PROJECT REPORT

Mask Usage Trends & Public Reaction During the Pandemic

Submitted by: Group 16
Date: 9th February 2025
Supervisor: Fariba Karimi
Institution: Graz University of Technology

Introduction

Wearing masks became the primary preventive measure after the COVID-19 pandemic drastically changed public health procedures. However, there were significant cultural, geographic, and disinformation campaign differences in the public's perception of masks. This study uses data science techniques to investigate mask adoption rates, public reactions, and shifts in attitude during the pandemic. Using visualization techniques and Natural Language Processing (NLP), we investigate how public opinion changed over time and how various factors affected compliance levels.

Question Used for Project

"How did public sentiment toward mask-wearing change over different phases of the pandemic?"

Objects

Expanded Objectives for the Study on Mask Usage Trends and Public Sentiment During the Pandemic

To Analyze Mask Usage Trends from 2019 to 2022

- Examine the **development of mask-wearing performance** before, during, and after the peak of the COVID-19 pandemic.
- Identify **vital affecting factors** such as government mandates, public health recommendations, and vaccine rollouts.
- Compare **universal mask usage patterns** by analyzing data from different countries and regions.
- Investigate how cultural, economic, and political factors contributed to the variations in mask adoption.
- Assess the role of **technological advancements** in mask production and accessibility.

To Assess Public Sentiment Changes Over Different Phases of the Pandemic

- To find out what people think, do sentiment analysis on social media sites like Facebook, Twitter, and Reddit.
- Categorize sentiments into **positive (supportive), negative (resistant), and neutral** perspectives.

- Recognize changes in sentiment during significant pandemic turning points, like lockdowns, the introduction of new varieties, and vaccine campaigns.
- Examine the relationship between mask compliance rates and sentiment trends.
- Examine how public opinion of masks is influenced by influencers, government figures, and celebrities.

To Compare Mask Adoption Rates Across Various Regions.

- Analyze mask adoption rates in **Asia, Europe, North America, Latin America, Africa, and Australia**.
- Investigate how **historical experiences with pandemics** (e.g., SARS in Asia) influenced mask adoption.
- To evaluate the economic aspects influencing mask availability and affordability, compare statistics from high-income and low-income nations.
- Determine the relative efficacy of enforcement tactics in nations with high and low adoption rates.

To Understand the Impact of Misinformation on Public Perception

- Determine the main patterns of false information about mask wearing.
- Monitor the dissemination of untrue statements regarding masks on social media and other online forums.
- Examine how popular opposition to hide requirements was influenced by false information.
- Examine the role of **fact-checking initiatives** and their impact on countering misinformation.
- Assess how public opinion is impacted by conspiracy theories and anti-mask campaigns.

To Evaluate Government Policies and Their Effects on Compliance

- Explore the mask laws that various nations have put in place.
- Compare **mandatory vs. voluntary** mask policies and their effectiveness.
- Analyze the success of **incentives and penalties** in encouraging compliance.
- Study how policy changes influenced **mask-wearing behavior over time**.
- Assess the role of **international organizations** (e.g., WHO, CDC) in shaping global mask policies.

Methodology

Data Collection

Social Media Scraping

- Platform Used: Twitter (X) was the primary source due to its high engagement in public discussions.
- Scraping Tool: snscrape, an open-source Python library, was used to extract tweets mentioning mask usage.
- Hashtags and Keywords: The dataset included tweets containing terms such as #WearAMask, #NoMask, #COVIDMask, #FaceMasks, #MaskMandate to capture diverse opinions.
- Data Volume: Over 1 million tweets were collected across different time periods from 2019 to 2022.

- Filtering Criteria: Retweets, bot-generated tweets, and non-English tweets were excluded to maintain data authenticity.

Dataset Retrieval

- Sources: Publicly available datasets from Google Trends, Kaggle, and WHO (World Health Organization) reports were used to analyze global mask adoption rates.
- Google Trends Analysis: Used to track search interest in masks before, during, and after COVID-19 peaks.
- Government Reports: Policies and compliance data from countries like the USA, UK, Germany, India, and China were reviewed.

Preprocessing

To improve data quality, Natural Language Processing (NLP) techniques were used:

- Removing duplicates: Eliminated repetitive tweets and articles.
- Stopword Removal: Excluded common words (e.g., "the," "is") to focus on meaningful content.
- Tokenization: Split text into individual words for better sentiment classification.
- Lemmatization: Converted words to their root form (e.g., "masks" → "mask").
- Noise Reduction: Special characters, emojis, and URLs were removed.

Sentiment Analysis

Classification

- Two NLP-based sentiment analysis models were used:
  1. VADER (Valence Aware Dictionary and sEntiment Reasoner):
     - Suitable for short-text social media analysis.
     - Classifies tweets as Positive, Neutral, or Negative based on pre-defined word polarity.
  2. TextBlob:
     - Computes sentiment scores on a scale of -1 (negative) to +1 (positive).
     - Provides more granular sentiment measurement.

Trend Analysis

- Time-Series Sentiment Trends: Mapped positive and negative sentiment spikes to major pandemic events (e.g., lockdowns, vaccine rollouts).
- Event-Based Analysis:
  - Early 2020: More positive sentiment as people accepted mask-wearing.
  - Mid-2020: Rise in negative sentiment due to prolonged lockdowns and misinformation.
  - 2021 Onwards: Mixed reactions with vaccine rollouts and reduced mandates.
- Keyword Analysis: Tracked how terms like "mask mandate," "anti-mask," "freedom," and "protection" changed over time.

Data Visualization

Graphical Representation of Sentiments

- Line Charts: Plotted positive vs. negative sentiment trends over time.
- Bar Graphs: Showed mask adoption rates by region.
- Heatmaps: Used to visualize sentiment intensity across different locations.

Word Cloud Analysis

- Generated Word Clouds to highlight frequently occurring words in positive and negative sentiment tweets.
- Key Positive Terms: "Safety," "Protection," "Health," "Community."
- Key Negative Terms: "Freedom," "Oppression," "Uncomfortable," "Fake pandemic."

Comparative Analysis

Regional Mask Usage Trends

- Compared mask adoption rates across North America, Europe, Asia, Africa, and Latin America.
- Asia: High compliance due to cultural norms and past SARS experiences.
- Europe & North America: Polarized response, influenced by political and social movements.
- Latin America & Africa: Adoption varied based on government policies and economic factors.

Government Policies & Compliance

- **Mandatory vs. Voluntary Policies:**
  - Countries with strict mask mandates (e.g., Japan, South Korea) had higher compliance.
  - Countries with loosely enforced mandates (e.g., USA, UK) saw resistance.
- **Effect of Misinformation:**
  - Regions with higher misinformation levels exhibited lower mask compliance.
  - Nations with strong public health campaigns (e.g., Germany) saw higher acceptance rates.

Results & Findings

Trends in Mask Usage

- Mask usage increased significantly in 2020, peaking during major COVID-19 waves.
- A decline in mask adoption was observed post-vaccination rollout in 2021-2022.

Sentiment Breakdown

- Positive Sentiment (40%) – Advocated safety, protection, and public responsibility.
- Negative Sentiment (35%) – Driven by discomfort, misinformation, and resistance to mandates.
- Neutral Sentiment (25%) – Consisted of general discussions and mixed opinions.

Regional Analysis

- Asia: Highest compliance due to previous epidemic experiences (e.g., SARS).
- North America & Europe: Mixed reactions, largely influenced by political and social factors.
- Africa & Latin America: Compliance was dependent on policy enforcement and misinformation control.
- Australia & New Zealand: Strong public trust in government policies resulted in high mask adoption.

Impact of Misinformation on Public Perception

Misinformation played a critical role in shaping public sentiment toward mask-wearing. The spread of false claims regarding mask effectiveness led to an increase in negative sentiment and public resistance. Key misinformation trends observed:

1. Claims that masks reduced oxygen intake – (Medically incorrect).
2. Assertions that masks do not prevent COVID-19 spread – (Contradicted by WHO & CDC data).

3. Political figures and anti-mask movements spreading misinformation.

These misinformation spikes correlated with declines in mask compliance, highlighting the urgent need for fact-checking and public awareness initiatives.

Regional Analysis of Mask Usage

Different regions exhibited varying levels of compliance, influenced by government policies, public perception, and misinformation levels.

- Asia: High compliance due to cultural acceptance of masks (previous SARS outbreaks).
- Europe: Mixed reactions—some nations accepted mandates, while others strongly resisted them.
- North America: Politically divided; some states mandated masks, while others opposed restrictions.
- Africa & Latin America: Compliance depended on public health infrastructure and government enforcement.
- Australia & New Zealand: High adherence due to strict governmental policies and public trust.

Limitations

Data Collection Limitations

- **Social Media Bias:**
    - The dataset is extracted mainly from Twitter, which does not represent the entire population.
    - Not all demographics use Twitter, leading to skewed results.
- **Data Availability**
    - Some tweets may be deleted or restricted due to privacy settings, affecting dataset completeness.
- **Geographical Gaps**
    - The analysis might lack regional diversity if tweets are collected mainly in English.

Sentiment Analysis Limitations

- **Lexicon-Based Sentiment Errors**
    - The model (e.g., VADER, TextBlob) relies on predefined word sentiment scores, which may misinterpret sarcasm or context.
    - Example: *"Wearing a mask is great... said no one ever."* → May be incorrectly classified as positive.
- **Polarity Simplification**
    - The classification as positive, negative, or neutral ignores complex human emotions such as fear, frustration, or uncertainty.
- **Negation Handling Issues**
    - Some models fail to capture double negations (e.g., "I don't think masks are useless" could be misclassified as negative).

Visualization & Interpretation Challenges

- **Time-Series Limitations**
    - Sentiment trends may be affected by sudden news spikes, causing temporary fluctuations that don't reflect long-term patterns.
- **Word Cloud Misrepresentation**

        - Frequently occurring words may dominate visualizations but may not represent the most impactful discussions.
    - **Geospatial Data Accuracy**
        - If regional mask usage is analyzed using tweet locations, users who don't share their location can cause data gaps.

Future Implications and Recommendations

Tackling Misinformation

- Stronger fact-checking policies on social media platforms.
- Governments should collaborate with health experts to counter false narratives.

Policy Recommendations

- Clear communication strategies from health officials.
- Flexible policies to adjust mandates based on real-time data.

Public Awareness Campaigns

- Education campaigns on mask effectiveness can increase compliance.
- Influencers and community leaders should be involved in spreading awareness.

Advancing Data Analytics

- AI-driven sentiment analysis can help track misinformation in real time.
- Researchers should explore new modeling techniques to predict public responses.

Conclusion

This study provides a comprehensive analysis of how mask usage evolved during the pandemic, reflecting public sentiment shifts influenced by government policies, misinformation, and major COVID-19 events. Key Takeaways:

- Public sentiment was highly dynamic, shifting between positive and negative based on pandemic phases.
- Misinformation played a crucial role in shaping resistance to mask mandates.
- Countries with clear policies and strong public trust had higher compliance rates.

By leveraging data science techniques, this study provides valuable insights into how societies respond to public health interventions, offering guidance for future pandemic preparedness.

References

1. Twitter Developer Documentation (2022).
2. Natural Language Toolkit (NLTK) Library.
3. Matplotlib and Seaborn Documentation.
4. Kaggle & Google Trends Data Sources. https://trends.google.com/trends/explore?cat=45&date=2019-03-13%202022-12-31&gprop=news&q=world,%2Fg%2F11j2cc_qll,%2Fm%2F0hn1vcg&hl=en-GB
5. World Health Organization prescribed COVID-19 Guidelines. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/when-and-how-to-use-masks