step analytical process including sentiment analysis, user-classification, message classification and statistical analysis (Table 1).

Sentiment Analysis

A subset of 260 tweets was randomly extracted for manual annotation by three coders with sentiment labels - positive, negative or neutral (Appendix 1). Three Machine Learning (ML) sentiment analysis models were applied to detect the sentiment for the same tweet subset:

- Distilbert-base-uncased-finetuned-sst-2-english [12]
- Finite automata/bertweet-base-sentiment-analysis [13]
- RoBERTa-base for Sentiment Analysis [14]

The Kappa statistic was calculated between the three coders and between each coder and model. The model with the highest agreement with manual coders based on accuracy score [15] and F1 score [16] was applied to the full dataset.

PHASE	TASKS	METHODS	OUTCOME
Data Collection	Identification of keywords related to COVID-19	• Identification of 15 keywords • After discussion among research team, reduced to 10 keywords for data extraction	Final keywords
	Data extraction	• An academic researcher access was applied for with Twitter • 867,485 tweets extracted	
Sentiment Analysis	Allocate sentiment to each tweet	• Random selection of 260 tweets for sentiment allocation (positive, negative, neutral) • Three coders manually assigned sentiments to one set of 260 random tweets • Using majority voting, out of 260 tweets, coders agreed on 247 tweets (2 or 3 coders voted the same) • Kappa statistic calculated between all coders and the models • RoBERTa-base model (highest agreement) applied to the whole dataset	Manual coded tweets Kappa statistic results Tweets sentiment assigned - full dataset

User Classification	Identify user categories	• User categories identified based on literature on social media supported public health interventions • Definition of 5 user categories: health institute, health professional, influencer, researcher and public	User categories
	Coding user profiles	• Abductive coding by 4 Manual coders on 1000 randomly selected tweets to identify new user categories • After 3 rounds of manual coding, most discrepancies or disagreements resolved through discussion • Using majority voting, out of 250 tweets, coders agreed on 165 tweets (at least 3 coders voted the same) • Three ML models selected to assign user categories to same set of 250 tweets used in Round 3 of manual coding • Bag of words were defined for each user category for user categorisation by the ML models • Accuracy score and F1 score calculated between ML models and manual coders • SetFit model (highest agreement) applied to the whole dataset	User classification coding - Round 1, 2 & 3 Bag of words Accuracy and F1 score Tweets users assigned - full dataset
Message Classification	Identify message categories	• Message categories defined based on review of public health communication literature • Definition of 5 message categories: Humour, Shock/disgust, Informative/Educational, Opportunistic, Personal stories	Message categories
	Coding tweets	• Abductive coding by 5 manual coders on randomly selected tweets in three rounds: 100 tweets in round 1, 100 tweets in round 2 and 250 tweets in round 3 • After 2 rounds of manual coding, discrepancies or disagreements resolved through discussion • Six final message categories after addition and reduction of categories over three rounds • Using majority voting, out of 250 tweets, coders agreed on 203 tweets (3 or more coders voted the same) • GPT 3 and Setfit model to assign message categories to set of 250 tweets from the final round using 6 message categories • Accuracy score and F1 score calculated between models and manual coder • SetFit model (highest agreement) applied to the whole dataset	Manual coding - Round 1, 2 and 3 Tweets message assigned - Tweet users assigned
Statistical Analysis	Engagement calculation	• Exclusion of zero-follower users (N=537) • Calculation of engagement (sum of likes, replies, retweets and quoted tweet count divided by the respective user's followers)	
	Zero-inflation model	• Exclusion of public user group (outside of objective of research) due to 87% zero-engagement • Application of zero-inflated Poisson and zero-inflated negative binomial model due to remainder of 26% zero-engagement • Selection of zero-inflated negative binomial model (best fit) with informative/educational message type and neutral sentiment as comparator	Final model results

Table 1 – Data analysis process

User Classification

A directed content analysis with abductive coding was used to explore the sources of information. User categorisation was based on the profile description and categorised according to an adaptation of the user categories from Cole-Lewis [17]: health institute, health professional, influencer, researcher and public.

User coding was performed in 3 cycles. 1000 randomly selected tweets were classified by four coders with an overlap of 10% for double coding i.e. coders independently assigned codes to the same set of tweets. The 1000 tweets were categorised into six distinct categories with a directed content analysis approach [18] with an additional category 'others'. This 'others' category, was further defined through exploring the profile descriptions resulting in a total of 12 categories.

The second round aimed to ensure consistency and accuracy between coders. Hundred randomly selected tweets were allocated to 12 user categories by each coder (Table 2) and agreements, disagreements and potential additions to the categories were discussed. A 'bag of words' was compiled for each user category, providing descriptive insights into the characteristics of the users

(Table 2 and Appendix 2).

Table 2 – User category and bag of words

Index	User Category	Profile Keywords – 'bag of words' (Version 6)
1	Health Institute	ICGP WHO NHS Public health ECDC HSE HPSC clinic hospital
2	Health Professional	healthworker GP consultant Nurse MD Specialist Physician clinician surgeon
3	University/Researcher	university researcher PhD student scientist academic professor academia principal lecturer
4	Influencer	influencer blogger vlogger coach YouTube
5	Teacher	teacher teach school education children
6	Politician	politics government governor cabinet council minister councillor ambassador MP Secretary of state Fine Gael TD Mayor
7	Sports	football rugby run swim tennis exercise sportsclub pickleball
8	Journalist	journalist report news reporter columnist reviewer media correspondent editor
9	Charity	charity church ngo foundation donations
10	Public	community union group nature lover adventure travel live life world freedom farm pet cat dog walks
11	Known Personality	views my own, 'True' in verified status
12	Artist	artist actor actress music writer singer photography movie sing play cinema orchestra

In the third round, 250 randomly selected tweets were coded by four coders and compared to three different ML models using the same bag of words:

- Lbl2TransformerVec model (unsupervised) [19]
- SG Rank model [20]
- SetFit model [19]

The ML models classified many Influencers as "Public" which was rectified by allocating influencer to any user with more than 3000 followers. The three models' performance was evaluated using 250 tweets (third round of coding) from four coders. Majority voting was used to generate a final coding for the 250 tweets, and filtering out tweets that had less than 3 coders agreement. A final dataset of 165 tweets was left after this filtering. The three models' performance was compared to the manual allocation and the final classification was based on the majority allocation.

Message Classification

Similar to the user classification, a directed content analysis with abductive coding was applied. A review of literature resulted in identification of five message categories [21]: humour, shock/disgust, educational/informative, personal stories and opportunistic. The dataset was divided into 2 subsets – public tweets and non-public tweets to determine which type of messages the public engages with most.

Three manual coding cycles were applied, starting the allocation of 100 random non-public tweets to the five message categories and an ‘other’ category. Two additional categories emerged: fear and advocacy.

In Round 2, five coders allocated 100 tweets to seven message categories and discussed agreements and disagreements leading to a refinement of the message categories. Fear-based messaging was combined with shock/disgust, personal stories was combined with personal statements and a ‘not enough information’ category was added. In the final round, 250 tweets were categorised into seven message categories - humour, shock/disgust/fear-based, educational/informative, personal stories/statements, opportunistic, advocacy and not enough info and compared to two ML models (GPT 3 and SetFit) (Appendix 3).

Statistical Analysis

For each tweet, engagement was calculated as the sum of likes, replies, retweets and quoted tweet count divided by the respective user's follower count.

For 87% of the tweets, the engagement was zero due to the lack of followers or likes, replies or quotes (mainly public users). The final dataset excluded this user category resulting in the reduction to 26% zeros. Zero-inflated Poisson and zero-inflated negative binomial models were applied.

Results

The total number of tweets extracted was 867,485 which reduced to 802,042 after deleting duplicates. Majority of the tweets (729,619) came from the UK and 72,350 from Ireland and 73 were without a location.

The follower count for the dataset showed a wide range, from a maximum of 14,065,098 followers to zero followers, with an average of 4,296 followers. Accounts (users) without followers were investigated to identify inactive accounts or bots and 537 users were removed from the dataset.

Public user category tweets (430,760) were removed from the final dataset as they were not a user category of interest. The final dataset included 370,745 tweets.

Sentiment Analysis

Out of 260 tweets, coders agreed on 247 tweets (this is 2 or 3 coders voted the same) which were compared with the accuracy score and F1-score (weighted) of the three ML models. The RoBERTa-base (Model 3) performed the best and was used to assign sentiment to all tweets (Table 3).

Sentiment was negative for 138,379 tweets (37.3%), positive for 84,939 (22.9%) and neutral for 147,427 tweets (39.8%). Positive sentiment tweets had the highest engagement (29.3%) followed by negative (26.7%) and neutral (20.4%), (Fig 1).

Table 3 - Accuracy and F1-score for sentiment models with ML models

Model	Accuracy	F1-score (weighted)
1 – Distilbert-base-uncased-finetuned-sst-2-english	0.68	0.61
2 – Finite automata/bertweet-base-sentiment-analysis	0.58	0.61
3 – RoBERTa-base	0.74	0.76

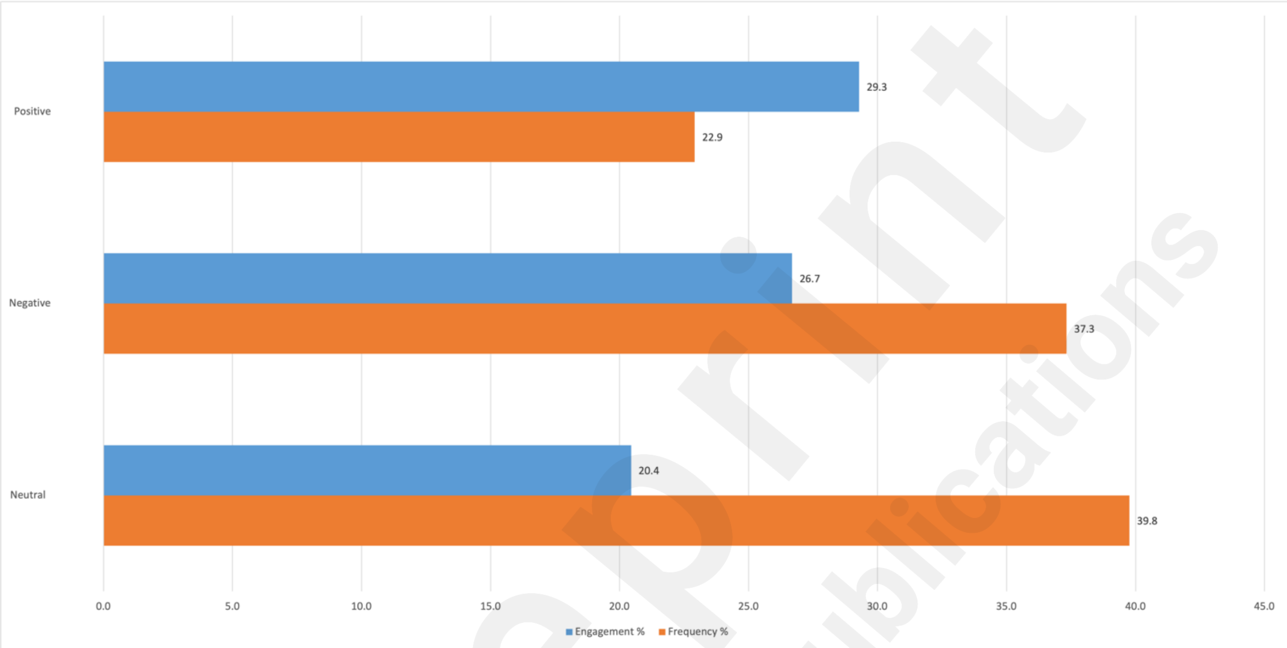


Fig 1: – Frequency and engagement for each sentiment category

User Classification

Model 3 (assisted) achieves 0.73 accuracy score when 4 and 5 coders were in agreement and 0.77 accuracy when there was at least one match with one coder - 192/250 tweets (Table 4).

Table 4 – Accuracy and F1-score for user classification with ML models

Model	Accuracy	F1-score (weighted)
1 - Lbl2TransformerVec	0.26	0.21
2 - SG Rank	0.43	0.43
3 - SetFit	0.69	0.67
3 - SetFit (assisted)	0.73	0.73

Health professionals (8%) significantly outnumbered health institutes (1%), while the number of influencers (32%) was more than twice that of journalists (15%) and politicians (13%). Artists (6%) outnumbered individuals associated with sports (2%), and teachers (3%) were one-third in comparison to university/researchers (14%), Table 5.

Table 5 – User categories

User Categories	Frequency	Frequency %
Influencer	119,711	32.3%
Journalist	54,384	14.7%
University/Researcher	50,275	13.6%
Politician	47,694	12.9%
Health Professional	28,963	7.8%
Artist	21,730	5.9%
Known Personality	15,095	4.1%
Teacher	12,019	3.2%
Charity	11,788	3.2%
Sports	5,659	1.5%
Health Institute	3,427	0.9%

Fig 2 shows the frequency and percentage of engagement for each user category provides valuable insights into their impact and effectiveness in engaging audiences. health professionals have the highest level of engagement (15%), followed by university/researchers (13%) despite a lower frequency (8%). Even though influencers have high frequency (32%) it doesn't translate into high engagement with influencers having a lower percentage of engagement at 12%.

Journalists and politicians account for 15% and 13% respectively with 8% engagement each. Teachers, known personalities and charities received engagement of 6%, 4% and 3% at lower frequencies. Sports and health Institutes have the lowest engagement each at 1%.

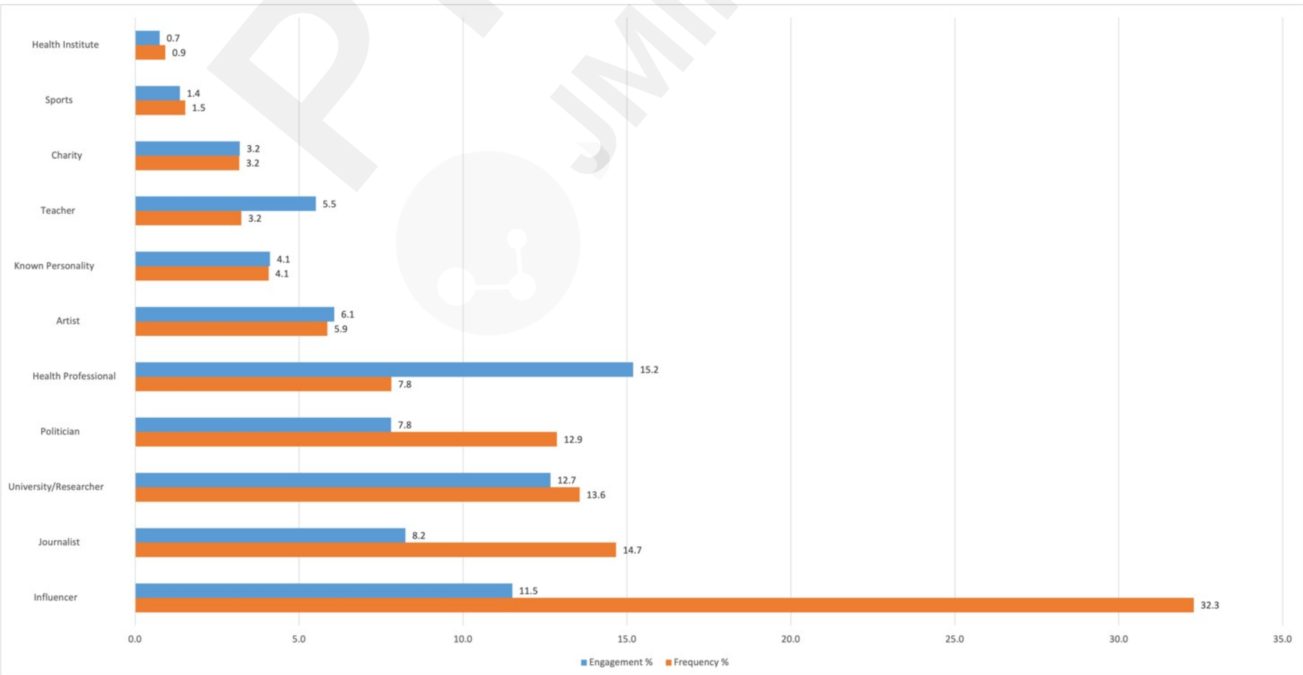


Fig 2 – Frequency and engagement for each user category excluding public

Message classification

Out of 250 tweets, majority coding from the five coders resulted in 203 classifications. The remainder had less than 3 coders agreement and 11 tweets were removed due to “Not enough information”. Setfit outperformed GPT 3 and this model achieved 80% accuracy when considering a match with at least 1 coder (192/239 tweets) (Table 6).

Table 6 – Accuracy and F1-score for user classification with ML models

	4 and 5 coders agreement		3, 4 or 5 coders agreement	
	Accuracy	F1-score (weighted)	Accuracy	F1-score (weighted)
GPT 3	0.60	0.60	0.51	0.49
Setfit	0.74	0.74	0.64	0.62

Personal stories/statements have the highest engagement at 27%, but are not the most frequent tweeted category (22%). Shock/disgust/fear-based messages (32%) have 21% engagement. Informative/educational messages have high frequencies (33%) and have 16% engagement. Advocacy messages (8%) have 9% engagement and humour and opportunistic messages have engagements of 4% and 0.5% and low frequencies 5% and 1% respectively (Table 7).

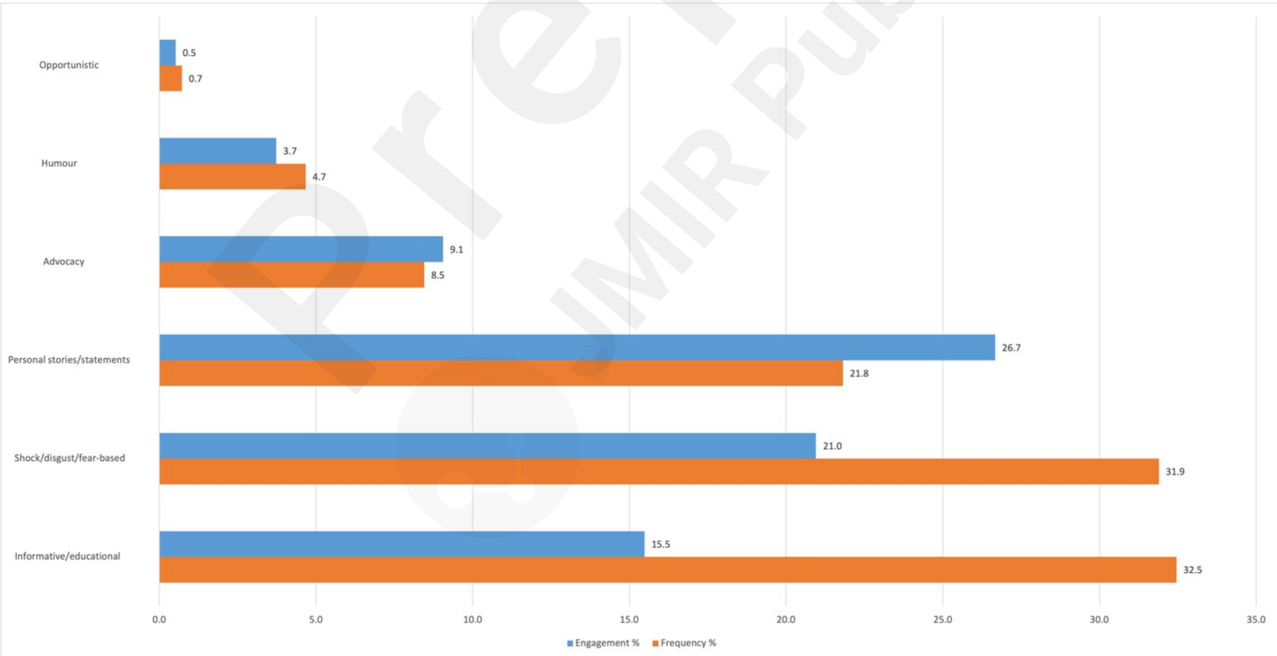


Fig 3 – Frequency and engagement for each message type

Table 7 – Message types frequency and engagement percentage

Message Category	Frequency	Engagement %

Informative/educational	120,317	15.5%
Shock/disgust/fear-based	118,238	21.0%
Personal stories/statements	80,881	26.7%
Advocacy	31,340	9.1%
Humour	17,302	3.7%
Opportunistic	2,667	0.5%

Statistical Analysis

A zero-inflated negative binomial model was applied with informative/educational tweets and neutral sentiment as reference categories. Health professionals received more engagement with advocacy, personal stories/statements and humour. Health Institutes observe higher engagement with advocacy, personal stories/statements and tweets with a positive sentiment (Appendix 3).

Journalists and teachers observe higher engagement with advocacy, personal stories/statements and humour while artists have more engagement with shock/disgust/fear-based messages and positive sentiment. Charity organisations, universities and researcher have more engagement with advocacy and personal stories/statements but not with shock/disgust/fear tweets.

Known personalities have most engagement with advocacy and humour-based which is opposite for sports entities. Sports entities have more engagement with personal stories/statements and positive sentiment. Politicians and influencers have more engagement with advocacy, personal stories/statements and humour, while they should avoid opportunistic tweets.

Table 8 – Findings of zero-inflated model

User Category	Message type to tweet	Message type to avoid
Health Institute	Advocacy, Personal stories/statements and Positive sentiment	Opportunistic, Shock/disgust/fear-based and Negative sentiment
Artist	Shock/disgust/fear-based and Positive sentiment	Humour and Opportunistic
Charity	Advocacy and Personal stories/statements	Humour and Negative sentiment
Journalist	Advocacy, Personal stories/statements and humour	Shock/disgust/fear-based and Negative sentiment
Known Personality	Advocacy and humour	Shock/ disgust/fear based
Teacher	Advocacy, Personal stories/statements and humour	Shock/disgust/fear-based and Negative sentiment
Health Professional	Advocacy and Personal stories/statements	Opportunistic and Shock/disgust/fear-based
Influencer	Advocacy, Personal stories/statements and Humour	Opportunistic and Negative sentiment
Sports	Personal stories/statements and Positive sentiment	Shock/disgust/fear-based
Politician	Advocacy, Personal stories/statements and Humour	Opportunistic and Negative sentiment
University/Researcher	Advocacy and Personal stories/statements	Shock/disgust/fear-based and Negative sentiment

Discussion

This analysis of type, sentiment and source of COVID-19 tweets showed what type of tweets have the most engagement for each user group. Overall, personal stories and positive messages have most engagement, even though not for every user group; known persons and influencers have most engagement with humorous tweets.

Positive sentiments in public health messages typically evoke feelings of hope, encouragement, and trust among users, leading to increased sharing behaviour [22]. Users are more inclined to engage with and share positive messages that resonate with them emotionally, as they perceive such content as uplifting and supportive [22]. Our initial manual categorisation ensured a reliable baseline for sentiment analysis in this study. The frequency of negative sentiment tweets and their engagement reflects the widespread anxiety, fear and uncertainty during the pandemic [23]. The high engagement with negative sentiment tweets further emphasises the need to consider emotional content in information dissemination on social media platforms such as Twitter. In this context, future studies should explore the specific impact of tweets by analysing the responses they generate, including retweets with quotes and replies. This approach would provide additional insights and allow to evaluate whether tweets achieve their intended impact.

The findings of this study revealed distinct patterns of public engagement across different user categories and message types. Trusted sources are important in shaping public behaviour and engagement with health information during crises [24]. Overall, in the case of users, health professionals received high engagement during the pandemic whereas health institutes received the lowest engagement, maybe reflecting their different use of messages. Additionally, health experts, such as GPs, communicate health information with greater credibility and persuasiveness than non-experts or institutes [25].

Online health communities and social media platforms influence public health behaviours and engagement levels [26]. The definition and expansion of sources (user categories) in this study provides a framework to develop specific messaging by user group. Our findings re-iterate the importance of understanding audience and tailoring engagement strategies based on category-specific behaviours for optimal engagement [27-29].

Comparison with Prior Work

Most studies have focused on the content of the tweets to understand public reactions/ sentiment [30, 31], trends during COVID-19 [32, 33] or vaccinations [34-36].

In one study, Twitter data was explored using machine learning to examine how public opinions and discussions changed throughout the COVID-19 epidemic [30]. Trends in social media discussions during the pandemic was explored using sentiment analysis and topic modelling which produced useful information about public discussion around the pandemic [32]. These studies focused mainly on the types of tweets and their engagement but did not explore their association with sources, message type or sentiments.

The classification of tweets based on types enriched the analysis by capturing the multifaceted nature of communication during the pandemic and provided an understanding of how different message categories influence public engagement and sharing behaviour. This study also added to the existing literature by introducing two new message categories – advocacy and personal statements while modifying the existing categories to enable application and provide guidance in framing future public health communications.

Public health literature on message types is very limited. A scoping review on the health risk communication with the public during a pandemic found a lack of studies on the modes of communication [37]. One study discusses the framing of effective COVID-19 messages to connect individuals to authoritative content, emphasising the importance of positive and gain-framed messages [38]. Similarly, personal experiences increased the salience of public health messaging, particularly in promoting sanitation and hygiene practices [39]. Public health messaging during lockdown in New Zealand showed the importance of consistent messaging principles such as transparency, timeliness, empathy, and clarity [40]. None of these studies used defined message categories and the definition and recommendation of message type for different user categories is a major contribution of our study. This will help content creators particularly health intervention planners in choosing the right mix of message and sentiment type to increase their engagement.

A similar study of social media messages explored account type and message structure taking elements such as hashtags, hyperlinks, mentions, and any images or videos into account but only counting retweets as engagement [8]. They found that tweets with hashtags, videos and pictures were retweeted more often while tweets with links had fewer retweets. Further, tweets with sentiment were more frequently retweeted than neutral sentiment tweets. In our study the user profile and engagement was explored through engagement metrics such as likes, retweets, reply count and quote count. We found health institutes to be least engaged user category while Xie et al. found national health authorities received more engagement when compared to provincial accounts [8]. However, their analysis was limited to the study of the official (national and provincial) public health agencies' Weibo posts only (a China-only microblogging platform).

Our findings suggest a correlation between message type, sentiment, source credibility and engagement. This is the first study to examine the engagement across different user categories for different messages, providing insight into twitter users responses towards different tweets and sources. Our study provides guidance for social media based public health campaigns for developing messages for maximum engagement.

Limitations

We included just 3 factors (sentiment, user type and message type) for the analysis which was leading to variance in our analysis. Other factors not recorded or captured may also influence engagement, for instance, time/day of post, hashtags, images etc. For our study, we also excluded tweets from the public user category which was almost 50% of the dataset as it was not required to address this study's research questions.

Conclusion:

Our study provides a framework to develop social media messages according to sentiment and message type for different users. Health professionals and institutes and other users can build on the results to improve effective communication through social media channels.

Abbreviations:
ML – Machine learning
API – Application Program Interface
IE – Ireland
GPT - Generative Pre-trained Transformer

Conflict of Interest: None

References:

1. Bernhardt, J.M., *Communication at the core of effective public health.* Am J Public Health, 2004. **94**(12): p. 2051-3.
2. *Public health communication: Evidence for behavior change*. Public health communication: Evidence for behavior change., ed. R.C. Hornik. 2002, Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers. xv, 435-xv, 435.
3. Plackett, R., et al., *Use of Social Media to Promote Cancer Screening and Early Diagnosis: Scoping Review.* J Med Internet Res, 2020. **22**(11): p. e21582.
4. Khan, Y., et al., *Retiring the Flip Phones: Exploring Social Media Use for Managing Public Health Incidents.* Disaster Medicine and Public Health Preparedness, 2019. **13**(5-6): p. 859-867.
5. Jang, H., et al., *Tracking COVID-19 Discourse on Twitter in North America: Infodemiology*

Study Using Topic Modeling and Aspect-Based Sentiment Analysis. J Med Internet Res, 2021. **23**(2): p. e25431.
6. Carter, M., *How Twitter may have helped Nigeria contain Ebola.* Bmj, 2014. **349**: p. g6946.
7. Bartlett, C. and R. Wurtz, *Twitter and public health.* J Public Health Manag Pract, 2015. **21**(4): p. 375-83.
8. Xie, J. and L. Liu, *Identifying features of source and message that influence the retweeting of health information on social media during the COVID-19 pandemic.* BMC Public Health, 2022. **22**(1): p. 805.
9. Ciotti, M., et al., *The COVID-19 pandemic.* Critical Reviews in Clinical Laboratory Sciences, 2020. **57**(6): p. 365-388.
10. Al-Dmour, H., et al., *Influence of Social Media Platforms on Public Health Protection Against the COVID-19 Pandemic via the Mediating Effects of Public Health Awareness and Behavioral Changes: Integrated Model.* J Med Internet Res, 2020. **22**(8): p. e19996.
11. Gan, C.C.R., et al., *#WuhanDiary and #WuhanLockdown: gendered posting patterns and behaviours on Weibo during the COVID-19 pandemic.* BMJ Glob Health, 2022. **7**(4).
12. Sanh, V., et al., *DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter.* arXiv preprint arXiv:1910.01108, 2019.
13. Pérez, J.M., et al., *pysentimiento: a python toolkit for opinion mining and social NLP tasks.* arXiv preprint arXiv:2106.09462, 2021.
14. Loureiro, D., et al., *TimeLMs: Diachronic language models from Twitter.* arXiv preprint arXiv:2202.03829, 2022.
15. Huilgol, P. *Accuracy vs. F1-Score*. 2019; Available from: https://medium.com/analytics-vidhya/accuracy-vs-f1-score-6258237beca2.
16. Kundu, R. *F1 Score in Machine Learning: Intro & Calculation*. 2022; Available from: https://www.v7labs.com/blog/f1-score-guide.
17. Cole-Lewis, H., et al., *Social Listening: A Content Analysis of E-Cigarette Discussions on Twitter.* J Med Internet Res, 2015. **17**(10): p. e243.
18. Hsieh, H.-F. and S.E. Shannon, *Three Approaches to Qualitative Content Analysis.* Qualitative Health Research, 2005. **15**(9): p. 1277-1288.
19. Schopf, T., D. Braun, and F. Matthes. *Semantic Label Representations with Lbl2Vec: A Similarity-Based Approach for Unsupervised Text Classification*. 2023. Cham: Springer International Publishing.
20. Eldallal, A. and E. Barbu, *BibRank: Automatic Keyphrase Extraction Platform Using Metadata.* Information, 2023. **14**(10): p. 549.
21. Gough, A., et al., *Tweet for Behavior Change: Using Social Media for the Dissemination of Public Health Messages.* JMIR Public Health Surveill, 2017. **3**(1): p. e14.
22. Voorveld, H.A.M., et al., *Engagement with Social Media and Social Media Advertising: The Differentiating Role of Platform Type.* Journal of Advertising, 2018. **47**(1): p. 38-54.
23. Melton, C.A., et al., *Fine-tuned Sentiment Analysis of COVID-19 Vaccine–Related Social Media Data: Comparative Study.* J Med Internet Res, 2022. **24**(10): p. e40408.
24. Latkin, C.A., et al., *Behavioral and Attitudinal Correlates of Trusted Sources of COVID-19 Vaccine Information in the US.* Behavioral Sciences, 2021. **11**(4): p. 56.
25. Jucks, R. and F.M. Thon, *Better to have many opinions than one from an expert? Social validation by one trustworthy source versus the masses in online health forums.* Computers in Human Behavior, 2017. **70**: p. 375-381.
26. Chen, X., *Online health communities influence people's health behaviors in the context of COVID-19.* PLOS ONE, 2023. **18**(4): p. e0282368.
27. Lustria, M.L.A., et al., *A Meta-Analysis of Web-Delivered Tailored Health Behavior Change Interventions.* Journal of Health Communication, 2013. **18**(9): p. 1039-1069.
28. Maibach, E.W. and R. Parrott, *Designing Health Messages: Approaches from*

Communication Theory and Public Health Practice. 1995: SAGE Publications.
29. Lutkenhaus, R.O., J. Jansz, and M.P. Bouman, *Tailoring in the digital era: Stimulating dialogues on health topics in collaboration with social media influencers.* DIGITAL HEALTH, 2019. **5**: p. 2055207618821521.
30. Xue, J., et al., *Twitter Discussions and Emotions About the COVID-19 Pandemic: Machine Learning Approach.* J Med Internet Res, 2020. **22**(11): p. e20550.
31. Xue, J., et al., *Public discourse and sentiment during the COVID 19 pandemic: Using Latent Dirichlet Allocation for topic modeling on Twitter.* PLoS One, 2020. **15**(9): p. e0239441.
32. Boon-Itt, S. and Y. Skunkan, *Public Perception of the COVID-19 Pandemic on Twitter: Sentiment Analysis and Topic Modeling Study.* JMIR Public Health Surveill, 2020. **6**(4): p. e21978.
33. Worrall, A.P., et al., *Online Search Trends Influencing Anticoagulation in Patients With COVID-19: Observational Study.* JMIR Form Res, 2021. **5**(8): p. e21817.
34. Liu, S. and J. Liu, *Understanding Behavioral Intentions Toward COVID-19 Vaccines: Theory-Based Content Analysis of Tweets.* J Med Internet Res, 2021. **23**(5): p. e28118.
35. Hussain, A., et al., *Artificial Intelligence-Enabled Analysis of Public Attitudes on Facebook and Twitter Toward COVID-19 Vaccines in the United Kingdom and the United States: Observational Study.* J Med Internet Res, 2021. **23**(4): p. e26627.
36. Lyu, J.C., E.L. Han, and G.K. Luli, *COVID-19 Vaccine–Related Discussion on Twitter: Topic Modeling and Sentiment Analysis.* J Med Internet Res, 2021. **23**(6): p. e24435.
37. Berg, S.H., et al., *Health authorities' health risk communication with the public during pandemics: a rapid scoping review.* BMC Public Health, 2021. **21**(1): p. 1401.
38. Andrew, B.P., et al., *Finding the facts in an infodemic: framing effective COVID-19 messages to connect people to authoritative content.* BMJ Global Health, 2022. **7**(2): p. e007582.
39. Pakhtigian, E.L., et al., *COVID-19, public health messaging, and sanitation and hygiene practices in rural India.* Journal of Water, Sanitation and Hygiene for Development, 2022. **12**(11): p. 828-837.
40. Officer, T.N., et al., *Experiences of New Zealand public health messaging while in lockdown.* Australian and New Zealand Journal of Public Health, 2022. **46**(6): p. 735-737.

Supplementary Files

Figures

Fig 1: Frequency and engagement for each sentiment category.

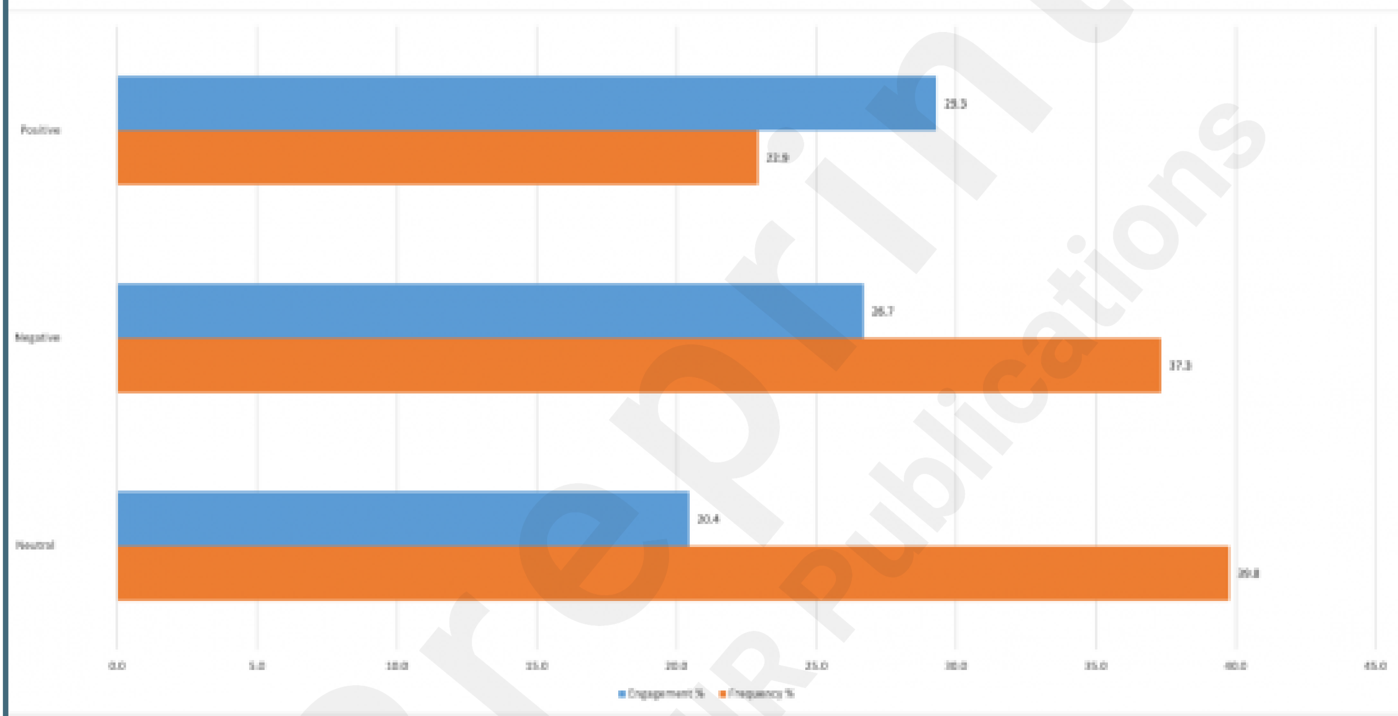


Fig 2: Frequency and engagement for each user category excluding public.

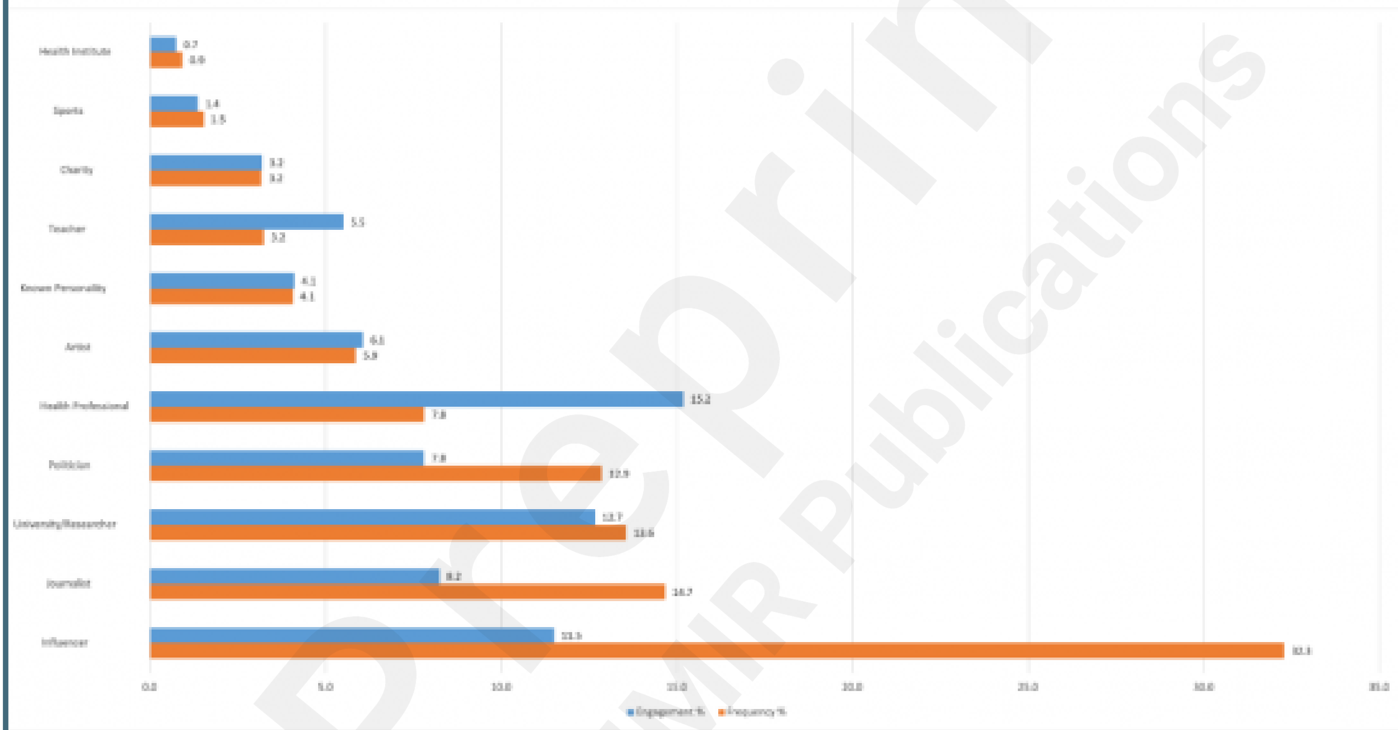
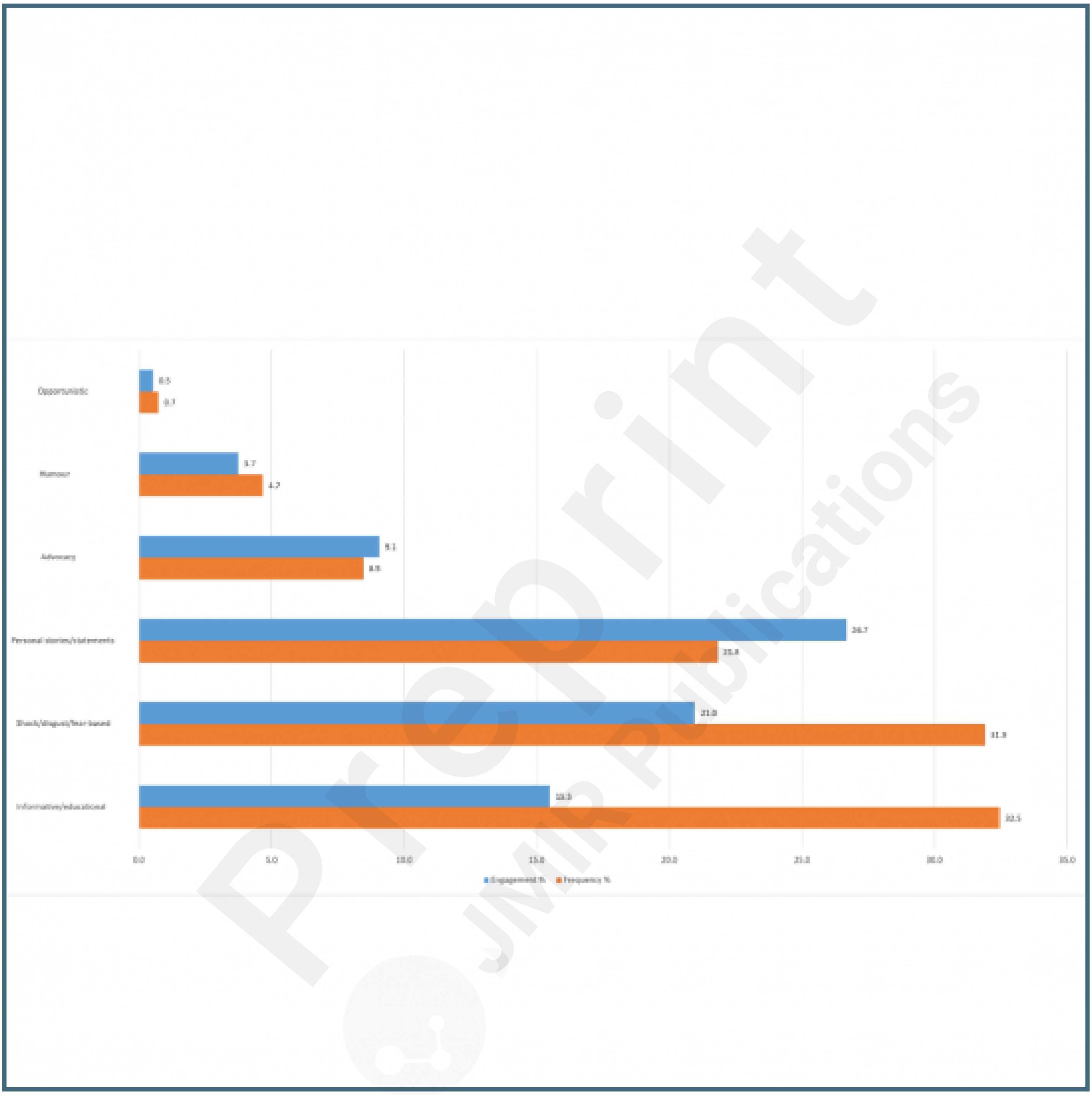


Fig 3: Frequency and engagement for each message type.



Multimedia Appendixes

Sentiment Analysis.
URL: http://asset.jmir.pub/assets/3f2fcdd22361dc90405f50045b1fa70e.xlsx

User classification.
URL: http://asset.jmir.pub/assets/2212cb848c401ef0c2791fc20620b36a.xlsx

Message classification.
URL: http://asset.jmir.pub/assets/d1f11760784483c0b12c27d8529936c8.xlsx

Results of zero-inflated model.
URL: http://asset.jmir.pub/assets/5ca4b8355a055def54ce848a5be6ba07.xlsx

Revised Manuscript with introduction.
URL: http://asset.jmir.pub/assets/1dc04c1454ea7dd3f993c1224bab8827.docx