

Online Supplementary Material for Social Media Amplification of Risk about COVID-19 Vaccination and Vaccine Acceptance Among Peruvian Social Media Users: A Longitudinal Time Series Analysis

S1. Topic Modeling

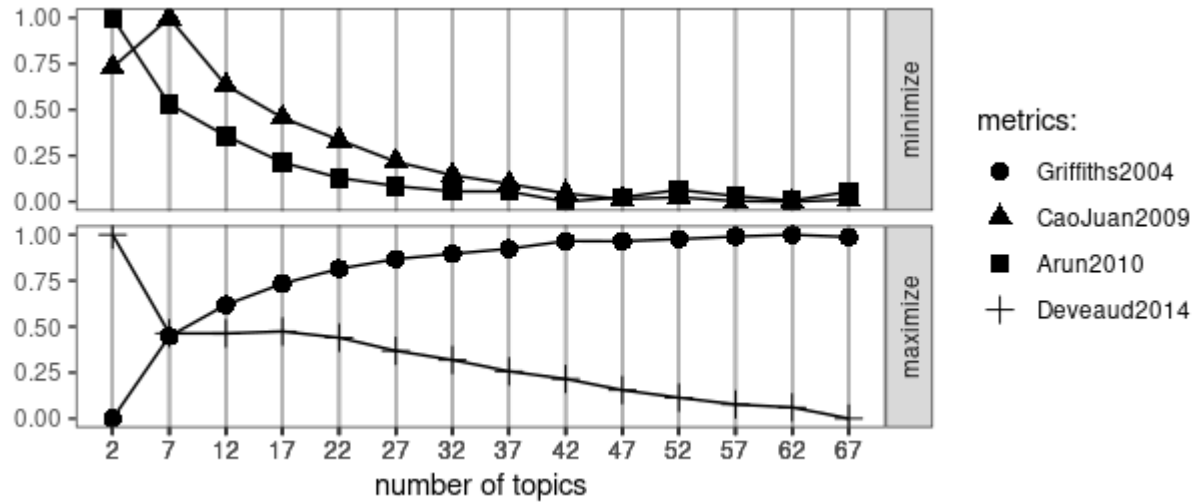


Figure S1 LDATuning findk results plot

The visualization of finding the optimal number of topics using the four algorithms provided by the LDATuning package [82].

Table S1 Top 10 Words for each topic and the assigned clusters

| <i>Cluster</i> | <i>Topic Name</i> | <i>Top Words</i> |
|---|--------------------------------|---|
| <i>COVID Economy</i> | Economy and the Pandemic | ninos, venezolanos, migrantes, personas, estan, colombia, miles, jovenes, padres, frontera |
| <i>COVID Economy</i> | COVID and Economy | pandemia, crisis, pais, politica, peor, mundo, situacion, medio, economica, economia |
| <i>COVID Economy</i> | Economy and the Pandemic | cambio, dolar, precio, mercado, precios, venezuela, peru, tipo, climatico, nuevo |
| <i>COVID Health</i> | COVID and Institutions | personas, ayuda, puedan, urgencia, instituciones, agradece, siguiente, favor, solicita, colaborar |
| <i>COVID Health</i> | Health Professionals and COVID | salud, COVID, hospital, personal, pacientes, oxigeno, medico, atencion, medicos, camas |
| <i>COVID Non-Pharmaceutical Interventions</i> | Non-Pharma COVID Precautions | maskarilla, puede, aire, hacer, usar, medidas, personas, maskarillas, seguir, pueden |
| <i>COVID Non-Pharmaceutical Interventions</i> | COVID | medidas, semana, clases, restricciones, COVID, pandemia, nuevas, gobierno, santa, cuarentena |
| <i>COVID Non-Pharmaceutical Interventions</i> | Lockdowns | millones, dolares, euros, dinero, pagar, soles, pago, pesos, empresas, casi |
| <i>COVID Others</i> | Latin America Pandemic | casos, COVID, nuevos, coronavirus, repo, horas, contagios, ultimas, fallecidos, registra |
| <i>COVID Others</i> | COVID | casos, COVID, datos, dias, mayor, aumento, espana, fallecidos, numero, cada |
| <i>COVID Others</i> | Global Pandemic English | people, need, know, just, health, dont, pandemic, like, says, many |
| <i>COVID Others</i> | Global Pandemic 2 English | year, china, the, global, climate, world, says, pandemic, years, billion |
| <i>COVID Others</i> | Governments during Pandemic | salud, impo, educacion, publica, ciencia, pandemia, ancia, mental, trabajo, desarrollo |
| <i>COVID Others</i> | COVID | COVID, estudio, virus, vacunas, riesgo, puede, enfermedad, ivermectina, personas, segun |
| <i>COVID Vaccination</i> | Vaccinations | vacunacion, mayores, anos, personas, COVID, adultos, dosis, poblacion, vacunar, proceso |
| <i>COVID Vaccination</i> | Vaccination | vacunas, dosis, millones, COVID, vacuna, pfizer, paises, pais, mexico, lote |
| <i>COVID Vaccination</i> | Vaccination | nueva, europa, unido, reino, paises, espana, york, coronavirus, union, europea |
| <i>COVID Vaccination</i> | Vaccinations | vacuna, dosis, COVID, astrazeneca, pfizer, primera, segunda, vacunas, coronavirus, sputnik |
| <i>COVID Vaccination</i> | Vaccination English | COVID, vaccine, cases, coronavirus, repo, people, deaths, vaccines, variant, million |
| <i>COVID Variants</i> | COVID Variants | COVID, variante, coronavirus, nueva, delta, positivo, virus, india, caso, china |
| <i>International</i> | US Protests | horror, laughing, like, house, heres, capitol, protrump, guns, stormed, doors |

| | | |
|----------------------|--|---|
| <i>International</i> | World News | mujeres, violencia, sexual, derechos, israel, humanos, genero, abuso, mujer, victimas |
| <i>International</i> | Global Politics | biden, trump, EEUU, presidente, unidos, casa, capitolio, donald, blanca, rusia |
| <i>International</i> | US Elections | biden, trump, president, says, house, white, former, election, first, trumps |
| <i>International</i> | US & UK News | police, people, death, killed, woman, prince, says, family, dead, found |
| <i>International</i> | World News | johnson, first, says, live, boris, minister, time, england, kong, tokyo |
| <i>International</i> | Global News (Miami Building Accident & Israel) | tras, menos, miami, personas, edificio, accidente, heridos, video, dejo, deja |
| <i>International</i> | News Headlines | luis, jose, albe, juan, fernandez, carlos, miguel, garcia, jorge, rodriguez |
| <i>International</i> | Olympics | juegos, tokio, olimpicos, final, depo, tras, mundial, gran, espana, historia |
| <i>International</i> | News Headlines | policia, video, seguridad, personas, banda, policias, detalles, armas, delincuentes, nacional |
| <i>International</i> | US Elections | agenda, open, georgia, much, senate, bidens, voting, determine, polls, controls |
| <i>International</i> | Politics Spain | madrid, real, sanchez, espana, gobierno, ayuso, directo, pablo, iglesias, tras |
| <i>Other</i> | Pop Culture News | madre, familia, hijo, padre, hija, vida, principe, reina, harry, tras |
| <i>Other</i> | Sports | fecha, liga, equipo, final, colo, boca, victoria, futbol, vivo, river |
| <i>Other</i> | Mixed News | detalles, aqui, saber, tener, puedes, hacer, info, conoce, debes, contamos |
| <i>Other</i> | Pop Culture | mundo, conve, tierra, espacio, primer, video, historia, primera, nuevo, irse |
| <i>Other</i> | Global Politics and News | anos, papa, historia, francisco, hace, gran, vida, celebra, amor, iglesia |
| <i>Other</i> | Sports | copa, america, final, messi, argentina, barcelona, seleccion, libe, brasil, futbol |
| <i>Other</i> | South America | ciudad, mexico, agua, metro, centro, depa, amento, capital, zona, linea |
| <i>Other</i> | Mixed Entertainment | vivo, programa, sigue, minuto, aqui, canal, senal, abie, directo, radio |
| <i>Other</i> | Peru Politics | elecciones, electoral, vuelta, segunda, resultados, votos, mesa, candidatos, voto, actas |
| <i>Other</i> | Entertainment | vivo, serie, nueva, cnmovista, nnen, cndirectv, cnbestcable, pelicula, netflix, mejor |
| <i>Other</i> | News Headlines | video, redes, sociales, fotos, foto, imagenes, viral, tras, hizo, compa |
| <i>Other</i> | Headlines Mix | noticias, hora, nacional, ultima, internacional, impo, peru, diario, compa, oficial |

| | | |
|-----------------------------------|---|---|
| <i>Peruvian Politics Election</i> | Peruvian Elections | castillo, pedro, peru, keiko, fujimori, libre, cerron, popular, fuerza, equipo |
| <i>Peruvian Politics Election</i> | Peruvian Elections 2 | lopez, candidato, presidente, aliaga, rafael, obrador, presidencial, soto, guzman, julio |
| <i>Peruvian Politics Election</i> | Social Media | america, cuenta, twitter, latina, whatsapp, facebook, informacion, google, traves, internet |
| <i>Peruvian Politics Election</i> | Peru Politics | keiko, izquierda, derecha, votar, voto, peru, solo, ahora, castillo, fujimori |
| <i>Peruvian Politics General</i> | Politics | ministro, presidente, gobierno, sagasti, salud, vivo, prensa, francisco, consejo, ministros |
| <i>Peruvian Politics General</i> | Politics - Constitution | congreso, comision, proyecto, presidente, constitucional, reforma, constitucion, mesa, pleno, popular |
| <i>Peruvian Politics General</i> | Politics | estan, medios, politicos, solo, comunicacion, ahora, hacen, haciendo, dicen, tambien |
| <i>Peruvian Politics General</i> | Peru Politics | vizcarra, dice, ahora, gobierno, solo, sagasti, senor, hizo, presidente, debe |
| <i>Peruvian Politics General</i> | Peru Politics | libe, democracia, pais, derecho, pueblo, debe, poder, peru, vamos, resion |
| <i>Peruvian Politics General</i> | Politics - Corruption | caso, fiscal, fiscalia, justicia, investigacion, prision, juez, judicial, corrupcion, tribunal |
| <i>Regional Protests</i> | South America Politics & Cuban Protests | cuba, colombia, protestas, presidente, duque, gobierno, venezuela, ivan, tras, haiti |
| <i>Venezuela</i> | Venezuela | gobierno, publico, sector, transpo, plan, nacional, empresas, trabajo, servicio, ministerio |
| <i>Venezuela</i> | Venezuelan Politics | maduro, venezuela, regimen, guaido, nicolas, presidente, detalles, alex, venezolanos, rodriguez |

Among the COVID-related topics, COVID vaccination stood out most clearly as prominent, including 8.2% of the tweets, with the most temporal variability and the greatest standard deviation of prevalence (SD=.7%) followed by COVID Non-Pharmaceutical Interventions (e.g., lockdowns, masking, quarantines, travel restrictions) at 4.5%. The variances in topic prominence of other COVID-related topics such as Non-Pharmaceutical Interventions (SD=.3%) and COVID Health impacts (SD=.2%) was substantially less. The lower variation in non-vaccine COVID-related topics may harm the efforts to associate their prevalence with risk factors.

S2. Sentiment Analysis

The sentiment calculations were done using a crowdsourced sentiment lexicon in English and Spanish [89]. The lexicon is open-source and can be downloaded via the website <https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm>, or by the Tidyverse package [109] in R Studio. The lexicon works by giving a score to the words in the sentence, with corresponding sentiment and emotion. At Figure S2.1 you can see an example from the corpus and the sentiment scoring.

Figure S2 Sentiment analysis example

Tweet

- "bes falso que la vacuna china sinovac de coronavirus sea ineficaz de acuerdo con datos del ministerio de salud de chile la eficacia para evitar enfermedad supera el y el para evitar la mue"

NRC Dictionary in English and Spanish

- negative score: falso (5) + ineficaz (2) + evitar (2) + enfermedad (5) + evitar (2) = 16
- positive score: sea (1) + acuerdo (3)
- trust score: acuerdo (3) + ministerio (1) = 4

Net Sentiment

- Net sentiment: positive (5) - negative (16) = -11

There are multiple limitations to using a lexicon based approach to sentiment analysis, which Mohammad & Turney describe in detail in their paper introducing NRC [89]. First and foremost, lexicon approach does not take context into account, such as the sentence could be satirical, cynical, or a using word with local or temporal homonyms. Secondly, the word-sentiment scoring does not consider preceding and anterior words in sentiment calculations.

S3. Sentiment Analysis weighed with topic prominence

From the LDA object we receive for each document, in our case, tweet's gamma value which represents the probability of the topic in each of the documents. For each tweet we multiplied the gamma value of the tweet for the topic cluster Covid Vaccination with net sentiment and trust (figure S3.1).

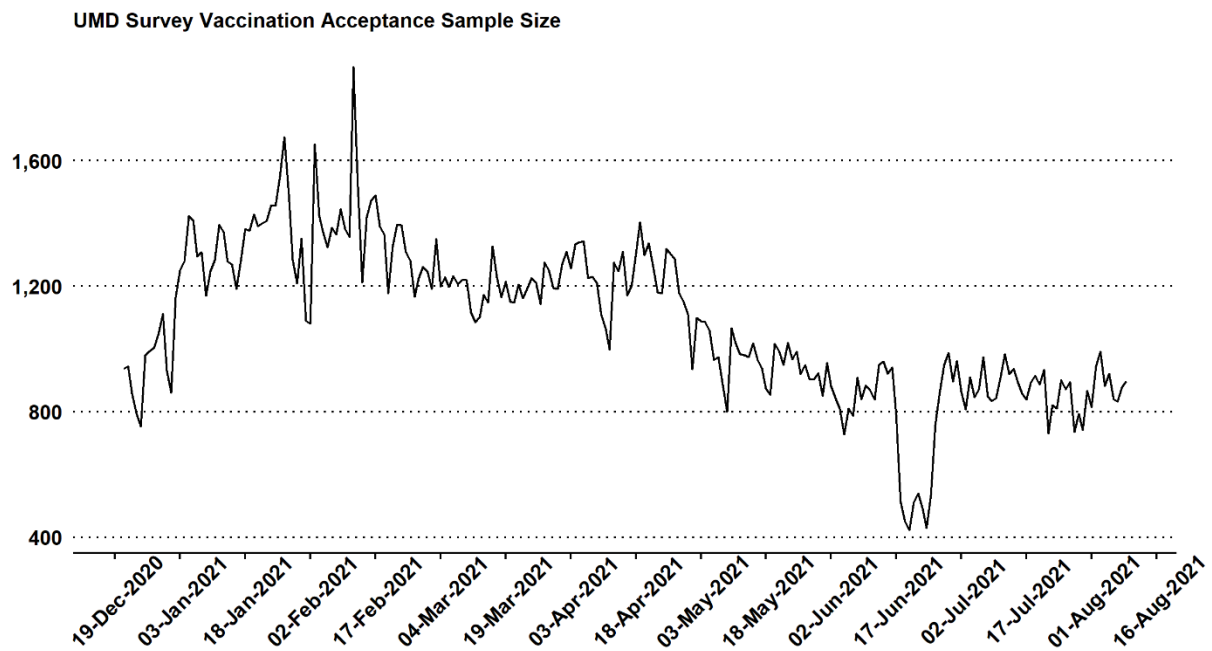
Figure S3 Sentiment scores weighed with topic prominence example

| | |
|---|--|
| Tweet | <ul style="list-style-type: none">• "bes falso que la vacuna china sinovac de coronavirus sea ineficaz de acuerdo con datos del ministerio de salud de chile la eficacia para evitar enfermedad supera el y el para evitar la mue" |
| Sentiment Scores | <ul style="list-style-type: none">• Net Sentiment: -11• Trust: 4 |
| Gamma Value for Covid Vaccination Cluster | <ul style="list-style-type: none">• 0.6164384 |
| Sentiment weighed with topic probability | <ul style="list-style-type: none">• Net Sentiment Covid Vaccination: $-11 \times 0.6164384 = -6.7808224$• Trust Sentiment Covid Vaccination: $4 \times 0.6164384 = 2.4657536$ |

S4. The Global COVID-19 Trends and Impact Survey Open Data API [4]

The dependent variable Vaccination Acceptance in Peru was retrieved from the API of The Global COVID-19 Trends and Impact Survey Open Data API [110]. The dependent variable was created with two separate API indicator names as the initial indicator was replaced in Wave 11:

- For 12/20/2020 to 05/19/2021 the indicator vaccine_acpt, defined as “Respondents definitely or probably choosing to get vaccinated if a COVID-19 vaccine was offered to them, out of the respondents who have not been vaccinated. Note: Replaced by appointment_or_accept_covid_vaccine in Wave 11”; and,
- For 05/20/2021 to 08/09/2021 the indicator vaccinated_appointment_or_accept, defined as “Respondents who had a vaccine, an appointment to get vaccinated or who would definitely or probably choosing to get vaccinated if a COVID-19 vaccine was offered to them” [18].

S4 Fig Sample Sizes of Vaccine Acceptance from The Global COVID-19 Trends and Impact Survey Open Data API [110]

S5. Robustness Checks

Table S2 Reverse Time Series

| | Net Sentiment | | Trust | |
|--|-------------------|--------------------|-------------------|--------------------|
| | <i>Estimates</i> | <i>CI</i> | <i>Estimates</i> | <i>CI</i> |
| Vaccine Acceptance % (lag 1) | -0.036 (0.019) | [-0.073, 0.001] | -0.031 (0.018) | [-0.067, 0.005] |
| Vaccine Acceptance % (lag 2) | 0.016 (0.019) | [-0.021, 0.053] | 0.027 (0.018) | [-0.009, 0.064] |
| Vaccine Acceptance % (lag 3) | -0.033 (0.019) | [-0.070, 0.003] | -0.029 (0.018) | [-0.065, 0.007] |
| trend | 0.000 (0.000) | [-0.000, 0.000] | -0.000 (0.000) | [-0.000, 0.000] |
| Observations | 227 | | 227 | |
| R ² / R ² adjusted | 0.416 / 0.392 | | 0.556 / 0.538 | |

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table S3 Time Series Analysis with Only Vaccinated Survey

| covid_vaccine (v1) | | | covid_vaccine (v1) | | |
|--|--------------------|--------------------|--|--------------------|--------------------|
| <i>Predictors</i> | <i>Estimates</i> | <i>CI</i> | <i>Predictors</i> | <i>Estimates</i> | <i>CI</i> |
| Trust (lag 1) | 0.471 (-0.24) | [-0.002, 0.944] | Net Sentiment (lag 1) | 0.274 (-0.247) | [-0.214, 0.761] |
| Trust (lag 2) | -0.052 (-0.258) | [-0.561, 0.456] | Net Sentiment (lag 2) | -0.079 (-0.248) | [-0.568, 0.411] |
| Trust (lag 3) | 0.039 (-0.239) | [-0.432, 0.509] | Net Sentiment (lag 3) | -0.251 (-0.242) | [-0.727, 0.226] |
| trend | 0.000 * (0) | [0.000, 0.000] | trend | 0 (0) | [-0.000, 0.000] |
| Observations | 212 | | Observations | 212 | |
| R ² / R ² adjusted | 0.990 / 0.990 | | R ² / R ² adjusted | 0.990 / 0.989 | |

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table S4 Time Series Analysis with Respondents more likely to get vaccinated if recommended by friends and family as Covariate.

| <i>Predictors</i> | Vaccination Acceptance Model 1 | | Vaccine Acceptance Model 2 | |
|--|---|--------------------|---------------------------------------|--------------------|
| | <i>Estimates</i> | <i>CI</i> | <i>Estimates</i> | <i>CI</i> |
| Trust (lag 1) | 0.730 ** (-0.272) | [0.191, 1.269] | | |
| Trust (lag 2) | -0.262 (-0.293) | [-0.840, 0.317] | | |
| Trust (lag 3) | 0.039 (-0.293) | [-0.541, 0.618] | | |
| Trust (lag 4) | 0.456 (-0.254) | [-0.047, 0.959] | | |
| Net Sentiment (lag 1) | | | 0.728 ** (-0.261) | [0.212, 1.244] |
| Net Sentiment (lag 2) | | | -0.433 (-0.287) | [-1.001, 0.136] |
| Net Sentiment (lag 3) | | | 0.167 (-0.287) | [-0.400, 0.735] |
| Net Sentiment (lag 4) | | | 0.151 (-0.245) | [-0.334, 0.635] |
| Vaccination Acceptance with Family Recommendation (lag 1) | -0.002 (-0.057) | [-0.115, 0.112] | 0.003 (-0.058) | [-0.112, 0.118] |
| Vaccination Acceptance with Family Recommendation (lag 2) | -0.028 (-0.062) | [-0.150, 0.094] | -0.021 (-0.062) | [-0.144, 0.102] |
| Vaccination Acceptance with Family Recommendation (lag 3) | -0.052 (-0.06) | [-0.171, 0.067] | -0.029 (-0.062) | [-0.150, 0.093] |
| Vaccination Acceptance with Family Recommendation (lag 4) | 0.003 (-0.056) | [-0.108, 0.114] | -0.023 (-0.057) | [-0.135, 0.089] |
| trend | 0.001 *** (0) | [0.000, 0.001] | 0.000 ** (0) | [0.000, 0.001] |
| Observations | 145 | | 145 | |
| R ² / R ² adjusted | 0.892 / 0.881 | | 0.889 / 0.878 | |

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$