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Public responses to jihadist terrorism on social media

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ABSTRACT

Over the past decade, several major Jihadist terror attacks have shaken Europe. This study examines how social media users respond to Jihadist terrorism when discussing immigration-related issues from a comparative perspective. The theoretical predictions, derived from integrating theories of terror management, group threat, and social resilience, are empirically tested using LLM-validated Keyword-Assisted Topic Modeling (keyATM). Unlike traditional topic modeling approaches, keyATM is a semi-supervised method that combines data-driven discovery with theory-driven guidance. It incorporates pre-specified keywords, enhancing both the precision and interpretability of results while mitigating the impact of researcher subjectivity. The study is based on over 100,000 time-stamped and geo-coded Tweets on immigration and related issues across four languages in the week following eleven major Islamist terrorist attacks in nine European cities. Consistent with the theoretical predictions, the findings reveal that both threat-related and tolerance-related topics emerge prominently across all four languages. Deeper analyses uncover temporal shifts in the post-attack discourse: While initial reactions often reflect nationalist views (but not prejudice), later stages show a rise in inclusionary and tolerance-oriented topics. These results highlight the dynamic nature of social media debates on migration issues after dramatic events, where initial threat-driven responses often give way to more inclusive and tolerance-oriented discussions as time progresses.

1. Introduction

The rise of social media has transformed how societies respond to crisis events, including acts of terrorism. While traditional media historically played a central role in drawing attention to crisis events, social media platforms have become increasingly prominent venues for addressing such topics. After crisis events, platforms like Twitter (now X) and Facebook facilitate real-time emotional expression and political discussion (Belcastro et al., 2025; Bove et al., 2024; Hurtado Bodell and Menshikova, 2026; Tambuscio & Tschiggerl, 2023). Jihadist terror attacks are particularly relevant to national migration debates, as some public speakers and political actors blame Jihadist terror attacks on immigration (Kaminski, 2015; Waterfield, 2015).

Given the important implications of such attacks on intergroup relations, both online and offline, this study aims to identify and compare threat-related (Blumer, 1958) and resilience-related (Garcia & Rimé, 2019) topics in migration-related Twitter discourse following jihadist terrorist attacks, and to trace how their prevalence changes over time. To this end, it draws on comparative digital trace data coming from over 100,000 geolocated Tweets in four languages in the week following eleven major terrorist attacks in nine European cities.

As such, the study makes several contributions. Theoretically, it integrates theories of terror management, group threat, and social resilience into a single framework for the post-attack migration discourse. Methodologically, it applies semi-supervised keyword-assisted topic modeling across four languages, combining theory-driven topic identification with inductive discovery, based on large-scale data spanning multiple attacks, countries, and languages. Moreover, it validates these topics through LLM classification. Empirically, it shows comparatively how exclusionary and inclusionary reactions coexist and shift over time across countries and languages. Compared with previous single-case studies, this comparative, multilingual design makes it possible to assess whether the same discursive dynamics recur across contexts rather than being specific to one case.

The remainder of the paper proceeds as follows. The next section develops the theoretical framework to derive expectations about threat-related and inclusionary reactions to jihadist terrorist attacks in migration-related online discourse, as well as their temporal dynamics. This is followed by an outline of the modeling approach used to identify the theoretically grounded topics. The subsequent results section

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presents the identified topics and examines how their prevalence changes between the immediate aftermath of attacks and the following days. The paper concludes with a discussion of the findings, their implications for understanding online intergroup dynamics after terrorist events, and directions for future research.

2. Theory

2.1. Online and offline effects of terrorist attacks

Terrorist attacks are dramatic events that create fear and uncertainty. Beyond the direct harm caused by such attacks, they can shape political trust (Dinesen & Jæger, 2013), voting behavior (Vasilopoulos et al., 2019), labor market discrimination (Reichelt & Müller, 2024), and immigration attitudes (Hopkins, 2010; Legewie, 2013). In this process, social media platforms play an important role, as they provide access to and production of digital content and foster real-time interactions that shape how such events are interpreted and politicized (Neubaum et al., 2014). Generally, discussions with others in one's social network can serve as a coping mechanism, as demonstrated by Yum and Schenck-Hamlin (2005), who surveyed 121 US-American undergraduate students after 9/11 and reported that "interpersonal communication is an important means of eliminating or reducing existential terror" (265).

In Europe, jihadist terrorism is frequently tied to debates about immigration, with public discourse often framing these attacks as linked to broader issues of migration (Kaminski, 2015; McGuinness & Gozzi, 2024; Waterfield, 2015). Consequently, jihadist attacks can heighten perceptions of threat and provoke immigration-hostile reactions. A few studies have examined the impact of terrorist attacks on social media, usually focusing on negative consequences and hate speech. Giavazzi et al. (2023) show that the language used on German Twitter became more aligned with that of the right-wing Alternative für Deutschland (AfD) party following terrorism and crime-related events. Czymara et al. (2023) observed an increase in ethnic insults in YouTube comments on migration-related issues before and after several attacks in Europe. Based on ten terror attacks across Europe, Czymara and Gorodzeisky (2024) report that such a pattern is even more pronounced on Twitter, driven by both a fluctuation of users and within-user changes in tweeting behavior. Bove et al. (2024) show that these attacks can also lead to a rise in negative emotions and feelings toward immigration. Grobelscheg et al. (2022) employ structural topic modeling on tweets posted after four terror attacks and find emotions and narratives directed toward authority accounts dominate the social media discourse after these events. Darwish et al. (2018) demonstrate that reactions to a jihadist terror attack depend on users' network interactions and tweets before the attack. Additionally, Jović et al. (2023), analyzed Wikipedia page views and found that attacks increased interest not only in pages related to the attackers (e.g., terrorism or Islam) but also in pages about security and national or religious identities. Hurtado Bodell and Menshikova (2026) demonstrate that the salience of security and cultural themes in a Swedish discussion forum increased after terrorist attacks and Kostakos et al. (2018) identify threat-related topics after the Manchester bombing in 2017. However, public reactions are not uniformly exclusionary, but may also include expressions of tolerance across ethno-religious groups. Accordingly, social media debates after terrorist attacks may not only convey nationalistic sentiments and out-group hostilities, but also calls for solidarity (Fischer-Preßler et al., 2019; Garcia & Rimé, 2019). This is further supported by Kušen and Strembeck (2022) who show that the tendency to spread hope and empathy often dominates social media after terror attacks.

While these studies laid the groundwork for the question of how social media discussions on migration are shaped by jihadist terrorist attacks, many of them focused exclusively on hate speech and anti-immigration sentiment, and most are based on single case studies. This study extends this literature by systematically examining content across several major attacks in different countries and languages. By using a semi-supervised method, it identifies both hostile and supportive discourse. This approach allows for a more comprehensive understanding of how such events reshape online debates about migration and their potential to influence public attitudes across cases and countries.

In the following, I will first discuss the common reactions to terrorism based on terror management theory, as developed by Yum and Schenck-Hamlin (2005). Then, I will integrate group threat theory and the concept of social resilience into terror management theory to identify which reactions are particularly relevant for the migration discourse on social media after jihadist terrorist attacks.

2.2. Terror management theory

Terror management theory is a psychological theory that posits that humans have a fundamental fear of death, which drives much of their behavior, particularly after existential threats such as terrorist attacks. To manage this existential anxiety, people cling to cultural worldviews and self-esteem to help cope with the fear of their mortality. This idea was developed by Greenberg et al. (1986). Based on this reasoning and qualitative evidence, Pyszczynski et al. (2003) developed four proximal and six distal common reactions to the 9/11 attacks. While proximal defenses involve strategies aimed at reducing anxiety, distal defenses focus on reinforcing cultural worldviews. The distal reactions included a search for meaning and value (e.g., praying, going to religious services), patriotism and nationalistic sentiment (e.g., wearing patriotic symbols, listening to patriotic songs, derogating different cultural values), prejudice or stereotyping, counterbigotry activism (e.g., calling for tolerance and understanding, awareness), altruistic or prosocial behaviors (e.g., empathy or comforting), and appreciation of helpers.[2] Yum and Schenck-Hamlin (2005) tested these theoretical predictions by surveying 121 US-American undergraduate students after 9/11 and expanded the theory by introducing three additional types of distal reactions: communication for relationship investment, information sharing, and no action. Applying terror management theory to Twitter data following the 2016 terrorist attack on the Berlin Christmas market, Fischer-Preßler et al. (2019) identified several topics that can be mapped into the categorization theme of Yum and Schenck-Hamlin (2005). While not all the topics emerging in the aftermath of terrorist attacks are tied to the migration discourse, which is the focus of the present study, there are four that are particularly relevant in this context, as I will elaborate in the following. Two of these reactions are connected to *group threat*, and two to *social resilience*.

2.3. Topic expectations: nationalism & prejudice

According to sociological *group threat theory*, negative views of out-groups such as immigrants and ethnic or religious minorities arise when the social majority perceives them as threatening their interests, well-being, or the social status quo. In his influential work on racial prejudice in the US, Herbert Blumer posited that events "loaded with great collective significance" are "particularly potent in shaping the sense of social position" (Blumer, 1958, p. 6). Put differently, significant events play a crucial role in fostering exclusionary and discriminatory views and hostile behavior by reinforcing the majority's perception of minority groups as threats. Jihadist terror attacks, often attributed to immigrants, are examples of such significant events, as they threaten both individual and collective security as well as social norms (Czymara & Schmidt-Catran, 2017; Legewie, 2013).

In line with this reasoning, several studies reported greater levels of anti-immigration attitudes after jihadist terrorist attacks based on quasi-

[2] The proximal reactions include shock and disbelief, diverting attention, withdrawing, and willingness to sacrifice individual freedom and privacy (Pyszczynski et al., 2003).

experimental secondary survey data (Finseraas et al., 2011; Hopkins, 2010; Nägel & Lutter, 2020; Nussio et al., 2019). It should be noted, however, that there is also an increasing number of studies showing limited to no effect of terrorism on immigration attitudes based on similar research designs (Brouard et al., 2018; Castanho Silva, 2018; Savelkoul et al., 2022). Existing research on social media content suggests that public reactions to terrorism on these platforms tend to be more pronounced compared to those typically observed in survey data (Czymara et al., 2023; Czymara & Gorodzeisky, 2024; Giavazzi et al., 2023; Hurtado Bodell and Menshikova, 2026; Spörlein & Schlueter, 2020). A likely explanation is that people actively turn to social media to process and discuss events. Thus, Twitter is an excellent case to study how jihadist terrorism shapes the prominence of exclusionary topics in social media debates about migration.

Such exclusionary sentiments correspond to terror management theory's reactions of “patriotism and nationalistic sentiment” and “prejudice or stereotyping” (which Yum and Schenck-Hamlin (2005) merge into one category). Thus, I expect that posts relating to migration after terror attacks feature *nationalism* as well as *prejudice*.

“Prejudice or stereotyping” refers to hostile reactions against outgroups or prejudice and stereotypical thinking, which can manifest as racist hate speech and ethnic insults on social media (Kaakinen et al., 2018; Spörlein & Schlueter, 2020). “Patriotism and nationalistic sentiment”, on the other hand, captures strengthened positive attitudes toward ethnic, religious, and political ingroups (Pyszczynski et al., 2003), although it can be accompanied by derogating different values. While the former is a negative evaluation of an outgroup, the latter is mostly a positive reference to one's ingroup.

2.4. Topic expectations: prosocial behavior & counterbigotry

Reactions to terrorist attacks are not always hostile or exclusionary. For example, Fischer-Preßler et al. (2019) reported that users also expressed sympathy for the victims and advocated for tolerance after the terror attack in Berlin. Notably, this also concerns terrorist attacks against ethno-religious minorities, which can lead to higher levels of acceptance among the majority population (Bulbulia et al., 2023). Garcia and Rimé (2019) explain this phenomenon with the *social resilience* that can follow from the collective trauma caused by such events. Shared emotional experiences can foster solidarity among ethno-religious groups and promote prosocial communication through the peer-to-peer perspective offered by social media. Ultimately, the shared distress can unite people by strengthening a common identity. Accordingly, while negative reactions to an attack are often short-lived, the resulting increase in solidarity tends to have a longer-lasting impact (Garcia & Rimé, 2019).

Tolerance and solidarity-related topics are captured by terror management theory's reactions of “altruistic or prosocial behaviors” and “counterbigotry activism” (Yum & Schenck-Hamlin, 2005). I thus expect that posts relating to migration after terror attacks feature altruistic or *prosocial* content as well as *counterbigotry* activism.

Both are supportive social reactions, connecting individuals across ethnic, religious, and political groups. The former can include expressions of empathy, offering support, or the sharing of emotions (Pyszczynski et al., 2003). The latter encompasses activities such as a call for tolerance and against hate and nationalism, and can as such be viewed as the counter-reaction to the nationalist and prejudiced reactions (Hohner et al., 2022). Such topics are regularly found in social media data following terrorist events (Fischer-Preßler et al., 2019; Garcia & Rimé, 2019; Kušen & Strembeck, 2022).

2.5. The dynamic nature of topics

The impact of terrorism on online discussions about migration issues evolves over time. Studies of social media activity reveal that initial spikes in online hate speech following terrorist attacks decrease over time (Czymara & Gorodzeisky, 2024; Kaakinen et al., 2018; Kostakos et al., 2018). This mirrors the survey research finding that the negative effects of Jihadist terrorist attacks on attitudes toward immigration tend to be short-lived (Hopkins, 2010; Legewie, 2013; Turkoglu & Chadefaux, 2022). Aligned with trends of declining hate speech, the content of online discussions about terrorism fluctuates. For example, Garcia and Rimé (2019) found that negative emotions in Tweets surged immediately after the November 2015 Paris terrorist attacks but subsided within days, followed by an increase in expressions of solidarity that persisted for a longer period. Similarly, Fischer-Preßler et al. (2019) observed that users were more likely to post emotionally charged Tweets in the immediate aftermath of an attack, while opinion-driven content became more prevalent in the days that followed.

Following this line of research, I investigate how Twitter users' reactions to eleven major terrorist attacks in the context of the migration discourse evolve over time. Topics indicating group threat, such as nationalistic or prejudiced reactions, should occur more often in the days directly following the attacks, given that they are more immediate reactions.

Yet, hate speech also has a “half-life” as Williams and Burnap (2016) put it (p. 234), as such negative content de-escalated in the days following the attack. Following this argumentation, topics relating to social resilience and positive aspects of intergroup relations, such as prosocial behaviors or counterbigotry activism, are expected to be more prevalent in the later days following the attacks, as they are often counter-movements and should thus follow at a somewhat later stage.

In brief, I expect both threat-related and resilience-related topics to emerge, with threat-related reactions (nationalism, prejudice) concentrated in the immediate aftermath and resilience-related reactions (Counterbigotry, prosocial) becoming more prominent in the following days.

3. Data & method

3.1. Cases and scraping

I draw upon Tweets posted in the week after eleven major jihadist terror attacks in Europe. This includes all major terrorist attacks that took place in Europe after the establishment of Twitter (before it was rebranded to X), defined as attacks that killed at least five and injured more than ten people. Table 1 gives an overview of the attacks that were included in the analysis.

All Tweets were scraped between December 2022 and January 2023 from the v2 API endpoint for the Academic Research Product Track using Barrie and Ho (2021). The goal was to identify original tweets concerned with migration and Islam, as Muslims are perhaps the most debated immigrant group in the European context. Based on prior research investigating migration-related attitudes on social media (Czymara & Gorodzeisky, 2024; Menshikova & van Tubergen, 2022), I used a search string including keywords such as “immigration”, “foreigners”, “refugees”, “Muslims”, “Islam”, and “Jihad”. Tweets were collected when they included at least one of these keywords. The query did not include attack-specific hashtags or other terrorism-related keywords, as the aim was to capture shifts in discussions tied to migration and related issues rather than the events themselves. For each term, I searched for its direct appearance in a tweet as well as its hashtag. The English search string was translated into French, German, and Spanish by native speakers for language-specific queries. I did not include retweets in the sample as they do not constitute original content.

The analyses are based on accounts located in the city where the respective attack took place to examine reactions of those who were most likely affected and exposed to the event. People in the affected city are not only more likely to feel a heightened sense of threat and vulnerability, but they may also display stronger expressions of solidarity in response to shared trauma (Kušen & Strembeck, 2023). The target population of this study is residents of cities affected by an attack.

Table 1
Overview of attacks.

City	Date	Attack	Deaths	Injuries	Abbreviation	N
Paris (FR)	7-9 January 2015	Charlie Hebdo + kosher supermarket shootings	17	19	FR15_CH	28,195
Paris (FR)	13 November 2015	Bataclan shootings and other attacks	137	413	FR15_BATA	18,083
Brussels (BE)	22 March 2016	Airport and metro station bombings	32	340	BE16	994
Nice (FR)	14 July 2016	Bastille Day truck attack	87	270	FR16	475
Berlin (DE)	19 December 2016	Christmas market truck attack	13	48	DE16	1692
London (UK)	22 March 2017	Westminster Bridge attack	5	48	UK17_west	19,104
Manchester (UK)	22 May 2017	Manchester Arena bombing	22	239	UK17_man	3662
London (UK)	3 June 2017	London Bridge attack	8	48	UK17_lon	24,130
Barcelona (ES)	17 August 2017	Van attacks	15	104	ES17	5342
Strasbourg (FR)	11 December 2018	Christmas market attack	5	11	FR18	298
Vienna (AT)	02 November 2020	Shootings	5	22	AT20	1012

I identified these users based on the location they provided in their profiles, following previous studies (Flores, 2017; Menshikova & van Tubergen, 2022). This strategy yielded a dataset of 102,987 Tweets posted by 36,413 accounts, which are the basis of the analysis. Appendix A documents data collection, preprocessing, validation, and analysis in detail.

Fig. 1 shows the distribution of Tweets after each attack by plotting the minutes after the attack on the x-axis and the distribution of the tweet density on the y-axis, standardized so that each case's maximum has a value of 1. The peaks thus indicate when tweet activity was most

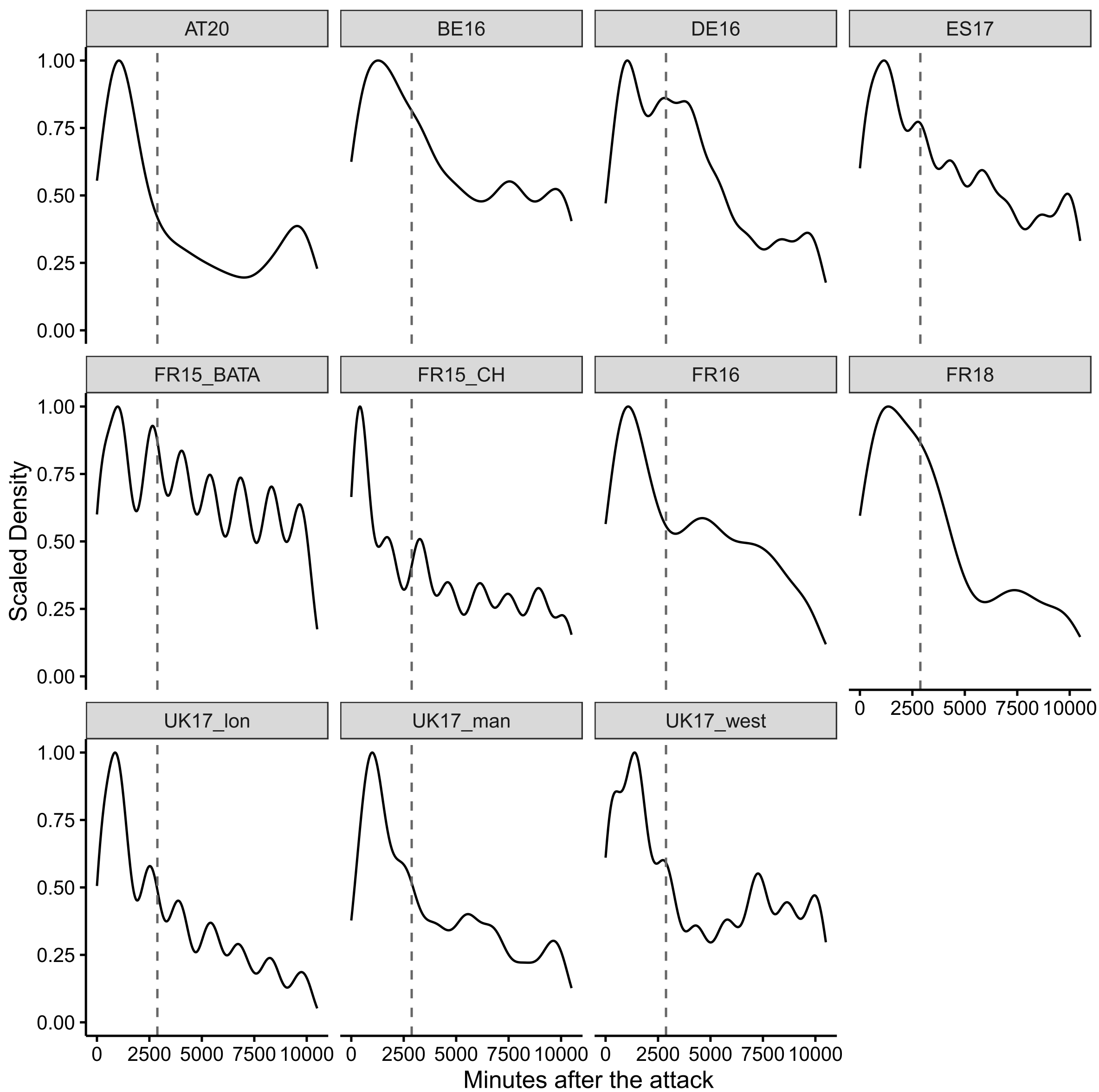

Fig. 1. Distribution of Tweets over Time
Note: Minutes after an attack on the x-axis; and the Kernel density estimate (scaled to a maximum of 1) of tweets on the y-axis. Dashed vertical lines separate days 1 and 2 from days 3 to 7.

concentrated for each case. One can see that, generally, users tweeted most in the hours following the attacks, which then levels off over time.

Looking at the distribution of tweets by language reveals that the data are dominated by French and English, each making up roughly 46 percent of the data. With over 2700 German tweets and over 5300 Spanish tweets, however, the dataset provides enough texts per language to enable a meaningful quantitative analysis. One should also keep in mind that each case includes only tweets written in the respective national language.

3.2. Keyword-assisted topic modeling

I employ Keyword-Assisted Topic Modeling (keyATM) developed by Eshima et al. (2024). keyATM is a semi-supervised machine learning model that identifies topics predefined by keywords and estimates the prevalence of these topics in each tweet. This method offers significant advantages over traditional topic modeling approaches like Structural Topic Modeling (STM) or Latent Dirichlet Allocation (LDA), as well as other common techniques such as word frequency analysis (Eshima et al., 2024; Hurtado Bodell et al., 2024). Unlike word frequency techniques, keyATM can uncover unexpected patterns of words that tend to co-occur with the keywords. Moreover, the approach is not deterministic, as these words are only the starting point from which a model begins to learn word associations (Hurtado Bodell et al., 2024). Building on STM and LDA, keyATM uses the initial keywords linked to concepts of interest, such as nationalism or counterbigotry activism, to identify and refine relevant topics. Yet, the model can also discover previously unknown topics not captured by any predefined keywords, corresponding to fully unsupervised topic models (Eshima et al., 2024). Together, this approach enables the detection and measurement of both expected and unexpected ways in which twitter users discuss terrorist attacks.

The concept of keyATM is thus perfectly suited for the research questions of this paper and offers a key advantage to alternative approaches such as STM. As discussed above, there are theoretical expectations about the topics to be found, yet these expectations are unlikely to cover all content exhaustively. This tackles the issue of having to identify relevant topics in an ex post facto manner from the output generated by the machine (as in Fischer-Preßler et al., 2019), and the problem of having to work with unclear topics. Instead of retroactively forcing the empirical topics into preexisting theoretical concepts, keyATM searches for the theoretical concepts directly (Hurtado Bodell et al., 2024). An additional advantage to STM and other fully unsupervised topic modeling approaches is that, because certain topics are specified, the results of keyATM are much less sensitive to the number of topics (Eshima et al., 2024, p. 11).

In particular, I employ the *Covariate keyATM model*, which allows for the incorporation of document-level covariates to test the relationship between these covariates and the topic probabilities (Eshima et al., 2024, p. 9f.). Following Fischer-Preßler et al. (2019), I model the topic probabilities as a function of a binary variable that distinguishes Tweets posted in the first two days after an attack from those posted on days three to seven. The robustness checks show that the results are largely similar when using other reasonable bandwidths.

3.3. Topic identification

I am particularly interested in the terror management theory reactions that relate to group threat and social resilience. As argued above, reactions following group threat include “patriotism and nationalistic sentiment” and “prejudice or stereotyping”. I call the first topic *Nationalism*. It includes concepts of nationalistic sentiment and anti-immigrant exclusionism. The second topic, which I call *Prejudice*, refers to prejudiced or stereotypical views of minorities. As discussed above, reactions related to social resilience, often countering group threat, include “counterbigotry activism” and “altruistic or prosocial behaviors”. The topic that I call *Counterbigotry* captures tolerant and accepting views of minorities, and the topic *Prosocial* contains support and empathy with affected groups.

The next step is to select the keywords that define these topics. As Hurtado Bodell et al., 2024 point out, good keywords stand for a topic but are not polysemic, i.e. do not have ambiguous meanings. With these considerations in mind, I scanned previous research for relevant keywords and empirically assessed these keywords with the data at hand (i.e., removing keywords that were not found, adding theoretically relevant keywords that appeared in a topic). For example, the topic of *Nationalism* includes keywords such as “proud”, “patriot”, or “culture”, but not terms such as “country”, as it can appear in various meanings in migration contexts. The most relevant type of *Prejudice* here is that of “violent”, “criminal” migrants that pose a “danger” or “threat” to the receiving society. While the keywords reflect this stereotype, one might think that they may, in part, also reflect descriptions of the attack. However, the validation of topics shows that these keywords work well empirically in capturing prejudice. Counterbigotry is about “peace”, “tolerance”, and “solidarity” against “racism”. Finally, *Prosocial* includes terms such as “victims”, “sympathy”, and “condolences”. For comparability, each topic contained five to seven keywords. The keyword lists were developed in English and then translated for each topic and, if necessary, adapted to French, German, and Spanish by native speakers. The full set of keywords is listed in Table 2. In addition to the four keyword topics, the model includes 20 non-keyword topics to capture other aspects of the discourse. The robustness checks show that using 10 or 30 non-keyword topics does not change the conclusions.

To validate the topics, I sampled the 150 most representative tweets for each topic-language combination based on the model's document-topic distribution θ, and then employed GPT-3.5-turbo-0125 for zero-shot classification, which has been shown to mirror well or potentially even exceed (Törnberg, 2023) the judgment of human coders, which is usually considered the gold standard (Gilardi et al., 2023; Ornstein et al., 2025). I developed language-specific instructions and fed ChatGPT each tweet (see Appendix A for details). For the interpretation of these numbers, it is important to remember that not all texts assigned to a topic are expected to exclusively focus on that topic, as these are probability-based mixed-membership models. I manually

Table 2
Keyword lists for each topic by language.

	Nationalism	Prejudice	Counterbigotry	Prosocial
English	proud, tradition, culture, patriot, patriotic	criminal, danger, illegal, violence, violent, threat, barbarism	love, peace, tolerance, racist, racism, solidarity	victims, relatives, thoughts, condolences, sympathy, mourn
French	fier, fière, fiers, culture, tradition, patriote, patriotique	criminelle, danger, illégale, violence, violente, menace, barbarie	amour, paix, tolérance, raciste, racisme, solidarité	victimes, proches, pensées, condoléances, sympathies, deuil
German	stolz, tradition, kultur, patriot, patriotisch, volk	kriminell, gefahr, illegal, gewalt, gewalttätig, bedrohung, barbarei	liebe, frieden, toleranz, rassist, rassismus, hetze, solidarität	opfer, angehörige, gedanken, gedenken, beileid, trauer
Spanish	orgulloso, tradición, cultura, patriota, patriótico	criminal, peligro, ilegal, violencia, violenta, amenaza, barbarie	amor, paz, tolerancia, racista, racismo, solidaridad	víctima, familiares, pensamientos, condolencia, pésame, dolor

double-checked these classifications. The results show that the topics work reasonably well: On average, each topic overlapped 70 percent with the GPT classification, ranging from 49 percent (*Nationalism* in English, *Prosocial* in French) to 89 percent (*Prejudice* in French and German). The full comparison scores can be found in Table A1 in the Appendix. Crucially, there is no reason to assume that measurement error is systematically related to time and, thus, the temporal analysis should not be affected by this. Yet, one might keep these differences in mind when interpreting the results.

4. Results

4.1. Topic estimation

Table 3 presents the four empirical keyword topics in each language, displaying their ten most probable terms. The keywords are most prominent in the *Prejudice* topic, with three to five keywords appearing in the top 10 terms for each language. In three cases, topics feature one keyword in their top 10 (*Nationalism* in French and German, *Prosocial* in English), while the remaining topics show two to four keywords in their top 10 terms.

Table 3
Top terms of keyword-assisted topic models.

Nationalism	Prejudice	Counterbigotry	Prosocial
English			
cultur [✓]	muslim	muslim	muslim
muslim	islam	islam	attack
immigr	violent [✓]	peac [✓]	victim [✓]
islam	violenc [✓]	love [✓]	london
refuge	true	racist [✓]	islam
migrat	call	peopl	terror
tradit [✓]	rape	religion	terrorist
migrant	crimin [✓]	terrorist	peopl
religion	threat [✓]	terror	westminst
chang	illeg [✓]	hate	communiti
French			
islam	barbar [✓]	musulman	musulman
djihad	musulman	paix [✓]	victim [✓]
musulman	menac [✓]	l'islam	c'est
franc	l'islam	c'est	pens [✓]
cultur [✓]	islam	religion	l'islam
anonymous	franc	terror	terror
sit	violenc [✓]	islam	islam
l'islam	terror	racist [✓]	franc
charl	criminel [✓]	juif	charliehebdo
jihad	acte	franc	qu'il
German			
asyl	gewalt [✓]	hetz [✓]	opf [✓]
turk	illegal [✓]	rassismus [✓]	muslim
deutschland	gefahr [✓]	fried [✓]	trau [✓]
stolz [✓]	muslim	muslim	gedenk [✓]
turkei	fluchtling	islam	islam
beantrag	migration	lieb [✓]	berlin
muslim	einwander	islamismus	fluchtling
fluchtling	asyl	fluchtling	anschlag
islam	wien	terror	islamist
land	turkisch	glaub	terror
Spanish			
cultur [✓]	amenaz [✓]	musulman	musulman
musulman	musulman	islam	victim [✓]
orgull [✓]	violenci [✓]	paz [✓]	terror
islam	islam	terror	islam
inmigr	violent [✓]	racist [✓]	yihad
necesit	yihad	religion	barcelon
abraz	terror	barcelon	dolor [✓]
padr	atent	racism [✓]	refugi
años	vide	amor [✓]	atent
muert	criminal [✓]	yihad	gent

Note: Columns list the most probable terms for a given keyword topic per language, ranked by their estimated within-topic probability. Keywords are indicated by [✓].

A qualitative examination shows that many Tweets on the *Nationalism* topic blame open border policies for the terrorist attacks or emphasize national identification. For example, an English user writes: “Europe's woes result from an erosion of shared national identities - this has been exacerbated by mass migration”. An Austrian user wrote after the Vienna attack that “It was not a natural disaster, the perpetrator was an Islamist and came to Austria via the asylum route. Your appeasement policy is dangerous”.[3] The *Prejudice* topic includes many Tweets that are derogatory toward migrants in general and Muslims in particular. An English user tweeted: “Mass 3rd world immigration has brought crime, disease, open drug dealing, violence, child grooming rape on an industrial scale & now terror!”. A French user wrote: “immigration is the mother of (almost) all our ills”.

In contrast to the two topics discussed so far, the *Counterbigotry* topic captures openness and inclusivity. For example, an English user reports that “Christians giving flower & “You Are Loved” card 2 Muslims @ North Mcr Jamia Mosque after Fri prayer 2day. Wonderful gesture of solidarity”. After the Christmas market attack in Strasbourg, a French user wrote: “To put all Muslims on the same level is to play into the hands of these criminals, because their aim is to divide by terror and to set us against each other”. Finally, the *Prosocial* topic captures processes involved in understanding and sharing the feelings of others. This includes an English user writing: “Muslim taxi drivers taking people home, Sikh and Jewish communities offering food and water, local business supplying brews”, or a German user writing: “Our thoughts are with the relatives and victims […] It is not a particular religion or “culture”, but the breeding ground for misanthropic ideologies that must now be combated”.

Overall, the two inclusive and empathizing topics, *Counterbigotry* and *Prosocial*, are more prevalent than the group threat-related topics of *Nationalism* and *Prejudice* in all four languages, as shown in Fig. 2 (*Counterbigotry* and *Prosocial* also rank in the top five topics overall, as shown by Figs. A1–A4 in the Appendix).[4] Fig. 2 indicates that the two threat-related topics, *Prejudice* and *Nationalism,* occur with 3.1 to 5.2 percent in all languages. This, thus, confirms the theoretical expectations, particularly for the Counterbigotry and Prosocial topics, and somewhat less for the Prejudice and Nationalism topics.

Combined, the four keyword topics comprise roughly a quarter of the English and of the Spanish corpus, and just over a fifth of the French and of the German corpus, respectively. Given that the expected proportion of these topics would be 17 percent if all topics occurred with the same frequency (1/24*4, as they are four out of 24), the four keyword topics jointly account for a disproportionately high share of the total data (see Tables A2.1 to A2.4 in the Appendix for all topics). Yet, as argued above, one benefit of the keyATM approach is that it also learns other, non-keyword topics from the data. This residual part of the data allows for identifying aspects that were not identified ex-ante. While discussing all of the 20 non-keyword topics in four languages is not feasible, there are some interesting patterns. There are some attack-specific topics (e.g. the French topic 10, which discusses the Charlie Hebdo attack, or the German topic 7 on the Breitscheidplatz Christmas market attack). Others refer to the broader political contexts of the attacks. For example, there are several topics mentioning Brexit and its relation to asylum and immigration in the English data (e. g., “Mass immigration [is] part of being in EU”). The occurrence of Merkel in various topics in the German data points to users blaming the then chancellor Angela Merkel and her

[3] All translations were done with the neural machine translation service DeepL, with manual corrections in some cases to improve readability or ensure anonymity.

[4] Note that the proportion of each topic depends on the number of topics in the model – more topics in total imply a smaller share for each. Thus, the relative position of a topic vis-à-vis others and the changes in topics over time are more meaningful than the mere percentages.

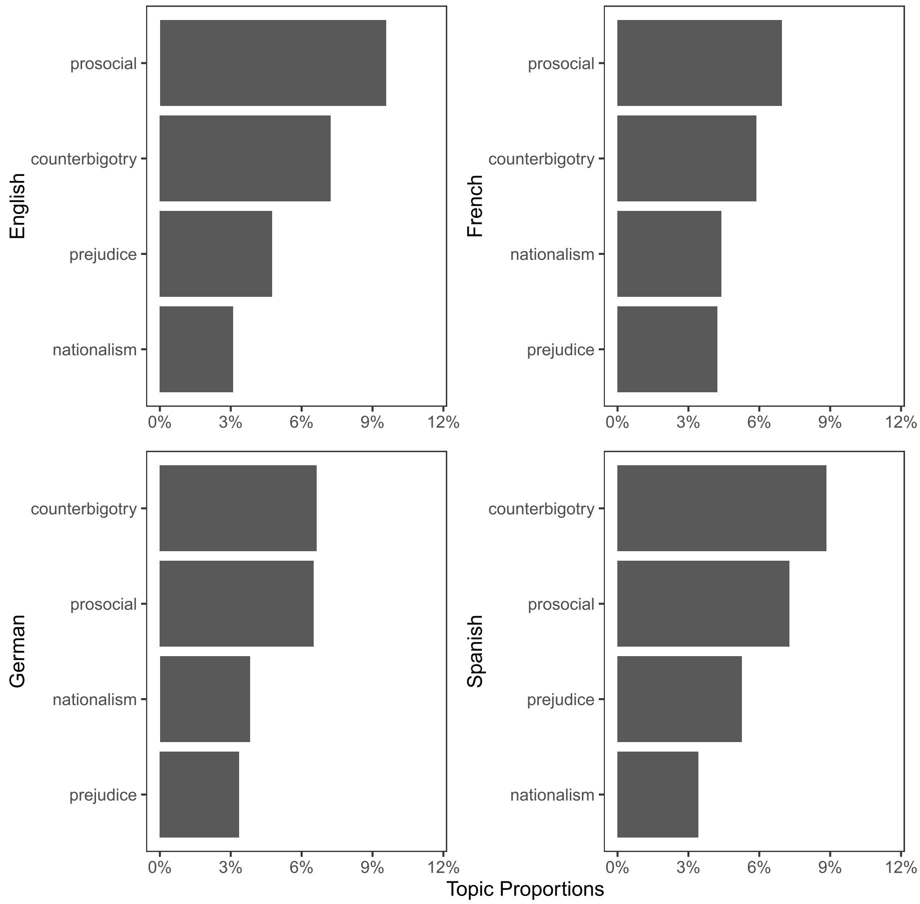

Fig. 2. Overall Prevalence of Keyword Topics

liberal border policy for the attack (e.g. "Merkel wanted refugees as truck drivers - The result: Breitscheidplatz BerlinAttack. Resign Mrs. Merkel!"). Comparing these topics across cases is difficult, however, since they are very context-specific.

4.2. *Temporal analysis*

Turning to the second part of this study's research question, Fig. 3 tests whether the occurrence of the four keyword topics differs between the first two and the last five days. It is based on the marginal posterior means of the topic probability distributions for the two levels of the predictor (Days 1 and 2 vs. Days 3 to 7) and their 90 percent credible intervals (Eshima et al., 2024).

In the upper left panel of Fig. 3, one can see that the *Nationalism* topic was statistically significantly more likely to occur in the first two days after an attack in all cases. The difference between the first and last days ranges from −0.9 percentage points in the Spanish case to −2.3 percentage points in the French data. The pattern that this topic was more pronounced in earlier stages is consistent across all languages, which is in line with the theoretical reasoning postulated above.

The *Prejudice* topic was also somewhat more present in the first days in German and Spanish, but these differences are not statistically significant, as the upper right panel of Fig. 3 shows. In contrast to theoretical expectations, the *Prejudice* topic was actually significantly more prevalent during the later days in the English and French data. In sum, the evidence largely does not confirm the theoretical claims regarding the *Prejudice* topic. I will return to these mixed results in the discussion.

The two topics *Counterbigotry* and *Prosocial* were clearly more present at later stages after the attacks, as Fig. 3 indicates. The lower left panel of the figure shows that the increase in the *Counterbigotry* topic over time ranges from about 1.9 percentage points in the English data to 4.9 in the Spanish data, and is statistically significant in all four cases. Accordingly, this topic is most prevalent overall in the Spanish data for days 3 to 7, with a predicted probability of 8.3 percent. But even in the English case, the probability of this topic rose over time to about 5.5 percent in total. These findings are consistent with the theoretical argument that these topics often relate to counter-movements that are meant to tackle hate and aggression.

Finally, the lower right panel of Fig. 3 shows that the *Prosocial* topic was also clearly more prevalent during later days in all languages. This increase ranges between four percentage points in the German data to 6.7 percentage points in the English data. These differences are statistically significant in all cases. This topic has its strongest peak in the English data on days 3 to 7 after the attack, when it amounts to almost ten percent. Taken together, this evidence clearly supports the expectations.

In sum, the results are largely, but not always, in line with the theoretical expectations. While the fact that nationalistic content was more frequent at earlier stages and the two empathizing and inclusionary topics became more prevalent at a later point is consistent with the theoretical predictions, the unclear pattern of the *Prejudice* topic was unexpected.

4.3. *Robustness checks*

I assess the robustness of the findings reported above to the choice of the temporal cut-point and the number of topics specified in the model.

First, the main analysis contrasts the aftermath of an attack (Days 1–2) with the subsequent period (Days 3–7). However, defining these periods may have consequences for the observed early-versus-late

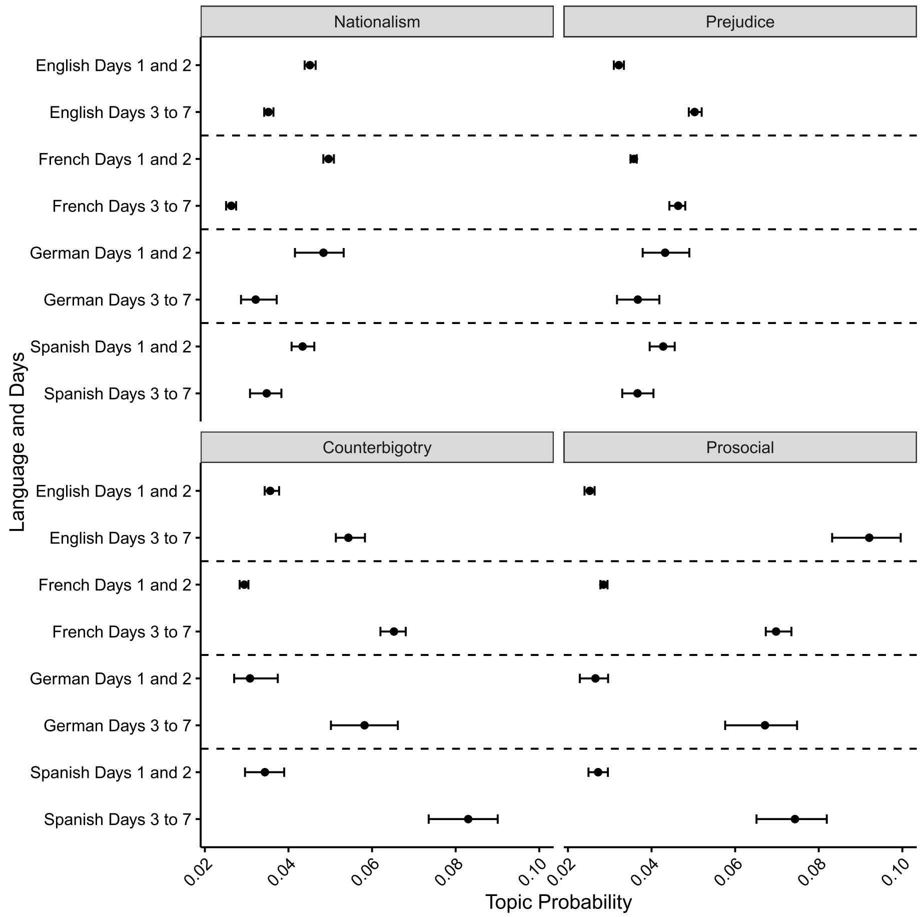

Fig. 3. Changes in Topic Prevalence Over Time
Note: Posterior topic-probability estimates with 90% credible intervals.

dynamic. To examine this, I re-estimate topic prevalence under two alternative splits, comparing Day 1 against Days 2–7, and Days 1–3 against Days 4–7 (Panel A in Fig. A6 in the Appendix). The substantive pattern is robust to the cut-off: Nationalism was more prevalent in the earlier window (except Spain) and declined thereafter, while Counterbigotry and Prosocial content were consistently more prevalent in the later window in all cases. Prejudice increased in the later period in English and French, but is flat or somewhat higher early in German and Spanish. The direction and ordering of effects, therefore, by and large do not depend on the specific cut-point, though Prejudice remains the topic that does not behave as theoretically expected.

Second, keyATM requires the analyst to fix the number of topics the model should identify. Eshima et al. (2024) note that keyATM is less sensitive to the number of topics compared to other topic model approaches. I nevertheless re-estimated the model with 10 and with 30 non-keyword topics (Panel B in Fig. A6 in the Appendix). Naturally, absolute topic probabilities are lower when the overall content is divided among more topics, but the substantive contrasts are stable: Nationalism was higher in the first two days across all languages, though this change is weaker for Germany in the 30- and for Spanish in the 10-topic model, where the difference is rather small and, in some cases, not statistically significant. The later increase in Counterbigotry and Prosocial content holds across both specifications and all four languages. Prejudice is again heterogeneous, as it remains larger in the later period in English and French, but significantly more prevalent in the early period in German and Spanish in the 30-topic model.

Taken together, these checks indicate that the early nationalist reaction and the later increase of counter-bigoted and prosocial discourse are largely robust to reasonable alternative specifications of both the time window and the topic count, whereas Prejudice shows a mixed pattern.

5. Conclusion

5.1. Summary and implications

Jihadist terrorist attacks shape public debates on migration-related issues on social media. Integrating psychology's terror management theory with sociology's group threat theory and the concept of social resilience, this study examined the heterogeneity in such responses. Employing Keyword-Assisted Topic Modeling on tweets from eleven case studies, the paper has shown that such discussions reflect empathetic and inclusionary as well as prejudiced and nationalistic topics.

Deeper analyses revealed that the content in these discussions fluctuated with time. During the first days after an attack, tweets were more likely to feature nationalism. This pattern suggests a mechanism by which the threat induced by terrorist attacks leads some users to post nationalist content in direct response to the event, as predicted by group threat theory (Blumer, 1958; Legewie, 2013). However, the prevalence of this topic diminished over time, consistent with prior research demonstrating that the negative effects of terrorist attacks tend to wane over time, both in regard to ethno-religious hostility on social media (Czymara & Gorodzeisky, 2024) as well as public opinion toward immigration more broadly (Hopkins, 2010; Legewie, 2013; Turkoglu & Chadefaux, 2022). In contrast to theoretical expectations, prejudice content showed more inconsistent patterns and actually peaked at the later period in English and French. While this should not be overinterpreted, this may suggest that the initial reaction to terror attacks boosts in-group affirmation more than out-group derogation. However, this is only part of the story. As the picture shifts in the later days following an attack, positive views of intergroup relations and tweets countering bigoted arguments become more important. Inclusionary topics relating to counter-activism and prosocial behavior that have become more frequent in later days indicate the long-term effects of the attacks on solidarity. Thus, existential threats can also evoke efforts to affirm shared values and foster inclusivity and solidarity (Weber et al., 2023). This dual response suggests a temporal dimension to how online communities process traumatic events, where initial fear and exclusion are gradually tempered by calls for solidarity and tolerance. Such a pattern would have been difficult to detect with secondary survey data, as it usually relies on predefined standardized items and cannot capture shifts in the composition of a discourse. Social media data, in contrast, provides insights into the organic and diverse expressions of users, enabling a more detailed understanding of these dynamics.

5.2. Limitations and future research

Of course, this study has its limitations, which might inspire future research on the matter. The finding that inclusive and empathizing topics were more prevalent in the data than group threat-related topics is somewhat surprising given previous research on negative emotions and hate speech in social media debates about migration (Bove et al., 2024; Menshikova & van Tubergen, 2022), although, other studies suggest that the effects of terrorism on solidarity tend to be longer lasting than the rise of intolerance (Garcia & Rimé, 2019). One possible explanation is that hate speech may manifest not only as prejudice, but as direct insults or slurs, forms of expression that the topic was not designed to capture, as insulting is not part of terror management theory (see, e. g., Spörlein & Schlueter, 2020). Another explanation for the relative lack of hateful content in the data is that extreme forms of hate speech violated Twitter's terms of service and were thus more likely to be instantly deleted by the platform. Assuming that hate speech is most likely to occur in the context of the *Prejudice* topic, this study likely underestimates the prevalence of this topic (although it is still among the 10 most prevalent topics in three of the four languages). This is a common problem when working with historical social media data, as deletions inherently limit access to certain extreme expressions. While this limitation cannot be resolved ex post facto, real-time collection of social media data in the future could help address the issue of data deletion. Instead, this study analyzed the visible and accessible discourse, which is representative of the content most users encounter.

Furthermore, it would be interesting to examine how the activity of different user groups shapes the mixed results. A plausible expectation is that nationalistic and prejudiced users are unlikely to also post empathetic and inclusive content, and vice versa. As a result, one group might drive a particular discourse in response to specific news, while the other group reacts to these accounts. Such reasoning is supported by previous research showing that rising levels of hate speech on social media are, to a large degree, driven by changes in the composition of the accounts that post before and after significant events (Czymara & Gorodzeisky, 2024; Flores, 2017; Hurtado Bodell and Menshikova, 2026). This is particularly likely for topics such as Counterbigotry activism, which are reactive to prejudice and nationalism. In general, prior research indicates that conservative Twitter users were more likely to post hostile and prejudiced content compared to liberal users (Badaan et al., 2023) and that users' preexisting networks and interactions predict their reaction to an attack (Darwish et al., 2018). Unfortunately, the structure of social media makes a more fine-grained demographic or psychological characterization difficult, particularly as users who post hateful content are predominantly posting anonymously (Lindenmayr et al., 2021). Yet, understanding how user characteristics, group dynamics, or network effects contribute to polarization in migration-related debates in the context of terrorist attacks – or major events in general – could be a fruitful endeavor for future research (Belcastro et al., 2019).

Finally, it is unclear to what extent the findings generalize to different social media platforms (including X in its current form) or even the general population. Historically, Twitter users were younger, wealthier, and better educated than other Internet users, and especially more so than nonusers (Blank, 2017). However, significant changes occurred after Elon Musk's acquisition and rebranding of Twitter as X, with a deliberate effort to retain more controversial content. This shift prompted many liberal users to leave the platform. These developments likely altered the migration debates following terrorist attacks. Unfortunately, the shutdown of the free academic API under Musk's leadership poses a substantial obstacle to any future research using Twitter or X data.

These limitations notwithstanding, this paper offers valuable insights into the dynamics of public debates on social media regarding migration-related issues in the aftermath of jihadist terrorist attacks. Given that online rhetoric can translate into offline behavior, such as xenophobic violence (Müller & Schwarz, 2021) and far-right voting (Giavazzi et al., 2023), understanding the emergence of hostile as well as inclusive narratives on social media remains a crucial area of study.

Data availability

The data generated during the study are not publicly available owing to privacy issues and Twitter's terms of service. However, corresponding Tweet identifiers are available from the corresponding author upon request. Supplemental materials and code to reproduce the analysis are available at https://doi.org/10.17605/OSF.IO/HFJ7Y.

Ethical statement

Ethical approval is not applicable to this manuscript.

Declaration of generative AI use

Grammarly and ChatGPT were used to assist with language polishing. The author reviewed, verified, and takes full responsibility for the content.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssaho.2026.103569.

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