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Perceived oppression and online support for COVID-19 non-compliance: the 2021 Trieste port protests

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The enforcement of COVID-19 containment measures, such as lockdowns or mandatory vaccination, can have significant consequences for both public health and the economic stability of institutions. As a result, widespread non-compliance poses a particular challenge for governments. In October 2021, workers in Trieste, Italy, blocked the city's commercial port in protest against new restrictions, triggering large-scale demonstrations and an explosion of related activity on Twitter. We analyze this unique case of mass non-compliance by collecting tweets about the protests and applying sentiment analysis, topic modeling, opinion analysis, user clustering, and diffusion modeling. Our findings reveal a strong connection between online support for non-compliance and emotions such as anger and mistrust, particularly toward the government, which are often framed as reactions to perceived injustice or oppression. The results suggest that social media played a key role in amplifying and normalizing non-compliant sentiment. While this study does not make normative claims about the legitimacy of either side, it offers a methodological lens for understanding how polarizing debates unfold online. This approach can also be extended to other divisive issues such as climate policy, military conflict, or artificial intelligence, or in general with regards to contrasting or diverse opinions discussed online. By better understanding the motivations and narratives of non-compliers, institutions may be better equipped to foster dialogue and reduce reliance on force.

KEYWORDS

Twitter, COVID-19, Trieste, protests, sentiment analysis, negative binomial regression, topic modeling, clustering

1 Introduction

Although there is a rich body of work on online activism, protest dynamics, and compliance with public health measures, important gaps remain in the literature. Social media platforms such as Twitter have been widely studied in connection with political unrest, protest coordination, and digital mobilization (Varol et al., 2014; Conover et al., 2013; Choudhary et al., 2012). Similarly, numerous studies have examined online discourse related to COVID-19 restrictions, focusing on themes such as vaccine hesitancy, attitudes toward mask mandates, and compliance behaviors (Fatemi et al., 2022; Bir and Widmar, 2021; Mladenović et al., 2023). However, research at the intersection of these fields, specifically, online support for non-compliance with COVID-19 restrictions in the context of a concrete protest event, remains scarce. Addressing this gap would provide valuable insights into how online discourse not only reflects but potentially fuels organized acts of health-related non-compliance, an underexplored dimension of online political communication.

The literature also offers conflicting explanations for why individuals defy public health measures. Much of the scholarship has emphasized psychological or individual-level characteristics, including empathy, altruism, and susceptibility to social pressure (Józefacka et al., 2022; Lu et al., 2021; Mladenović et al., 2023; Bir and Widmar, 2021; Fatemi et al., 2022). At the same time, an emerging line of research highlights structural and political drivers, such as mistrust of institutions, dissatisfaction with government communication (Costa et al., 2025), and reactions to police crackdowns (Roach, 2025). Other studies point to opinion polarization and the amplification of conspiratorial narratives online as central to understanding non-compliance (Lee et al., 2021). These strands of scholarship underscore the need for empirical studies that examine how online discourse, sentiment, and protest events interact to shape attitudes toward restrictive measures.

The anti-compliance October 2021 protests in Trieste, Italy, provide a unique opportunity to address this gap. The large database of Twitter discourse in support of non-compliance can illustrate how narratives of resistance to COVID-19 measures emerged and spread online. In September 2021, Italy introduced a law requiring all workers to present the EU Digital COVID Certificate, or "green pass," effectively imposing a vaccine mandate. This policy sparked strong opposition in Trieste, a key commercial port where around 40% of port workers were unvaccinated. On 1 October, port employees threatened to halt operations, and by mid-October, after the mandate took effect, they launched a blockade. Protests escalated on 11 October, drawing thousands of demonstrators who defied social distancing rules to oppose the mandate. Table 1 outlines the main events of the protests. Notably, this event marked the first coordinated action by a group of workers explicitly refusing vaccination while also mobilizing widespread public and union support across the country. Importantly, the spread of narratives online is significant: in parallel to the physical demonstrations, the protest also catalyzed a large-scale response in online discourse, particularly on the social media platform Twitter (now "X"). The events were widely discussed, with thousands of users posting hundreds of thousands of messages expressing a range of perspectives. While some users criticized the protest and framed it as an act of irresponsibility, others voiced strong support for the demonstrators. Figure 1 displays the number of tweets collected per day over the relevant period.

The contributions of the present research are multiple. This paper directly addresses the gap in the literature by examining online support for COVID-19 restriction non-compliance in the context of a concrete protest event, an intersection that remains underexplored. By focusing on the Trieste port protests, this study provides a rare opportunity to investigate how digital discourse reflects and amplifies organized acts of public health non-compliance, offering empirical evidence of the interaction between online sentiment and offline mobilization. Therefore, we complement existing research on individual and structural drivers of non-compliance by analyzing unfiltered user-generated content—tweets, reactions, and network interactions—to uncover the motivations and narratives expressed. Finally, this case study illustrates how digital platforms mediate dissent during politically sensitive health crises, providing insights that can inform future analyses of protest dynamics, public trust, and compliance during emergencies (e.g., Drescher et al., 2021). To achieve this, we employ a multi-method approach, combining sentiment analysis, topic modeling, user clustering, and diffusion modeling.

Findings indicate that expressions of anger from a relatively small group of users prior to the main protest played a significant role in amplifying online malcontent. User clustering further reveals that a limited number of highly active individuals drove the majority of the online engagement, aligning with previous findings (e.g., Conover et al., 2013). These patterns support previous work demonstrating that online and offline events are closely intertwined (Varol et al., 2014; Choudhary et al., 2012).

Consistent with (Costa et al., 2025; Roach, 2025), our results indicate that political discourse and perceptions of injustice directed toward law enforcement and political leaders were major drivers of anger, discontent, and online support for non-compliance. Notably, narratives involving hoaxes, misinformation, or conspiracy theories represented only a minor fraction of the overall content, suggesting that distrust and grievances, rather than disinformation, were the dominant forces shaping online sentiment and protest support.

1.1 Related works in compliance and noncompliance research

A current point of contention in the literature is the reasons attributed to non-compliance. Research regarding COVID-19 restriction policies shows that non-compliance is strongly related to trust in government institutions. Individuals with low trust in authorities were significantly less likely to comply with public health measures or accept vaccination (Nivette et al., 2021). Similarly, institutional trust was found to mediate the effect of fear and information source on compliance levels (Hrbková and Kudrnáč, 2024). Official narratives and use of force are also related to non-compliant behavior, as highlighted by emerging research, as in Costa et al. (2025); Lee et al. (2021); Roach (2025). At the same time, research links compliance to a multiplicity of factors, such as altruism and personal choice (Bir and Widmar, 2021), consensus and societal pressure (Thelwall and Thelwall, 2020), conformity (Mladenović et al., 2023), cultural factors (Lu et al., 2021), or individual psychological characteristics (Józefacka et al., 2022). Generally, the reasons for non-compliance are linked to a variety of factors. Among this multiplicity, it might be difficult to pinpoint the most relevant motivations or causes that might trigger actual offline action or political unrest. Our paper addresses this gap in the literature: by studying the Trieste protests, we investigate the weight of health-related concerns, conspiracy-oriented narratives, and perceived oppression in the drive for compliance.

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TABLE 1 Timeline of events.

Date	Event description	Example tweet
September 1, 2021	Italian parliament renders COVID-19 EU digital certification mandatory for all workers. Named "green pass" the certification basically makes vaccination mandatory. This generates protests by anti-vax movements.	Forcing a Green Pass, even on students who could easily take exams remotely, isn't about logistics it's about pushing them into vaccination. And if that's not discrimination, what is? N of likes: <10, date: 2021-09-01
September 8, 2021	No parliment opposition for green pass. The law is officially promulgated.	While they rile people up with the same old rhetoric, behind closed doors they're handing over the ports of TRIESTE and TARANTO. Understand? Silence... silence... N of likes: <10, date: 2021-09-08
September 20, 2021	First large anti green-pass protests in Triste.	Trieste, Monday, September 20, 2021: thousands filled the historic center chanting "No Green Pass." N of likes: >400, date: 2021-09-20
October 1, 2021	Port workers in Trieste, of whom 40% do not have a vaccine, threaten to close the port in protest.	The port workers of Trieste have made it official: if the Green Pass requirement for work takes effect on October 15, they'll stop operations. And they mean it. This government is headed for a hard fall." N of likes: >800, date: 2021-09-28
October 11, 2021	The port is blocked, no cargo can pass through. Large protests of 15.000 people (in a city of 200.000) against government-imposed vaccination. The protests reach their peak, and demonstrations appear in other Italian ports. No-Vax and extreme right fringes join the demonstrations.	The dockworkers of Genoa and Trieste, along with truckers, are ready to paralyze the whole north! Add to that unlimited strikes and essential skilled workers refusing to show up. In short, unless the government scraps this nonsense, northern businesses are finished! N of likes: >200, date: 2021-10-09
October 18, 2021	In the lieu of far-right fringes joining the protest and other controversies, the protest leader, Stefano Puzzer, resigns from his role. Police forcefully break the protests, opening the port to transit once again.	In Trieste, police unleash water cannons and batons on dockworkers and demonstrators. A rave in Viterbo? No. The storming of the CGIL? No. Peaceful workers protesting? Yes. So tell me, who's acting like the fascist now? Draghi! N of likes: >3,000, date: 2021-10-18
October 21, 2021	The strike ends officially.	Just learned that Facebook has taken down the Trieste dockworkers' group, which had nearly 300,000 members. N of likes: >600, date: 2021-10-21
November 1, 2021	Trieste municipality declares all demonstrations illegal. Puzzer, the protest leaders, receives an estrangement order from Rome. The protests are officially over.	Stefano Puzzer, the Trieste port worker leading the no-Green Pass protests, has been banned from Rome for a year. He had set up a stand in Piazza del Popolo and was reported for holding an unauthorized protest. If this isn't a dictatorship, what is? N of likes: >3000, date: 2021-11-02

One of the highest retweeted tweet for each day as been appended. Hashtags have been removed and text translated to Italian.

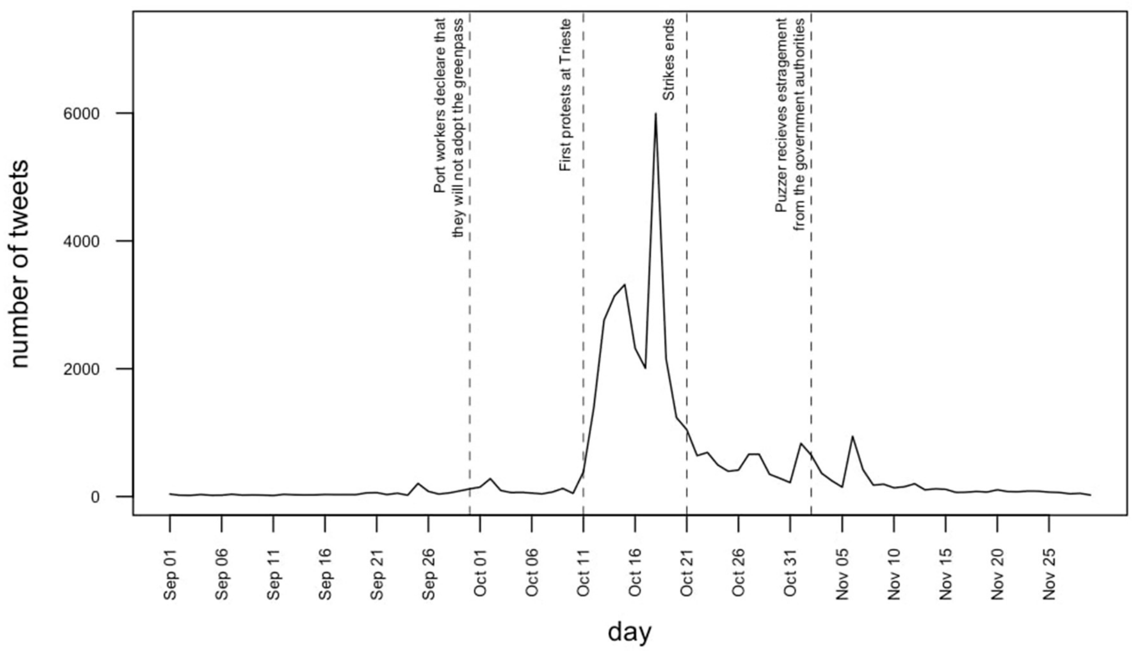

FIGURE 1
Number of collected tweets for each day, with timeline events added.

As indicated in the previous section, existing research has identified online activity in relation to civil unrest in different countries, as in the case of Varol et al. (2014) for Turkey, Conover et al. (2013); Thelwall and Thelwall (2020) for the United States, Choudhary et al. (2012) for Egypt, or Hrbková and Kudrnáč (2024) for the Czech Republic. At the same time, there is abundant literature on the online discourse regarding COVID restrictions (e.g., Thelwall and Thelwall, 2020; Fatemi et al., 2022). Nonetheless, the existing literature lacks an examination of COVID-related anti-compliance support during an offline event. Therefore, the present work enriches the literature on compliance and non-compliance research by analyzing the events of the Trieste anti-restrictions protests.

1.2 Situating Trieste in the European protest landscape

Considering the broader political frame in which the unrest took place, it is useful to note that the Trieste protests were not an isolated case, but were part of a broader European context of resistance to COVID-19 restrictions. While most protests across Europe during the pandemic were peaceful, their composition and intensity varied significantly across countries, depending on factors such as trust in institutions, political alignment, and local pandemic policies (Neumayer et al., 2024; Kriesi and Oana, 2023). In Germany, for example, the Querdenken ("lateral thinking") movement combined health-related skepticism with populist and anti-establishment narratives, often amplified through social media (Weigand et al., 2022). Similar movements have also emerged in the United Kingdom, as in the case of "The Light" newspaper, which is accompanied by a proprietary Telegram channel (Wischerath et al., 2025). In general, the Trieste protest aligns with broader patterns of European contentious politics during the COVID-19 pandemic, where movements combined anti-establishment sentiments with critiques of state-imposed restrictions. Studies have shown how protests framed around government overreach often emerge when perceived legitimacy erodes, especially during states of emergency (Lalot et al., 2023). It remains to be clarified, however, how these grievances are amplified online in connection to protest events, and to what extent online support of non-compliance contributes to offline mobilization. The present study examines the Trieste case as a unique opportunity to observe how digital platforms mediated grievances and fueled support for protest and non-compliance during a critical moment of political contention in a major European country. Findings in such will support and expand recent literature on the role of moral outrage as a mobilizing emotion (Brady et al., 2017) and will help clarify the broader political scenario of European conspiracy thinking and sanitary non-compliance.

It is important to note that, while the topic of COVID-19 vaccination is central, it is also divisive due to reported side effects (Saeed et al., 2021; Kadali et al., 2021) and differing risk perceptions (Caserotti et al., 2021). This study does not aim to judge policy positions but rather to propose a methodological approach for analyzing the online diffusion of polarizing content. The present framework can extend to online discourse of other contentious issues, such as the war in Ukraine, artificial intelligence, or climate change.

1.3 Digital politics and dissent

While the study of offline events per se is crucial in case of unrest and sanitary non-compliance, the investigation of online and social media dynamics is increasingly more relevant. The internet and social media platforms have played a crucial role in shaping public discourse around compliance with COVID-19 restrictions. They have also become contested arenas: platforms may enable mobilization while simultaneously being used to monitor, moderate, or suppress dissent (Earl et al., 2022). On the one hand, recent research shows that both state and platform actors employ digital repression to curb dissent (Earl et al., 2022). In fact, during the Trieste protest, users often accused mainstream media and platforms of downplaying or censoring their mobilization, fostering a shared narrative of marginalization and institutional mistrust. On the other hand, prior research has demonstrated the role of such platforms in facilitating protest coordination and aggregating malcontent, in cases such as political uprisings and student mobilizations (Shirky, 2011; Haupt et al., 2021; Freelon et al., 2018; Onuch, 2015; Scherman et al., 2015). Among all social media platforms, Twitter stands out as a prominent medium for expressing political opinions and institutional distrust. This includes general political criticism (Downing and Brun, 2022), as well as reactions to global issues such as climate change and the COVID-19 pandemic (Setzmann, 2023). Moreover, social media may offer a space for expressing controversial or unfiltered opinions with fewer repercussions due to echo-chamber effects (Cinelli et al., 2021). In other words, online discourse can be a genuine registry of the political interactions between governments and the public during crises. In addition, online opinions may translate into offline non-compliance, carrying significant implications. Therefore, understanding these dynamics is crucial not only for interpreting online behavior but also for grasping broader sociopolitical mechanisms influencing real-world compliance and protest. Given this, the available data on the Trieste protests provides a valuable opportunity to examine the drivers behind the spread of non-compliance support and collect insights that can support policymakers in understanding the genuine concerns of restriction-opposing segments of the population.

The analysis of online content has received attention in previous literature, highlighting two main themes of importance. Firstly, Tweets can reveal broader mechanisms of misinformation. Users engaging in non-compliance discussions on Twitter may encounter misleading information or "fake news" about current events and the pandemic. Social media has proven to be fertile ground for health-related conspiracy theories (Bin Naeem and Kamel Boulos, 2021). Moreover, reliance on social media for health information has been linked to reduced compliance, as shown in the cases of Jordan (Pavelea et al., 2022) and Romania (Rosha et al., 2021). Secondly, the political dimension of online discourse is also crucial. Institutional distrust correlates with higher non-compliance, both among youth (Nivette et al., 2021) and the broader population (Rosha et al., 2021; Bălăeț et al., 2023). For example, Lenti et al. (2023) analyzed over 300 million vaccine-related tweets in 18 languages, showing that no-vax communities gained prominence, spread misinformation, and formed stronger global networks. Their findings indicate that digital platforms amplified low-credibility content and reinforced anti-vaccine group connections.

Taken together, prior research highlights the dual role of social media as both a channel for misinformation and a space for articulating political grievances. What remains less understood, however, is how these dynamics unfold in connection to specific protest events and contribute to the spread of support for sanitary non-compliance. By analyzing the Trieste protests, this study helps to bridge this gap, showing how online discourse around a concrete episode of unrest reflects, amplifies, and potentially sustains offline mobilization.

2 Materials and methods

The present work studies the characteristics of social media support for (a) the Trieste 2021 anti-restrictions protests and (b) restrictions non-compliance. It does so through three main approaches. Firstly, it employs topic modeling to examine the content of pro non-compliance and pro compliance tweets. Secondly, it uses clustering to identify different types of pro non-compliance users and their differences from pro compliance users. These analyses help understand the themes and justifications behind online support for non-compliance. Thirdly, the study uses sentiment analysis within a regression model to predict retweet counts based on tweet characteristics. In politically turbulent contexts, viral content can influence public opinion and behavior (Malecki et al., 2021). Thus, the study asks which content is most influential or "loudest," considering its spread and potential impact on user attitudes. This insight can help institutional actors refine audience targeting and engagement strategies (Pond, 2016). These analyses collectively illuminate the characteristics of online non-compliance support and highlight the most influential content. Topic modeling and clustering reveal user traits and motivations, while regression modeling uncovers what drives content virality.

2.1 Data mining

The data used in this study were collected using the Python requests library to get tweets and related information in JSON format. In addition to the text and the identifier of the tweet's author, other features have been collected, such as public metrics and the type of tweet. The complete list of parameters is available in the appropriate section of the API documentation. Different types of tweets can be extracted in this way: standard tweets, citation tweets, reply tweets, and retweets. For the analysis, these were divided into original tweets and retweets. The types of tweets that correspond to content actively written by a user (quoted, replied, and standard) have been grouped into the original tweet category. In the retweet category, only retweets have been included, which, unlike the original tweets, do not have any additions to the original content. The period taken into consideration runs between September 1st, 2021, and November 30th, 2021. The following query was used to identify the tweets centered on the events in Trieste: "lang: it Trieste (protest OR green pass OR green pass OR port OR port OR piazza)." This string returns, as a result, the tweets in Italian that include in the text the word Trieste and any of the terms contained in the parentheses, without distinction between uppercase and lowercase. The textual data obtained were saved in a dataset along with the other features that can be obtained from the API. The totality of all tweets corresponding to the query is collected, corresponding to 287.575 tweets.

All data were collected from publicly accessible Twitter (X) profiles. To further protect individual privacy, direct quotes from private individuals were paraphrased. All potentially identifying information, including exact likes and retweet counts, has been rounded to the nearest hundred. These measures ensure anonymity and are in accordance with established ethical guidelines for social media research.

2.2 Data preparation

Tweets are processed to remove blocked or deleted accounts. All duplicated tweets are also dropped, as well as tweets containing URLs and/or whitespace only. Further, we remove all tweets originating from the Twitter accounts of the main Italian newspaper companies (Il Corriere, Il Piccolo, etc.). These tweets are usually only reporting events without adding any political or personal connotation, but are nonetheless abundant and often retweeted. Comments or tweets quoting these accounts are included in further analysis. A custom code is used to remove all tweets whose language is other than Italian. Retweets, which are the simple reposting of another user's tweet without any addition or modification, and which compose 86% of the collected sample, are also removed, and unique tweets only are kept for analysis. Finally, all tweets that did not receive at least one like, one retweet, or one comment were dropped, as we consider those tweets noise and often contain irrelevant information, such as commercial promotions or incoherent text. The final dataset consists of 21.992 unique tweets.

2.3 Sentiment analysis

For sentiment analysis all symbols, links, emojis, hashtags, dates, URLs, account names etc. are removed from the tweet text body for ease of processing. The full list of regular expressions used for processing is available in the Supplementary material.

FEEL-IT (Bianchi et al., 2021) is a Machine Learning model performing sentiment analysis on Italian textual data. The model was obtained by performing the fine-tuning operation on umBERTo, the Italian adaptation of roBERTa (Parisi et al., 2020). There are two versions of the model: FEEL-IT-emotion and FEEL-IT-sentiment. The first one performs sentiment classification based on four categories: fear, sadness, anger, and joy. The second one collapses them to achieve polarity classification. For this study, FEEL-IT-emotion is chosen mainly because the sentiment classification gives more details about the tweets and allows us to gain more insight into the data. The model is implemented with Python, and every tweet is labeled with the emotion with the highest probability.

2.4 Opinion analysis

For the present analysis, separating which tweets are in favor or in support of the protests and which are not is vital. For this reason, we develop a custom model to assign an opinion score to each tweet, with 0 identifying a tweet in favor of non-compliance, 1 for a neutral tweet, and 2 for a pro-compliance tweet. To do so, we first draw a random sample of 1,100 tweets from the processed population. We then read and manually labeled the sampled tweets based on their content. The scores have been revised to achieve the same score on all tweets between all raters. BERT is then fine-tuned to process the full text of the unlabeled tweets and predict the label, using the labeled tweets as training data. The BERT-predicted label is then attached to the other tweet characteristics, such as sentiment analysis, date, number of retweets, etc., and fed to an XGBoost algorithm, used to further tune the prediction. The final model, using both the BERT-predicted label and the tweet characteristics, achieves an overall accuracy of 86% on out-of-sample tweets. This final value results from merging the neutral and pro-compliance tweets (classes 1 and 2) in order to achieve better class balance and increase model performance.

2.5 Topic modeling

For topic modeling, we employ BERTopic, a topic modeling software that allows for detailed, rich and easily interpretable topics. BERTopic involves a stepwise process, each step involving a different algorithm tasked with a specific operation. In the first step, BERTopic utilizes the Sentence-BERT (SBERT) framework to transform sentences and paragraphs into vector representations, using pre-trained language models. This approach benefits from state-of-the-art models trained on extensive datasets. Additionally, it provides flexibility, allowing users to choose from a wide range of sentence-to-vector models available on the Sentence-BERT framework leaderboard (Reimers). We utilize the all-MiniLM-L6-v2 model, known for its compactness and efficiency (https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2). This model has been fine-tuned on large datasets from various online sources, including Yahoo Answers, Stack Exchange, Wikipedia, Reddit, and scientific papers, among others. We feed the embedding step sentences to the single, completely processed tweets.

The next step is dimensionality reduction. Sentence embeddings typically have high dimensionality, which can make it difficult to extract meaningful topics. To enhance the performance of the clustering algorithm in the subsequent phase of the BERTopic pipeline, dimensionality is reduced. This is achieved using UMAP (McInnes et al., 2018), which excels at preserving local features when projecting high-dimensional data into lower dimensions. In BERTopic, we use UMAP with its default hyper-parameters: cosine distance, reducing the data to five dimensions, and using 15 nearest neighbors. After reducing the embeddings to a more manageable dimensionality, we can move on to extracting clusters. A cluster represents a group of sentences that are close to each other in the reduced-dimensional space. These clusters serve as the foundation for the final extracted topics. Clustering is performed using HDBSCAN (McInnes et al., 2017), which is notable for its ability to perform soft clustering and its effective handling of outliers, demonstrating strong empirical performance (Grootendorst, 2022). Once the clusters are identified, an important step is creating a meaningful topic representation. This representation provides a concise description of each cluster, useful for further analysis and interpretation. In BERTopic, this is achieved by selecting sentences from each cluster that are most distinct from other clusters, using a generalized version of TF-IDF called c-TF-IDF (class TF-IDF). This method assigns higher weights to words that are more unique to a particular topic, allowing for better differentiation between topics. Finally, after identifying the most descriptive items for each cluster using c-TF-IDF, we utilize the OpenAI API to generate topic descriptions, providing a concise and meaningful summary for each topic. Substantially, we prompt the OpenAI ChatGPT 3.5 LLM with the following:

Listing 1 OpenAI query

```
prompt = ''''''
I have a topic that contains the following
documents:
[DOCUMENTS]
The topic is described by the following
keywords: [KEYWORDS]
Based on the above information, can you
give a short label
of the topic?
''''''
```

The tags are used to replace the documents with the n-th most representative documents and words. Then, the AI generates topic descriptors, such as titles or brief descriptions. We use ChatGPT to create these topic descriptions, as topic labels are a crucial aspect of the topic modeling process. These labels are vital for future analysis, and having rich, precise labels is key to making sense of the model's output. In fact, they are considered the final and most important product of the BERTopic pipeline.

We allow BERTopic to determine the optimal number of topics, which, in our case, resulted in 32 topics. The final output of the topic modeling process is a list of these topics, each accompanied by a label and a collection of the most representative sentences and words. Additionally, every sentence in the database is linked to a score that indicates the probability of that sentence belonging to each topic. For topic i, we sum the probability scores of all sentences in issue j to obtain a final score that reflects the prevalence of topic j for issue i.

2.6 Further topic processing

Unfortunately, the 32 topics produced by BERT-topic are not ideal for further analysis. Firstly, 32 is a high number, which makes interpretation challenging. Furthermore, different topics might refer to the same content, or to different aspects of the same topic, and could therefore be grouped together. In addition, some topics might be irrelevant for the analysis. Therefore, we perform a qualitative analysis and further processing of the topics. We individually review the title, description, and the 13 tweets with the highest loading for each of the 32 topics produced by BERTopic. For each topic, we assess whether the topic is useful for further analysis, and we assign a higher grouping where applicable, defined as "meta-topic." Topics deemed not useful for analysis are classified as noise. This also contains the first topic with the highest prevalence. This qualitative analysis leverages the language and context expertise of the researchers to reduce the overall number of topics for a better interpretation. This analysis is also aided by the BERTopic API function `hierarchical_topics`, which obtains a hierarchical representation of the topics based on the distance matrix of the c-TF-IDF. A table with the complete ungrouped and grouped topics can be found in the Supplementary material.

2.7 Modeling approach

Our aim is to model the retweet count for each tweet based on tweet characteristics, such as number of retweets and the like, the time of its posting, its main sentiment and orientation toward non-compliance, and author characteristics such as number of followers and the like.

The distribution of retweets indicates that there might be different dynamics involved in why a tweet is retweeted for the first time compared to it becoming viral. More than two-thirds of all tweets during this period of time did not receive any retweets. Therefore, we decided to concentrate the analysis on the tweets that did receive at least one retweet, predicting the retweet count of each tweet. In this case, our response variable would be a discrete numerical variable indicating the `retweet_coun`. This solution allows us to examine the spread of a tweet once published.

Our dataset does not follow the Poisson assumptions, as most tweets are not being retweeted. This was indicated by the dispersion of the response variable (in our case, the retweet count), calculated as $\nu(y_i)/\varepsilon(y_i)$. Dispersion should be at most 2, as recommended by Cameron and Trivedi (1990). In our case, the dispersion was much higher, with $\nu(y_i)/\varepsilon(y_i) > 350$. Therefore, a Negative Binomial regression was used.

We defined a number of variables to operationalize the most important information regarding each tweet. The list is presented here:

- `sentiment`: Categorical variable indicating the main emotion expressed in the tweet's text, between joy, anger, sadness, and fear;
- `opinion`: Dichotomous variable indicating whether the tweet is pro non-compliance has a neutral/pro-compliance stance.
- `period`: Categorical variable indicating in which state of the protests the tweet was published. The total timeline of events is divided into three segments:
  - `pre-protests` segment: From the 1st of September 2021 to the 9th of October 2021. Characterized by mounting dissatisfaction and anger among the public regarding the government's anti-COVID measures, but major protests were yet to take place.
  - `during protests` segment: From the 10th of October 2021 to the 22nd of October 2022. Marked by the first series of protests in Trieste and vast coverage from mainstream national media.
  - `post-protests` segment: From the 22nd of October 2021 to the 27th of November 2021. Characterized by stronger repression of the protests by the government and law enforcement.
- `hashtags`: Discrete variable indicating the number of hashtags present in the tweet's text;
- `type_1`: Categorical variable with three levels: "replied_to," "quoted," or "None," indicating whether the tweet was, respectively, a reply to another tweet, was quoting another tweet, or none of the preceding;
- `log(tweet_count)`: Numerical variable indicating the logarithm of the total number of tweets published by the same author up to that point in time. Used a logarithm function to regularize the variable in the model.
- `log(followers_count)`: Numerical variable indicating the logarithm of the total number of accounts following the author. Excluded accounts with a follower count of 0.
- `ffratio`: Numerical variable for each user, obtained as the number of Twitter accounts followed by that user divided by the number of accounts that follow that user. High values indicate that the user follows many people but has few followers, while low values indicate the opposite;
- `mentions`: Discrete variable indicating the number of other Twitter users mentioned in the tweet's text;
- `author_id`: Unique ID associated with each different account.

We model a tweet's diffusion and virality, indicated by the retweet count, as the following:

$$
\begin{aligned}
\log(\mu_y) \sim \beta_0 &+ \beta_1 \,\text{hashtags} + \beta_2 \,\text{type\_1} + \beta_3 \,\text{ffratio} \\
&+ \beta_4 \,\text{mentions} + \beta_5 \,\log(\text{tweet\_count}) \\
&+ \beta_6 \,\log(\text{followers\_count}) + \beta_7 \,\text{sentiment} \\
&+ \beta_8 \,\text{opinion} + \beta_9 \,\text{period} + \beta_{10} \,\text{sentiment} \\
&\times \text{opinion} + \beta_{11} \,\text{sentiment} \times \text{period} \\
&+ \beta_{12} \,\text{period} \times \text{opinion} + \beta_{13} \,\text{sentiment} \\
&\times \text{period} \times \text{opinion} + u_j \,\text{author\_id} + \epsilon
\end{aligned}
$$

where:

- y is the count of retweets.
- β_0 is the intercept.
- β_1 to β_{13} are the coefficients associated with each respective variable.
- u_j represents the random intercept effect associated with each author.
- ϵ represents the error term.

This choice of variable is the result of a section process among different models. The chosen model presented the smallest value of Bayesian Information Criterion (Schwarz, 1978). The model is fitted by maximum likelihood with Laplace Approximation, through the R `lme4::glmer.nb` command.

2.8 Explorative clustering

The clustering of the pro non-compliance tweeter users leverages a k-means algorithm. The k-means algorithm is a well-known method to cluster multivariate data into k clusters, where the value of k is selected by the user (Krishna and Murty, 1999). The algorithm iteratively searches for p-dimensional k centroids, so that each centroid has the maximum distance from all other centroids and the distance to the closest points is minimized. To select the value of k, many strategies are available; a straightforward one is the "elbow method," in which the inertia for different values of k is calculated and plotted in a line plot. The inertia is a measure of goodness-of-fit of the clustering model, with smaller values indicating a shorter distance from each point to its assigned centroid. The elbow method consists in identifying the optimal number of clusters based on the angle of the line plot. The value of k, which sits at the dip of the elbow, is chosen as the optimal balance between complexity and flexibility.

We perform the explorative clustering at the user level using a selected set of variables grouped at the median value for each user: `in-friuli`, `retweet_count`, `anger`, `sadness` and the loadings for the topics "events at the protests," "indignation at the government," "police crackdown of protests," "protests, greenpass, and vaccination," "support for port workers," and number of total tweets for the user, indicated as n. All variables are normalized before the algorithm is fitted to the data. `in-friuli` is a custom-made variable which indicates if the tweet is posted inside the Friuli region, in Italy. Friuli Venezia Giulia (shortened to Friuli) is the region where Trieste is located. The explorative clustering is performed with the present selection of variables since we found that a smaller number of variables would help the model to obtain more interpretable results and a better fit. Moreover, these variables are the most indicative of pro non-compliance and pro-protest users. The selected topics are included since they emerged from the topic modeling as the most active for pro non-compliance users. `anger` and `sadness` are instead important as they increase a tweet's virality, as shown in the regression model results. `retweet_count` is essential in separating users since only a handful of users achieve a large number of retweets and can consequently be very influential. `in-friuli` can be very useful in the analysis as it might differentiate users who are acting as "events relayers" and are present at the events when tweeting.

3 Results

3.1 Topic modeling

The obtained topics, with the relative frequencies and sub-topics, are presented in Table 2. Of the original 38,627 tweets (62.5 %), 24,149 are left unassigned as they belong to the first, most common topic, which is routinely excluded from analysis in topic modeling (Grootendorst, 2022). The prevalence of four selected topics is plotted across time in Figure 2. The four topics ("indignation at the government," "police crackdown of protests," "port workers announce port block," and "support for port workers") have been chosen since they have a sensible change in time, compared to the other topics, which appear mostly constant across the period. It can be seen how "indignation at the government" peaks after the green pass is approved in parliament and subsequently rises again at the protest breakdown by police. The topic "police crackdown of protests," which also contains a discussion regarding Trieste's prefect banning all protests and assembly in the main square, peaks at the protest dissolution. On the 18th of October, police used water cannons to disperse the protests. Subsequently, the topic peaks again as Puzzer is handed an estrangement order from the capital, where he moved his protest, and Trieste forbids protests. The topic "port workers announce port block" also peaks coherently with the event at the end of September. Finally, "support for port workers" peaks as the protests have the most success before falling again as it becomes clear the non-compliance movement is coming to an end.

Continuing, we separate users who are predominantly pro non-compliance and pro-protests from users who have a neutral or pro-compliance stance. We use a frequency table to observe that users seem predominantly polarized toward one or the other opinion, with few users in the middle. We measure the difference in topic prevalence between the two groups. In other words, we find what distinguishes the tweets of non-compliance supporters from pro-compliance supporters. The results are plotted in Figure 3. The plot indicates that supporters of non-compliance are characterized by more discussion in the topics "indignation for the government," "protests, greenpass and vaccination," "protests and fascism," "support for port workers," "protests and media journalism," and "police crackdown of protests". In other words, supporters of non-compliance appear to have stronger negative feelings toward the government or the perceived "system," are more concerned with vaccination and the green pass than the other users, and are clearly having stronger support for the protesting workers who are defying vaccination. Moreover, they were more concerned with the connection between protests and fascism. Users who are neutral or pro-compliance discuss the topics "events at the protests," "puzzer," the port workers' leader, "port workers announce port block," "square of Trieste," "port blocking," "protests cause covid outbreak," "troubled protests and possible issues with protests" and finally "genova joins the protests." Pro-compliance or neutral users appear more focused on the events themselves and on the potential economic consequences of the port blockade at a national level. They are also highlighting the negative effects of the protests, as the aggregation of so many people caused a COVID-19 outbreak in the port city itself.

The results from this analysis indicate that, among pro non-compliance users, the main topic of discussion is "indignation at the government." This large topic comprises: anger at the government's ordered crackdown of the protests, anger at the government's imposition of the green pass certification and vaccination on the population, accusations of fascism, oppression, and dictatorship, especially toward the then-Prime Minister Mario

TABLE 2 Topics with respective description and number of sub-topics.

Meta-topic	Description	No. of sub-topics	No. of tweets	rel. freq.
Noise	Content non useful for further analysis and therefore excluded	5	4,904	12.6%
Police crackdown of protests	Reactions at forceful crackdown of protests by police	3	486	1.2%
Events at the protests	General descriptions of the events	3	1,436	3.7%
Port blocking	Consequences of port blockade	2	392	1%
Indignation at the government	Emotional condemnation of dictatorship and anger at the "system"	2	1,541	3.9%
Port workers announce port block	Reactions and support to workers announcing port blockade	2	281	0.7%
Foreign hidden influences on the port	Theories on German or Chinese control over the port and responsibility in the protests crackdown	2	413	1%
Support for port workers	Expression of support for non-compliance and protests	2	799	2%
Square of trieste	Content relative to the square of Trieste, where some events took place	2	863	2.2%
Troubled protests and possible issues with protests	Reactions to protests being suspended by Trieste's prefect	1	339	0.8 %
Protests and fascism	Connection between protests and alt-right fringes	1	360	0.1%
Puzzer	Reports on Puzzer's - the port workers leader - actions during the protests	1	361	0.1%
Protests and Rome	Repercussions of the protest on the Rome's government	1	313	0.08%
Protests cause covid outbreak	Allegation of covid outbreak due to protest congregation	1	255	0.06%
Genova port joins the protests	Support and announcement of genova port joining the protests	1	247	0.06%
Protests and media journalists	Criticism of journalists' portrait of the protests	1	149	0.03%
Port workers and workers union	Criticism of other worker's unions	1	101	0.02%
Protests, greenpass, and vaccination	Relationship between the protesters, the greenpass and vaccination	1	1,238	0.03%
	Total	19	14478	36.5 %

Draghi. These results indicate that pro non-compliance users have anger and negative feelings toward the government, which is perceived as oppressive and distant. For example, the words "resign" or "resignation" were found in 365 unique tweets and were retweeted 1,855 times. "Draghi" was mentioned in 1,484 tweets, which were retweeted 15,116 times in total. Therefore, it appears clearly that supporters of the protests and of non-compliance have a negative outlook on the government institutions and are angered by the green pass certificate. An example is included for illustration.

> *"Today feels like living under a #dictatorship. The brutal crackdown on a lawful, peaceful protest echoes the days of Pinochet. The #Draghi government is shredding the Constitution."*
> retweet count: >1,400, like count: >3,000, date: 2021-10-18

Another strong topic among supporters of non-compliance was topics related to the vaccine, green pass, and anti-COVID containment measures. It emerges from the topic modeling that pro non-compliance users are more concerned with these themes compared to all other users. Words such as "nogreenpass" or "nomandatorygreenpass" were used in 3,699 unique tweets and were retweeted 36,565 times in total. The vaccine, the green pass, and other measures of prevention are perceived as means of discrimination, used by the "system" or "establishment" to further oppress the masses. The words "system," "great powers," or "establishment" have been mentioned 160 times and retweeted 256 times. An example is reported here.

> *"While in #Trieste people's rights to gather and speak freely are being trampled, the mayor of Piazza was busy celebrating at a party on Friday, October 22. Masks and vaccines are treated as burdens for ordinary citizens, while the elites look after their own interests, live in comfort, and take advantage of us."*
> retweet count: >400, like count: >700, date: 2021-11-03

A set of 413 tweets with a total retweet count of 2,929 belonged to the topic "foreign hidden influences on the port" which attributed the protest crackdown at the hands of the police and government as the result of foreign influence from Germany or China. Many tweets discussed the idea that the crackdown was therefore due to economic losses to those countries, and therefore, pressure was put on governments abroad to open the port to

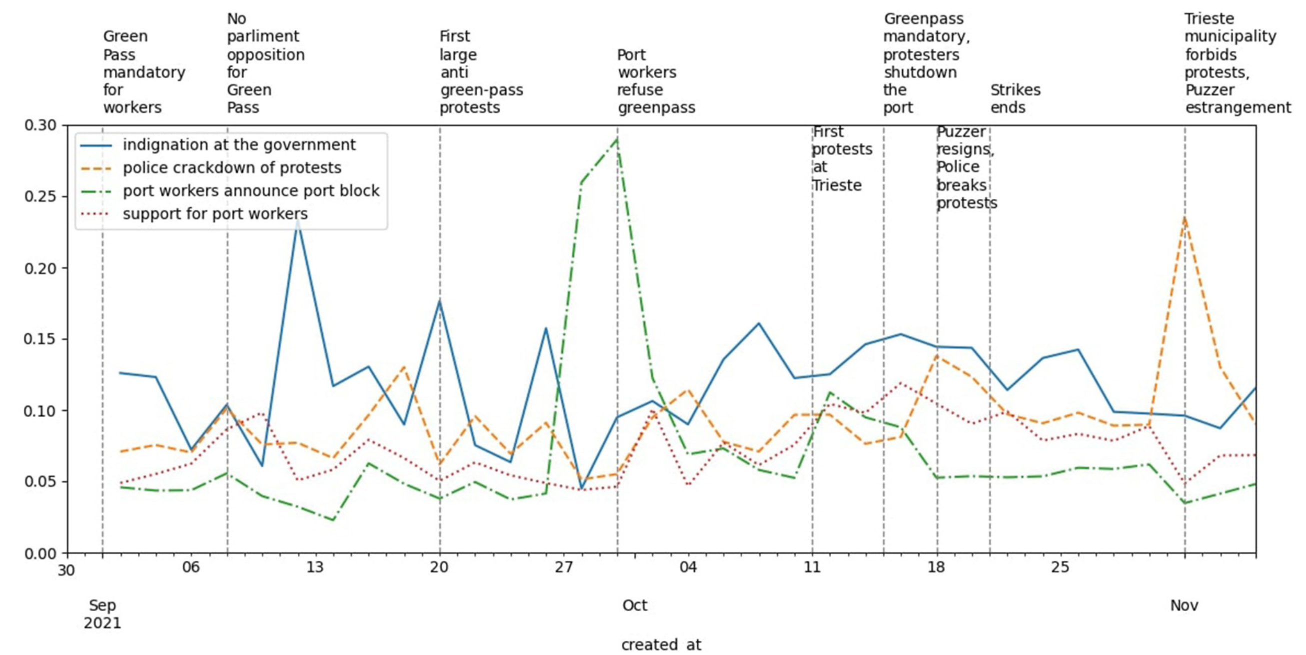

FIGURE 2
Relative prevalence of 4 topics in the tweet feed, for each day. Dashed vertical lines represent key events in the development of the protests.

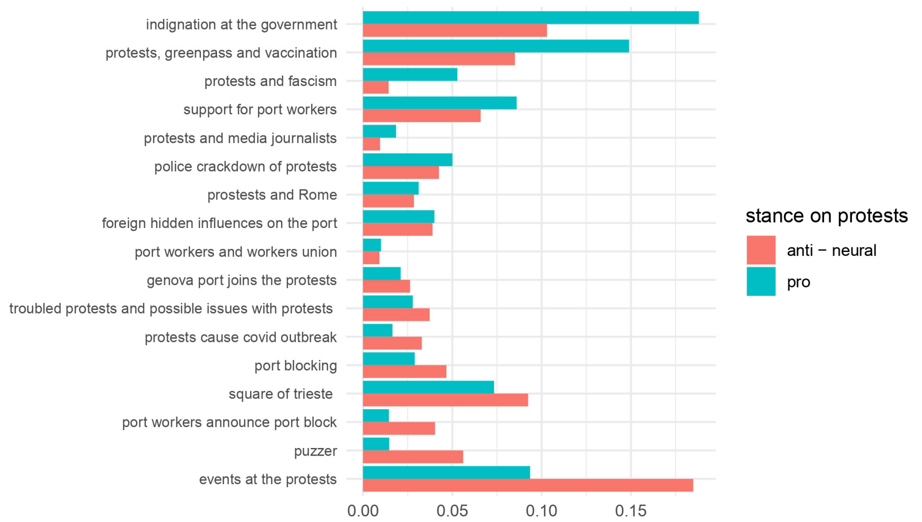

FIGURE 3
Difference in topic prevalence among non-compliance supporters and users with a neutral stance or pro-compliance.

traffic again. This is a relatively small portion of the overall dataset, both in terms of tweets and retweet count. Nonetheless, it can be considered an example of conspiracy theory as a method of explanation for coercive force at the hands of the government in repressing pro non-compliance movements.

3.2 Differences between pro non-compliance users and other users

We aim to present a descriptive illustration of the two groups of users, pro non-compliance and all others. To do so, we group all users based on their most expressed opinion toward compliance as described in section and we obtain the median value for the following variables: `retweet_count`, `during protests`, `post protests`, `anger`, `sadness` and the loading values for the following topics: "events at the protests" "indignation at the government," "police crackdown of protests," "protests, greenpass and vaccination," "support for port workers," and a count of the published tweets, indicated with n. The results are shown in Figure 4. The differences between supporters of the protests and non-compliance compared to users who instead displayed a neutral or opposing stance are that pro-protest users receive more retweets, are angrier, express more indignation toward the government, and talk more about the vaccination and green pass, and, as expected, vocally express their support for the port workers. The neutral or complier users instead exhibit more sadness, comment more on the events at the protest, and are generally less vocal.

While this study focuses on users' online behavior, it is important to acknowledge the heterogeneity in the motivations behind participation in the protests. Protesters may have joined for a range of reasons, including concerns over public health measures, anti-government sentiment, or economic interests such as defending their livelihood or job security. The clustering and categorization presented in this work rely on a data-driven approach that infers positions based on expressed opinions and behavior on social media. While this allows relevant differences to emerge from the data, we recognize that online activity may only partially reflect the complex and multifaceted motivations of participants on the ground.

3.3 Explorative clustering

We identify $k = 4$ clusters using the elbow method. The identified clusters' centroids are reported in Figure 5 together with their prevalence among the pro non-compliance users. From the analysis of the protest supporters, it emerges that there is a very large majority (98.6%) of very similar users, which we name "passive followers," who have a low number of tweets, a low retweet count, and mainly express sadness. The topics of their discussion revolved around indignation at the government, discussion on the events of the protests, and support for the workers. A smaller cluster (0.08%, 51 users) of users is similar to the first group for all other aspects, but it is different in its topic of discussion, since this group mainly talks about green pass and vaccination. We identify this group as the "no-vax followers." An even smaller cluster (0.04%, 22 users) is instead very vocal, with a high number of tweets, and has the highest amount of retweet count among all groups. It is the group that expresses the most anger and the least sadness, and mainly discusses indignation at the government and the police intervention, and the government's crackdown on the protests. We identify this group as the "agitators." A final cluster, with only 6 users (0.01%), is very vocal, but with few retweets, and expresses mainly sadness. Users in this group recount the events and post mainly from the Friuli region and Trieste. Therefore, we suppose this group identifies users who are tweeting from where the events are taking place and are therefore mainly acting as event relayers. We identify this group as the "locals."

3.4 Variable description

After filtering, the sentiment analysis is applied, and a descriptive analysis is reported together with opinion on non-compliance. For the overall tweet count, the sentiment analysis resulted in 2,591 tweets labeled with "fear" (6.7% of the total), 28,653 tweets labeled with "anger" (74.2% of the total), 2,807 labeled with "sadness" (7.2% of the total), and 4,576 labeled with "joy" (11.9% of the total). Around half of all tweets, 17,179, demonstrated pro non-compliance or pro-protest tones (44% of the total). Relative frequencies are presented in Table 3. The majority of tweets were published during the protests (24,698 tweets, 63.9%), which means between the 11th and the 21st of October 2021, included. Around 30% of tweets were published after the events (11,620 tweets), and 5.9% before the events (2,309 tweets). Around 35.3% of tweets had at least one hashtag (13,656 tweets), and a similar percentage, 35.7% had at least one mention (13,794 tweets). Of the tweets used in the analysis, around 32% were replies or were quoting other tweets (12,362 tweets). Both the tweet count and the followers count are highly skewed variables, with most users having few tweets and followers, and a small percentage of influential users having very high values of published tweets and followers. The median value of tweet count, which represents the total quantity of tweets by an author in their accounts, amounts to 9,929 for the analyzed sample. The median value of follower counts amounts to 383. The number of unique authors is 12,371, after processing.

3.5 Regression modeling

The coefficients for the fitted regression and the respective significance levels are presented in Table 4. The estimated intercept indicates that, taking the other variables into account, a joyful tweet pre-protest with a neutral or opposing stance toward the protest is predicted to receive 1.341 retweets ($\exp(0.294) = 1.341, p < 0.001$). Considering only results with a significant p-value: Regarding emotions (`best_result`), an angry tweet increases the retweet rate by $\approx$ 53%($\approx$ 1.53times). Regarding the period, tweeting during the protest increases the retweet rate by $\approx$37% ($\approx$1.37 times, $p < .01$). A tweet in support of the protests increases the retweet rate by $\approx$105% ($\approx$1.05 times, $p < 0.0000$). Adding hashtags to a tweet reduced the number of retweets of $\approx$2% ($p < 0.005$), and so did quoting or replying to other tweets, by respectively $\approx$50% ($p < 0.0000$) and $\approx$55% ($p < 0.0000$). The logarithm of the total number of tweets by the author predicted a lower count of retweets for each tweet by $\approx$22% ($p < 0.0000$) for each additional unit, while having more followers predicted a higher count of retweets, with the logarithm of the number of followers increased the number of retweets by $\approx$40% ($p < 0.0000$) for each additional unit. Also, mentioning other users in the message also was significantly related to $\approx$1% more retweets ($p < 0.05$). Tweeting an angry tweet during the protests decreases the retweet rate by $\approx$54% ($p < 0.005$). Anger also decreased the total number of retweets after the protests, with $\approx$39% ($p < 0.05$). All emotions except joy generated a decrease in the retweet rate of tweets in support of the protest, but in different measures, with sad tweets receiving $\approx$107% ($p < 0.01$) less retweets, angry tweets receiving $\approx$62% ($p < 0.01$) less retweets and fearful tweets receiving $\approx$83% ($p \leq 0.05$) less retweets. Tweets in support of the protests received $\approx$76% ($p \leq 0.001$) fewer retweets as the protests were happening, and the decrease for this type of tweets remained at $\approx$66% ($p \leq 0.01$) after the protests. Finally, angry tweets published during the protests in support of the protests themselves received $\approx$56% ($p \leq 0.005$) and $\approx$92% ($p \leq 0.05$) more retweets, respectively. After the protests, sad tweets in support of the protests gained $\approx$94% ($p \leq 0.05$) more retweets.

We seek to provide a clear picture of how the most important variables in the study: sentiment detected in the tweet, period

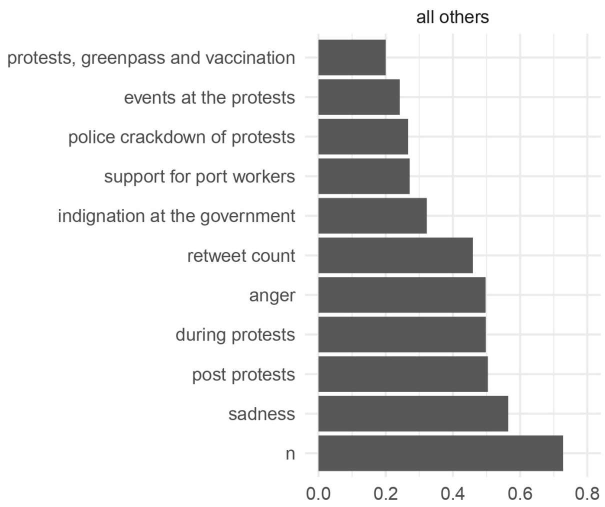

FIGURE 4
Normalized measured median value for each characteristic for the corresponding group.

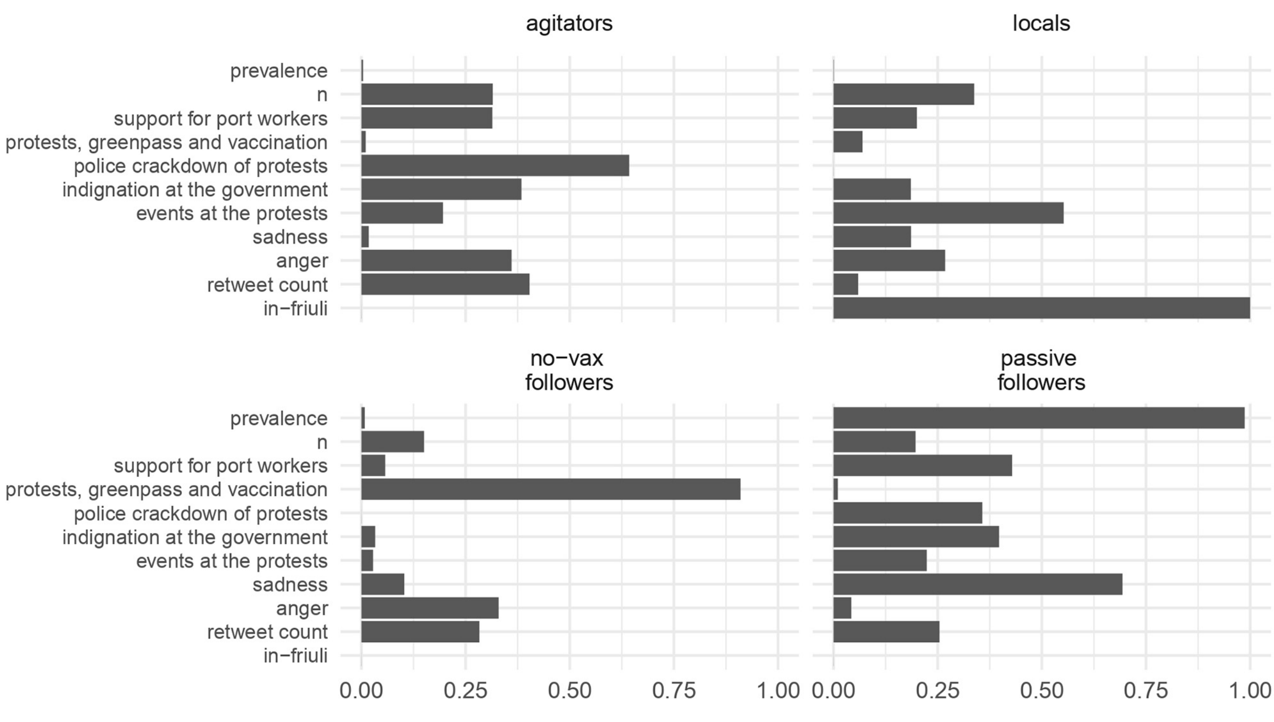

FIGURE 5
Normalized value of the cluster centroid for each group.

TABLE 3 Relative distribution of retweeted tweets in each categorization: detected sentiment (horizontal) and detected opinion on non-compliance (vertical).

Opinion	Anger	Fear	Joy	Sadness	Row total
Pro non-compliance	0.351	0.011	0.054	0.028	0.444
Neutral or pro-compliance	0.391	0.056	0.065	0.044	0.556
Column total	0.742	0.067	0.119	0.072	1.000

TABLE 4 Regression model fitted coefficients.

Variable	Est.	Std. Err.	z value	$P(>\|z\|)$	sig.
(Intercept)	0.294	0.168	1.747	0.081	.
best_result: anger	0.530	0.132	4.017	0.000	***
best_result: sadness	−0.026	0.212	−0.121	0.904	
best_result: fear	0.145	0.203	0.711	0.477	
period: during protests	0.380	0.126	3.024	0.002	**
period: post protests	0.108	0.132	0.822	0.411	
opinion: support	1.050	0.214	4.896	0.000	***
hashtags	−0.021	0.007	−3.127	0.002	**
type_1: quoted	−0.500	0.047	−10.595	0.000	***
type_1: replied_to	−0.556	0.040	−14.007	0.000	***
log(tweet_count)	−0.225	0.015	−14.527	0.000	***
log(followers_count_)	0.406	0.013	30.296	0.000	***
ffratio	−0.007	0.010	-0.686	0.493	
mentions	0.013	0.006	2.011	0.044	*
best_ result: anger, period: during protests	−0.542	0.146	−3.718	0.000	***
best_ result: sadness, period: during protests	0.055	0.228	0.244	0.808	
best_ result: fear, period: during protests	−0.260	0.221	−1.180	0.238	
best_ result: anger, period: post protests	−0.394	0.153	−2.572	0.010	*
best_ result: sadness, period: post protests	0.146	0.243	0.600	0.548	
best_ result: fear, period: post protests	0.007	0.227	0.033	0.974	
best_ result: anger, opinion: support	−0.628	0.240	−2.612	0.009	**
best_ result: sadness, opinion: support	−1.074	0.390	−2.751	0.006	**
best_ result: fear, opinion: support	−0.831	0.424	−1.960	0.050	*
period: during protests, opinion: support	−0.766	0.227	−3.371	0.001	***
period: post protests, opinion: support	−0.663	0.249	−2.663	0.008	**
best_ result: anger, period: during protests, opinion: support	0.565	0.254	2.227	0.026	*
best_ result: sadness, period: during protests, opinion: support	0.926	0.408	2.270	0.023	*
best_ result: fear, period: during protests, opinion: support	0.823	0.452	1.819	0.069	.
best_ result: anger, period: post protests, opinion: support	0.445	0.277	1.606	0.108	
best_ result: sadness, period: post protests, opinion: support	0.943	0.449	2.098	0.036	*
best_ result: fear, period: post protests, opinion: support	0.886	0.487	1.820	0.069	.

Signif. codes: '***': 0.001, '**': 0.01, '*': 0.05, '.': 0.1.

of publication, and opinion of the protest expressed in the tweet. To do so, in Figure 6 we plot the predicted number of retweets for each sentiment, for tweets either in support or neutral/against of the protests, for all three main periods, before, during and after the protests. The figure shows how angry and joyful tweets are predicted to receive more retweets when tweeted before the protests and in support of them. Users in favor of the protests then receive more retweets if posting sadder content during and after the protests. Generally, pro non-compliance content gets more retweets across the board. Angry tweets are also very successful regardless of the stance on non-compliance.

4 Discussion

4.1 Topic modeling

During the Trieste events, the port workers expressly refused vaccination and instigated thousands of people to join them in a protest outpouring in the city squares. Thousands of individuals were congregating in a time of high contagion risk, creating a new outbreak of the pandemic (ANSA, 2021). During the protests, a large number of pro non-compliance users expressed their support for the ongoing events on Twitter. Another large portion expressed instead worry, preoccupation or anger at the ongoing violation of

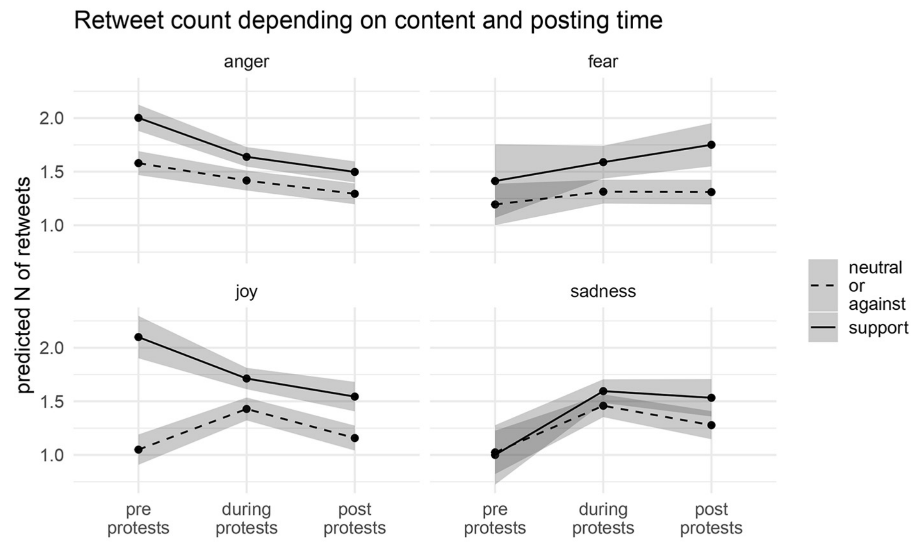

FIGURE 6
Predicted retweet count given tweet post time, tweet sentiment and opinion on protests. Bands represent standard errors.

restrictions. The topic modeling aims to explain the reasons behind support for non-compliance among the users. It first identifies a number of topics among the tweet feed using BERTopic. The topics are then qualitatively grouped and filtered into a set of larger meta-topics in order to improve the noise-to-signal ratio.

One of the first conclusions that can be identified is that anger is not mostly directed at the vaccine or green pass themselves, but rather at the government institution that rendered them mandatory. Indeed, "indignation at the government" emerged as a strong topic among pro non-compliers, rather than a no-vax or no-green pass topic. This seems to be coherent with results as Nivette et al. (2021) and Rosha et al. (2021), which indicated that distrust in the government was an indicator of non-compliance. For online support of non-compliance, we therefore observe similar results, with distrust, criticism, and anger at the government being among the most frequent topics among pro non-compliance users. These results also indicate that while most users were concerned with the events at the protests, it was the pro non-compliance ones that purposely brought vaccination and the green pass into the conversation. This might, in turn, indicate that pro non-compliance users are most attentive in finding links between world events and vaccination and anti-COVID restrictions. The text analysis also indicates that neutral or pro-compliance users were most concerned with possible negative repercussions of the events, such as a new COVID-19 outbreak or economic damage. Such users had the highest values of topic mainly concerned with the events themselves, such as "puzzer," "events at the protests," "square of trieste," "port blocking," "protests cause covid outbreak," etc.. We can conclude that pro-compliance users acted more as passive onlookers in the online arena.

4.2 Explorative clustering

The results from the explorative clustering on pro non-compliance users indicate that non-compliance online activism might be fuelled by a small number of "loud" users who achieve a high number of retweets with inflammatory content. This group, which emerged from the clustering as the "agitators," also works in directing the attention and emotion of the online crowd against the government. A few users mainly discussed topics regarding the vaccine or green pass, dubbed as the "no-vax followers," but their content was not particularly effective in terms of retweets. Therefore, this small group appears to be a minority, with the majority of pro-non compliance content being directed against the government. Presence of a small number of more influential users is coherent with large-scale analysis of Twitter data (Cha et al., 2010; Conover et al., 2013). Such individuals do not need to be politicians or official figures (Paoletti et al., 2024) and might work as catalyzers of more powerful action down the line of events in the protests (González-Bailón et al., 2011).

4.3 Regression modeling

The regression model coefficients indicate that anger is a powerful method to spread a message on Twitter. Angry tweets were more likely to be retweeted in most cases, especially when containing a pro non-compliance message. This indicates that angry, controversial content was the most shared on Twitter and that the social media area of the discussion was mostly dominated by the louder (and often angrier) pro non-compliance users. This result is partially in concordance with multiple findings indicating more emotionally polarized content being more successful in social media, such as Naseem et al. (2021) or Jenders et al. (2013). These results also indicate that timing was important, with angry or sad tweets posted before the main events, in the tension build-up that led to the port-closure, being retweeted more and possibly furthering the malcontent across users. This is in accordance with findings in the literature, such as Varol et al. (2014); Conover et al. (2013), where the offline events are tightly intertwined and trigger changes in social media content. Tweets in support of the non-compliance and protests were the most successful, indicating strong support among users for the victories of the protesting port workers. Content expressing fear, which is also pro non-compliance is most successful after the main events of Trieste, indicating a possible reaction to the defeat of the port workers and the use of strength by the government in order to return to order. From this analysis, it emerges that the most successful and influential content is the angry pro-non compliance content and the joyful content in support of the events, both mainly expressed against Italian government institutions. Therefore, high-engagement tweets helped fuel a collective sense of injustice. Such content may have amplified the emotional climate of the protest and served as a catalyst for further mobilization beyond the digital realm (Dacombe et al., 2021; Thiele, 2022).

4.4 Regional political-historical context

Trieste's political and cultural background adds important context to these events. Although reintegrated into Italy in 1954 after a period as the UN-administered Free Territory of Trieste, the city still retains a distinct regional identity (Pigliucci, 2020; Coloni and Clegg, 2022; Coda, 2022), with some groups advocating for greater autonomy or even independence. The city's multi-ethnic legacy and history of contested sovereignty contribute to a sense of marginalization and regional pride, encapsulated in the sentiment "Triestine first, Italian second" (Kappus, 1997). The port, in particular, and the associations of port workers have a powerful cultural and economic influence in the city. The port, in particular, is a strategic hub in global trade and a focal point in the city's identity, with external political influences, might it be from Rome or from foreign powers, felt close by the citizens of Trieste (Mohan et al., 2024; Ghiretti, 2021). Many locals might perceive the national, rather than local, control of the port as a missed opportunity for regional prosperity and as a symbol of marginalization by central authorities. These longstanding frustrations might have found resonance in the protests, which were widely interpreted by participants as a reaction to decisions imposed from above, particularly by the national government in Rome, without adequate local consideration. Against this backdrop, the port workers' leadership in the protests takes on additional symbolic weight, not merely as a labor dispute or anti-restriction mobilization, but as an expression of the long-standing cultural backdrop in which the actions take place.

4.5 Narrative frames: heroic defiance vs. public health risk

The topic analysis, both in the analysis of topic prevalence and in the analysis of the most frequent topic among non-compliers, shows government oppression and criticism of the police crackdown as very successful. From the topic, the emerging narrative is that non-compliance and the protests are heroic acts of defiance rather than a violation of law or an act that could put other people's health in danger. The explorative clustering shows how the large majority of users are conformative in their attitudes, following, liking, and sharing the content of a smaller, more influential minority. In this sense, the social media area portrayed quite a united and similar group of users with similar pro non-compliance opinions. The regression analysis supports this finding, indicating that angry or joyful pro non-compliance material is easily spread among other users, especially before the main events. This might indicate that social media acted to promote and expedite the circulation of pro non-compliance sentiment among other users before any action was taken by port workers. Tweets could have helped reinforce the support for port-workers and spread their ideas and messages, acting as a relayer. These results support previous literature on the topic, such as Fan et al. (2016); Brady et al. (2017) and more specifically, results for political unrest in the results of a regression analysis in Odabaş and Reynolds-Stenson (2018). Again, especially relevant is the role of early participants and spreaders in the Trieste protests, finding counterparts in other movements as highlighted in other sources such as González-Bailón et al. (2011); Gerbaudo (2012).

The leaders of the protests were perceived as "freedom fighters" standing heroically against international giants such as the Italian government, the EU or China. We find 85 instances of "Goliath against David" explicit rhetoric among the tweets. The government is perceived as malign, with dubious intent, and both the vaccine and green pass are perceived as methods of further control and oppression of the innocent masses. Journalists and the mainstream media (such as news channels) are also perceived as pawns trying to "sell" falsities. This seems connected with previous findings indicating the response of the government to the pandemic as a main theme of discussion (Tsao et al., 2021) and distrust in the government being a main topic of discussion on the matter (Bălăeţ et al., 2023).

These framings resonate with what recent scholarship has identified as a form of populist storytelling, which connects diverse grievances under the overarching narrative of a virtuous people betrayed by corrupt elites (Lamour and Carls, 2022). In the case of COVID-related protests, populist discourse often blends health skepticism, distrust of institutions, and moral polarization (Thiele, 2022), fostering a binary worldview that aligns well with the algorithmic logic of social media. In the Trieste protest, this was evident in the frequent juxtaposition of "truth-telling workers" vs. "censored journalists," or "real people" vs. "sold-out scientists."

4.6 Anger vs. misinformation: surprising nulls

Some surprising findings are observed in the present work: firstly, while green pass, vaccination, and COVID were frequently mentioned in the tweet feed, they played a relatively minor part in "moving the crowd." We also do not find a relevant presence of health-related disinformation material. This indicates that non-compliance seems to be mostly fuelled by anger and feelings of oppression rather than specific beliefs on the nature of the vaccine or the green pass. A very small minority of users emerged as concerned with such topics in the clustering analysis, but they did not seem effective in gathering attention. This might be in contraposition with findings such as Bridgman et al. (2020) or Bin Naeem and Kamel Boulos (2021), indicating social media as a platform ripe with misinformation and conspiracy theories. A second surprising and connected finding is that conspiracy theories, both health-related and not, seemed to have very limited space in the tweet feed. We find the presence of tweets mentioning the foreign influence of Germany and China in the mobilization of the police force to crack down on the protests. We classify this material as conspiracy-related. Nonetheless, such material seemed to have a small impact on the overall conversation, as its prevalence was quite small. In addition, it was shared and posted by both pro non-compliance and pro-compliance users alike, showing little difference between the two opinions. Therefore, it does not seem to be directly connected to generating negative emotions such as anger or promoting non-compliant opinions. This contrasts with existing evidence that online misinformation might contribute to offline mobilization (Weigand et al., 2022; Fominaya, 2024).

4.7 Social media as crisis-management infrastructure

These findings build upon and contribute to existing literature on the role of social media in shaping pandemic-related discourse and public attitudes. Several studies have analyzed the thematic construction and communication of COVID-19 information across digital platforms. For instance, Sia (2022) compares discourse across Telegram, Twitter (now X), mainstream television, and news outlets, finding that health and scientific information was often presented ambiguously or inconsistently—particularly on social media platforms. The present study aligns with broader research using thematic and topic analysis to explore how online discourse reflects or fuels social responses to the COVID-19 crisis (Aria et al., 2022; Punziano et al., 2023), as well as other politically sensitive issues such as immigration (Ambrosetti and Miccoli, 2025). In the Italian context, our results echo and extend previous critiques of institutional social media use during the pandemic (Costa et al., 2025). For example, Fissi et al. (2022) note that governmental communication strategies were often poorly timed and misaligned with citizens' informational needs. Other studies have observed that although institutional messaging on social media has had some success in countering fear and encouraging compliance, it has often done so through fear-based appeals (Lerouge et al., 2023). Taken together, these findings underscore that social media is not merely a platform for public discourse but a powerful tool for crisis management and institutional engagement. As argued by Cascini et al. (2022), public discourse through social media represents a critical instrument for governments to recognize, interpret, and address the population's evolving concerns and emotional reactions. Our study supports this view, highlighting how digital platforms can amplify both support and dissent in response to health measures, and calling for more proactive and empathetic institutional communication strategies.

This study is limited to digital data collected during the protests themselves. Future research could be enriched by incorporating data on vaccine non-compliers from before the events, allowing for longitudinal analysis. In particular, natural language processing methods could be used to extract individual-level characteristics from users' prior tweets. This would enable researchers to model the probability of a user joining one side of the discourse or becoming especially vocal or influential once the events unfold. Such models could help explain not only who participates in viral political debates, but also how online movements gain traction. Examples of such studies can be found in Mooijman et al. (2018); Gu et al. (2021); Bestvater et al. (2023).

4.8 Conclusions

In this study, we take a look at the vast universe of online pro non-compliance content. As port workers blocked the Italian port of Trieste and, in defiance of most COVID-19 restriction instructions, gathered thousands of protesters in the city square, online onlookers cheered the port workers and angrily criticized the government. This study examines the characteristics and topics of online support for non-compliance. The case study of the Trieste protests offered itself as a useful opportunity, as it generated large quantities of online textual material that was shared and liked by thousands of users.

The main conclusion of this study is that online support for non-compliance is mainly characterized by anger and distrust toward the government, and feelings of perceived injustice. The present study results might have important implications for policymakers. First of all, the focus could shift from preventing misinformation to promoting a positive image of the government's efforts. Especially, extreme care should be dedicated to ensuring a perception of fairness, equality, and respect for all strata of the population when enforcing anti-COVID measures. In addition, the lack of dialogue, confrontation, and interaction between the opposing parties is also a source of worry. The vast majority of pro non-compliance users appeared convinced of their opinions, and we did not register in the topic analysis any topic regarding exchanges, confrontation, or direct discussion. It might be therefore be useful for policymakers to attempt direct negotiation, confrontation, or open dialogue with pro non-compliance protesters or actors.

In the case of the protests of Trieste, order and compliance were restored as protests were dispersed with the use of police intervention, water cannons, and direct legislative emanations to prevent assembly. Surely, the Friuli Venezia Giulia region and the Italian government benefited from the found again stability, but we are left to wonder if a different, less intensive solution could have been found. This study brings the perspective of users who supported the protests, highlighting their motives and topics of discussion, in an effort to provide researchers and policymakers with more information that might be useful in reducing the use of force in the future, or in how to successfully engage the pro non-compliance public in conversation.

> *"I picture you sitting comfortably in your office, green pass on your phone, staring at footage of freezing water cannons hitting protesters in Trieste, smirking and thinking "those no-vax deserve it." And honestly, I can only feel deep pity for you."*
> retweet count: >700, like count: >3,000, date: 2021-10-18

On a final note, it is important to note that this study does not aim to establish what position is right or wrong in the broader debate on COVID-19 restrictions or vaccination. The topic is inherently divisive, and side effects from vaccines, as well as concerns over civil liberties, are part of a legitimate and complex public discourse. Rather, our goal has been to explore how such divisive issues unfold and gain traction on social media, offering a methodological lens that could be extended to similarly polarized topics such as the Ukraine war, climate action, or artificial intelligence.

Data availability statement

The anonymised version of the datasets presented in this study can be found in the following GitHub repository: https://github.com/alberto-arletti/twitter_non_compliance.

Ethics statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and the institutional requirements.

Author contributions

AA: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. AC: Conceptualization, Data curation, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. PC: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpos.2025.1515923/full#supplementary-material

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