Variations in Countermovements: Cause Diversity and Consistency in the “Lives Matter” claim

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Abstract. This article proposes a novel theory to study the variation within countermovements, with a focus on Black Lives Matter’s (BLM) countermovements - White Lives Matter, Blue Lives Matter, Police Lives Matter, and All Lives Matter. We introduce two novel concepts: ”cause diversity” and ”consistency.” *Cause diversity* captures the breadth of claims within countermovements, while *consistency* denotes the enduring nature of these claims over time. Our study is grounded in a dataset comprising 709,222 tweets from Twitter (January 2020 - December 2021), subjected to network analysis and natural language processing techniques. Drawing upon Laclau’s notion of the ”floating signifier” (Laclau, 2007), we explore how ’Lives Matter’ assumes varied meanings based on the specific lives it emphasizes, thereby influencing the breadth and depth of its claims. As the inclusivity of the ’Lives Matter’ slogan broadens, it engenders diverse interpretations, appealing to a wider spectrum of groups. However, this inclusiveness, while expanding the slogan’s reach, can also weaken its cohesiveness and commitment, as it becomes susceptible to appropriation by smaller interest groups pursuing their distinct agendas, albeit at the cost of reduced claim consistency. In such instances, certain claims may gain transient prominence depending on the size of the advocating group, while others may fade into obscurity. Conversely, when countermovements’ claims adopt a more specific focus, eliciting fewer interpretations, they resonate with a narrower array of groups. This results in a reduction in cause diversity but an increase in claim consistency. This research underscores the significance of the message’s inclusivity or exclusivity in shaping the impact, reach, and dynamics of a countermovement. This contributes to our understanding of the intricate sociopolitical dynamics in an era characterized by online activism and identity politics.

Black Lives Matter (BLM) has arisen as an influential online movement in response to the tragic deaths of Trayvon Martin and Michael Brown, both Black civilians who fell victim to extrajudicial killings. The ”Black Lives Matter” slogan has sparked a range of countermobilization efforts, including All Lives Matter, White Lives Matter, Blue Lives Matter, Police Lives Matter, and Palestinian Lives Matter. These countermovements strategically appropriate the ”lives matter” assertion by modifying it with specific adjectives to advance their unique objectives. For instance, White Lives Matter aims to further the interests of white citizens, often opposing BLM’s call for racial equality in the U.S. criminal justice system, and at times, promoting white nationalism (Bonilla-Silva, 2001). On the other hand, Palestinian Lives Matter seeks to raise awareness about the challenges faced by Palestinians and confront the Israeli state’s disregard for their well-being (Aziza, 2021). Consequently, despite their shared use of the ”lives matter” phrase, there exist substantial differences in the scope of countermovement claims, their target audiences, and the nature of their political initiatives. This article aims to explore these distinctions and shed light on what sets these countermovements apart.

This paper proposes two novel concepts to study the variation within countermovements. Building on Laclau’s concept of the ”floating signifier” (a signifier without a signified) (Laclau, 2007), our focus lies in understanding how the audience expands or contracts in response to the range of meanings that the ”Lives Matter” claim encompasses. *Cause diversity* captures the breadth of claims within countermovements, while *consistency* denotes the enduring nature of these claims over time. These concepts provide a framework for both conceptualizing and empirically measuring distinctions among countermovements. Recognizing these distinctions within countermovements holds significance, as it directly influences the groups they can effectively mobilize, as well as what Tilly calls ”unity” within the movement—group cohesion and consensus, often broadcast in logos or slogans (Tilly, 1993, p. 14). However, the existing literature primarily focuses on the origins and evolution of countermovements (Carney, 2016; Gallagher et al., 2018; Mason, 2022; Shanahan & Wall, 2021; Solomon & Martin, 2019). There seems to be a gap in the literature concerning the theoretical exploration of variation among countermovements. This paper aims to fill this gap.

We argue that the vaguer a countermovement’s claim, the more diverse the interpretations it garners, and the broader the range of groups with which the message resonates. Consequently, the cause diversity of that countermovement increases. However, high cause diversity can reduce the consistency of these claims because vague assertions tend to appeal to various small interest groups, each expressing unique viewpoints that may not find broad appeal among the wider population. Some claims may temporarily gain prominence depending on the size of the advocating group, while others may fade into obscurity. When countermovements’ claims evoke fewer meanings and resonate with a narrower range of groups, the cause diversity of that countermovement decreases. However, this reduced cause diversity tends to enhance the consistency of these claims. Less vague assertions often have a more universal appeal and are less likely to attract small interest groups with idiosyncratic viewpoints. Consequently, claims are more likely to maintain their prominence.

We test our theory on Black Lives Matter’s (BLM) countermovements, namely, All Lives Matter (ALM), White Lives Matter (WLM), Blue Lives Matter (BlueLM), and Police Lives Matter (PLM) as case studies. Our study is grounded in a dataset comprising 709,222 tweets from Twitter (January 2020 - December 2021), subjected to network analysis and natural language processing techniques. This paper is structured as follows: In Section 1, we explore the interplay between initial movements and countermovements, while introducing the concepts of ”cause diversity” and ”claim consistency” and our hypotheses. Section 2 outlines our methodological approach for testing our hypotheses. Section 3 presents our findings. In the concluding section, we discuss the implications of our results.

1 Theorizing countermovements and conceptualizing their distinctions

The existing literature defines countermovements as responses to initial movements, often opposing the latter’s claims without having their independent agendas (Meyer & Staggenborg, 1996; Mottl, 1980). Countermovements develop strategies and discourses in reaction to the movements they oppose (Carney, 2016; Gallagher et al., 2018; Mason, 2022; Shanahan & Wall, 2021; Solomon & Martin, 2019), addressing similar concerns but advancing competing claims and alternative solutions (Lo, 1982; Meyer & Staggenborg, 1996, p. 1631). Research indicates that countermovements often emulate initial movements’ strategies and frames (Hager et al., 2021; Solomon & Martin, 2019) seizing opportunities for countermobilization when the initial movement mobilizes (Mayer & Bert, 2017; Meyer & Staggenborg, 1996). Countermovements intensify their activities during periods of increased contention within initial movements (Hager et al., 2021; Meyer & Staggenborg, 1996; Solomon & Martin, 2019), but tend to wane when the demands of the initial movement are met (e.g., smokers’ rights countermovement (Meyer & Staggenborg, 1996, p. 1636)). While this framework focuses on the origin and evolution of countermovements, it does not address their distinctions. To the best of our knowledge, no work has theorized the variations among countermovements. Our goal is to introduce a novel perspective for theorizing variations among countermovements to fill this gap in the literature.

By advocating for the importance of Black lives, stands as a champion for racial equality. It highlights the disproportionate incidents of police violence targeting Black individuals and calls for law enforcement to treat Black civilians with the same level of caution and respect as their White counterparts (Holt & Sweitzer, 2020, p. 16). As evidenced by the statistics showing that ”Black men are about 2.5 times more likely to be killed by police over the life course than are white men” (Edwards et al., 2019), BLM’s core assertion is that Black lives matter, not exclusively, but equally to all lives.

Given the common practice of countermovements crafting their strategies and narratives in reaction to the movements they oppose, it is understandable that BLM’s countermovements also appropriate the ’lives matter’ claim. The counternarratives of White/Blue/Police/All Lives Matter serve to “reframe the issues rather than engaging them directly, masking the initial terms of the debate” (Fabregat & Beck, 2019, p. 3). To counter BLM’s grievances about police brutality, PLM and BlueLM emphasize the importance of law enforcement in maintaining order, Black criminality, as well as the challenges and hardships faced by law enforcement officers in the line of duty (Wall, 2020). It is worth noting that we take PLM and BlueLM as a single movement Blue/PLM. ”White” Lives Matter counters BLM on racial grounds, substituting Black with White. WLM argues that affirmative action for Black individuals leads to the persecution of

White individuals and asserts victimhood (Solomon & Martin, 2019). ALM adopts a color-blind discourse, asserting that ”race should not and does not matter” (Neville et al., 2000, p. 60). This perspective also highlights that BLM is sometimes interpreted as advocating that ”only” Black lives matter, thereby negating the significance of race in policing (Atkins, 2019). Hence, BLM’s countermovements diverge in their prioritization of which lives they believe matter the most. The way these countermovements frame their core claims fundamentally affects grievance construction and interpretation, attributions of blame/causality, movement participation, and the mobilization of popular support for a movement cause (Benford, 1997, p. 410). In the case of BLM’s countermovements, the adjective attached to the ”lives matter” claim influences the inclusivity and exclusivity of the message. A more inclusive message potentially targets a larger audience. Yet, as Tilly (1994) reminds us, the size of the potential audience does not guarantee mobilization. Mobilization depends on whether activists can signal *unity* (the cohesion and consensus within a group) and *commitment* (the perception that current participants are steadfast and dedicated) (Tilly, 1993).[3]. To theorize the link between the inclusivity and exclusivity of the message and mobilization, we refer to Laclau’s concept of floating signifier.

A floating signifier is “a signifier without a signified” (Laclau & Mouffe, 2001, p. 405). Floating signifiers are so vague that they gain a different meaning depending on the context in which they are used. Just like ”freedom” can encompass both freedom from government oppression and the pursuit of personal happiness (Chopra, 1998), social movements rally around signifiers to form their political identities and mobilize support (Laclau, 2007). These signifiers are floating because their articulation process hinges upon the specific historical and social context. We apply this concept to countermovements.

We propose two novel concepts to theorize this variation. **Cause diversity** defines the range of claims made by countermovements. **Consistency** refers to the continuity of these claims over time. In Laclau’s terms, counternarratives developed against BLM effectively strip the content of ”Lives Matter” and re-purpose it in contexts diametrically opposed to BLM’s original intentions (Garza, 2014). If Laclau’s framework holds true, the adjectives attached by these countermovements to ”lives matter” significantly influence the scope of their claims, their audience, and the nature of their political projects. Specifically, the term ”all” conveys a broader meaning than ”white” and ”police” or ”blue.” On the other hand, given its specific racial connotations, ”white” is likely to mobilize a more limited group. Building on this literature, we propose our first hypothesis:

H1: *All Lives Matter exhibits the highest level of cause diversity followed by Police/Blue Lives Matter and White Lives Matter.*

On the other hand, when the adjectives attached to Lives Matter claims give rise to multiple interpretations, they resonate with a wide range of groups. This broad appeal can be seen as the ability to garner support from a large audience. However, it may also open the door for various smaller interest groups, each seeking to advance its unique objectives. As the claim gains prominence, these groups may seize the opportunity to

[3]Tilly also adds worthiness (the perception of deserving or merit) and *numbers* (the size of the crowd) (Tilly, 1993).

voice their distinct viewpoints. This diversity in perspectives leads to a more heterogeneous audience and a broader array of claims. These claims vie for attention, with some failing to gain significant appeal and eventually fading into obscurity. Others may experience temporary prominence, contingent on the size of their advocating group. Consequently, claims exhibit varying levels of consistency over time. In contrast, when the adjectives associated with 'Lives Matter' claims evoke a narrower set of interpretations, the audience and their corresponding demands tend to be more specific. This results in a more consistent message over time. If this reasoning is correct, we should expect ALM to display the weakest consistency, followed by WLM and Blue/PLM. Hence, our second hypothesis.

H2: *All Lives Matter exhibits the weakest cause consistency followed by Police/Blue Lives Matter and White Lives Matter.*

2 Methods

We test our argument on cause diversity and consistency using the cases of ALM, BlueLM, WLM, and PLM. [4] We conducted a comprehensive data collection endeavor, encompassing all tweets posted between January 1, 2020, and December 31, 2021. To get this data, we used Twitter's Application Programming Interface (API) version 2, serviced specifically for academic purposes. In our data collection process, we utilized hashtags, such as #AllLivesMatter, denoting the movements' names as keywords for our search. Our query parameters included the specification of the English language and the exclusion of retweets.

Through the application of these rigorous search criteria, we successfully retrieved a total of 709,222 tweets emanating from the movements known as "AllLivesMatter," "WhiteLivesMatter," "BlueLivesMatter," and "PoliceLivesMatter."

Before the application of the pre-processing, we merge the datasets PLM and BlueLM to facilitate a more comprehensive analysis. This decision is underpinned by the relatively reduced quantity of data within the PLM dataset when compared to other movements and, significantly, by the shared thematic alignment between PLM and BlueLM.

Within our datasets, one encounters not only activists but also a contingent of spammers who aim to captivate the attention of the people. While most of these actors systematically post identical tweets, a subset adopts multifarious strategies, including the dissemination of identical textual content accompanied by distinct images to camouflage themselves as ordinary Twitter users. Our preliminary investigations underscore the disruptive influence of such spam tweets on our analytical outcomes.

Noteworthy techniques abound for the identification of spam within dataset, encompassing methods hinging on user profile information and interests (Koggalahewa et al., 2022), network-based spam detection (Shehnepoor et al., 2017), machine learning-based algorithms (Gao et al., 2012), and sentiment-driven detection mechanisms (Hu et al., 2014). However, there is no superior technique to others and the effectiveness of

[4] Other movements also make the 'lives matter' claim to defend some other cause (e.g., Palestinian lives matter). However, fewer tweets were sent under these hashtags. Therefore, we limited the scope of our analysis to these movements

these methods can vary depending on the dataset.

At this point, we have designed a spam detection algorithm that satisfies the needs of our preliminary research, detecting systematic posting of tweets and the embedding of different images within these tweets. To reveal these spam tweets, our approach initially extracts image information from the tweets. Subsequently, it checks whether tweets pass the rules we set to filter them. We institute a set of criteria for the classification of tweets as spam. According to these criteria, a tweet is labeled as spam if its textual content recurs twice or more within an interval exceeding two days and is posted by the same user. With the application of these steps, we determine spam tweets in the datasets. Our spam detection algorithm labels 33,975 tweets as spam in ALM, 27,164 tweets in P-BLM and 22,959 in WLM and as a result, we exclude these spam-labeled tweets for further analysis. After this filtering process, we have 332,008 tweets for ALM, 216,172 tweets for P-BLM, and 76,944 tweets for WLM.

	ALM	Police & Blue LM	WLM	BLM
Initial	365,983	243,336	99,903	5,961,970
Filtered Tweets	33,975	27,164	22,959	464,301
After Filter	332,008	216,172	76,944	5,497,669

Table 1. Number of filtered and total tweets for each hashtag.

It is important to clarify the primary aim of this study, which is to test our hypothesis within the context of counter-movements to the Black Lives Matter (BLM) movement. Consequently, the detailed analysis of the BLM movement itself is beyond the scope of this study. However, we have included the original BLM movement in our dataset to serve as a reference point in our quantitative analysis. The BLM dataset is employed to establish reference values for the metrics calculated in the Consistency section of our analysis. Given the substantially larger volume of originally collected tweets in comparison to the counter-movements, we have conducted a spam detection procedure and subsequently utilized a random sample of 500,000 tweets for our analysis to reduce the computational complexity.

We identify the causes of ALM, WLM, and P-BLM with topic modeling. In selecting the methodology for our research, we carefully considered several prominent techniques for text analysis, including BERTopic and LDA (Latent Dirichlet Allocation). After a thorough evaluation, we decided to employ the Top2Vec method as our primary approach. This decision was driven by several key factors. Firstly, Top2Vec offers a unique advantage by not relying on predefined topic numbers, unlike LDA (Blei et al., 2003). This flexibility allows us to discover the underlying structure of our data without imposing arbitrary constraints. Secondly, while BERT-based approaches excel in various natural language processing tasks, they often demand substantial computational resources and can be challenging to fine-tune to get best topic representation (Grootendorst, 2022). Top2Vec, on the other hand, offers a lighter and interpretable solution that aligns well with our research objectives. Lastly, Top2Vec's ability to capture semantic context and relationships among documents in a scalable manner aligns perfectly with the complexity and size of our dataset (Angelov, 2020). By choosing Top2Vec, we aim to achieve both robust topic modeling results and computational efficiency.

In addition to the theoretical comparison, we also conducted practical comparisons among three popular topic modeling methods while exploring various scenarios involving different numbers of topics. However, before embarking on this comparative analysis, we took a crucial preprocessing step by applying hierarchical topic reduction to both BERTopic and Top2Vec. This reduction was necessary to manage the total number of topics, which initially exceeded two thousand, making it unwieldy for comprehensive analysis. Our comparative study encompassed a range of topic counts, spanning from 10 to 50 topics. After thorough examination and evaluation, we settled on using 20 topics as our chosen threshold for topic reduction. This selection was not arbitrary but rather the result of a rigorous exploration of alternative topic counts. We aimed to ensure that the chosen 20 topics encapsulated the most salient and conceptually meaningful themes within our dataset, providing a solid foundation for subsequent analysis and comparisons of countermovements.

We assess consistency with a two-step approach. First, we identified the 50 most frequently co-occurring hashtags with #BlackLivesMatter, #AllLivesMatter, #BlueLivesMatter, #PoliceLivesMatter, and #WhiteLivesMatter as activists tend to convey their demands through hashtags and they provide high interpretability for different claims and demands raised by distinct subgroups in each countermovement (Guo & Liu, 2022). Subsequently, we first introduce a metric to measure the contribution of highly active users to each hashtag which indicates whether the popularity of the hashtag is a result of the collective contribution of individual users or a small group of highly active users. Second, we analyzed the monthly consistency of the posted tweets containing the hashtags for each data set for the two-year interval. Finally, we concluded the analysis with a weighted network representation of hashtags contributed by common authors to assess whether the subgroups under each movement support one another and used edge density to quantify the comparison among each countermovement.

3 Results

3.1 Cause Diversity

We start by examining the results of our topic modeling summarized in Table 1. These findings illustrate a substantial variation in cause diversity among countermovements. In line with H2, ALM covers a broad spectrum of topics, ranging from the Israeli-Palestinian conflict to animal welfare and from concerns about the Uyghur population to the status of Taiwan, reflecting high cause diversity. Significantly, ALM's focus extends beyond human lives, engaging with global issues as well as domestic U.S. politics. This wide-ranging thematic spectrum renders ALM unique in its cause diversity among the three movements.

Conversely, debates within P-BLM primarily revolve around the realm of law enforcement matters, including support for police officers who endure hard working conditions, accountability within law enforcement agencies, and the broader context of police actions. The movement's narrative also extends to activism, often in response to events associated with BLM. Notably, P-BLM debates also figure some high-profile cases, such as the Rittenhouse trial and the shooting of Jose Chavez, a police officer in the line of duty. In the Rittenhouse trial, Kyle Rittenhouse faced charges of shooting three individuals, resulting in two fatalities, during the civil unrest in Kenosha, Wisconsin, in August 2020. His self-defense plea led to his acquittal in November 2021, attracting extensive media attention and gaining prominence within rightwing circles.

On the other hand, WLM debates predominantly center around race, ethnicity, activism, and their intersection with the political landscape. The movement's discourse frequently invokes racial and ethnic references and identity, suggesting a close tie to discussions surrounding race. Additionally, the COVID-19 pandemic emerges as a significant theme. COVID-19 is a highly racialized issue, with then-President Donald Trump and his supporters resisting mask-wearing during a pandemic that disproportionately impacts the Black and Latino communities (Boyd, 2020). Given the higher mortality rates among racial minorities, BLM capitalized on mask-wearing. The mere inclusion of mask-wearing as a topic within WLM underscores the movement's reactionary nature.

ALM	PLM/BlueLM	WLM
US politics	Support for law enforcement	White genocide, Covid
The Israeli-Palestinian issue	Law enforcement actions and incidents	Activism (WLM, ALM, BLM, PLM)
Farmers' protests	The Rittenhouse case	Social issues and racism
India, Tigray, Uyghurs	Accountability of law enforcement	US politics and politicians
Race and gender-based equality (BLM)	US politics and politicians	Me Too
COVID	Activism and protests (BLM, ALM, PLM)	kpop activism
Rittenhouse and the Second Amendment	Police brutality and hard working conditions	the Second Amendment
Animal welfare	Police officers	Rightwing conspiracy theories
Social justice and activism (ALM, BLM, PLM)	Police killings	Racial and ethnic references
Sports and entertainment	NFL kneeling down	Law enforcement and support
Civil rights		Breonna Taylor
Racial justice		Black supremacy
Rightwing conspiracy theories		WLM counterprotests
Law enforcement		Media

Table 2. Summarized topics for each countermovement

Another significant finding is that all countermovement debates feature BLM and activism, which reinforces their reactionary nature. Interestingly, while ALM and P-BLM reference each other, they do not reference WLM. In contrast, WLM references all other countermovements.

Thus, the topic modeling results support H1. While all three movements share common threads of activism and political engagement, they diverge significantly in their primary areas of focus. WLM centers primarily on racial issues and activism, closely intertwined with political discourse. PLM places its emphasis on law enforcement support, accountability, and its intersections with the Black Lives Matter movement. In contrast, ALM encompasses a vast spectrum of topics, making it the most diverse among the three movements in terms of the scope of its causes.

3.2 Consistency of Demands

We analyzed the most frequently used hashtags within each movement to compare the effectiveness and continuity of their respective claims. In order to keep visual analysis possible, the number of hashtags to be analyzed is chosen to be 50 while the query terms such as the names of the movements are excluded.

To illustrate distinctions among hashtags, we employed two introduced metrics: i) ”High Active” User Fraction and ii) Average Consistency Score. Following (Bruns & Stieglitz, 2013; Tedjamulia et al., 2005), we utilize content analysis to infer the contributions of user sub-groups in online social networks. Employing a similar methodology, we divided users in each countermovement with respect to their contribution to the total number of tweets. Following the 1/9/90 rule, tweet authors ranked in the top 1% contributors are labeled as ”High Active” users whereas authors ranked between 10% to 1% are labeled as ”Medium Active” users and the remaining ones are labeled as ”Low Activity” users.

To assess the longevity of different hashtags we utilized a simple metric indicating the longevity of a hashtag's presence with respect to the time scope of our analysis. The time unit to calculate the metric is chosen as months, thus a specific hashtag is considered as present for that month if the number of tweets containing that specific hashtag exceeds a certain threshold. Then, the consistency score for that hashtag is calculated as the ratio of months that the hashtag was present to the total number of months (24 months) in our time horizon (2 years). Therefore, the consistency score falls within the interval [0,1], zero being not present at all, and one meaning the hashtag was present for every month in our time scope.

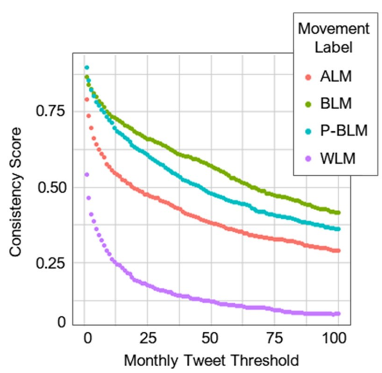

Fig. 1. Comparison of Consistency Scores for different movements.

One drawback of such a metric is that it does not differentiate whether a hashtag is present in consecutive time units or the presence fluctuates within the time interval with diminishing and reappearing bursts. However, preliminary analysis of the most frequent hashtags indicates that such cases are not present in our dataset. Another drawback is the dependability of the consistency score to the selected threshold. The plots in the upcoming section are provided for a threshold of 50 tweets per month whereas the consistency calculation for different threshold is depicted in Figure 1. The figure gives a clear comparison which indicates the largest consistency for Black Lives Matter, followed by P-BLM and ALM with WLM having the smallest score for consistency independent of threshold selection.

Figure 2 shows the resulting plots of the top 50 hashtags for ALM and P-BLM. The horizontal axis represents the consistency scores of hashtags whereas the vertical axis represents the fraction of tweets in each hashtag posted by "High Active" users. The size of the bubble represents the number of total tweets containing that hashtag and the number of unique users contributed to that hashtag also given in the color scale. A subset of hashtags are also given as text labels for discussion.

In Figure 2, hashtags located in the lower right corner of the graphs are high in consistency and low in highly active user contribution. Those hashtags represent the issues that resonate with broader audiences over time. For ALM, several hashtags closely related to core topics, such as #trump, #america, #love, #racist, #racism, #justice, and #peace, fall within this category. Similarly, for P-BLM, the primary collective discussion revolves around topics related to police officers and associated political issues, including hashtags like #backtheblue, #thinblueline, #law, #sheriff, #cops, #america, #gop. In this context, this category of hashtags in both datasets captures the core discussions, as they have a large number of total tweets, a higher number of unique users contributing, and a higher consistency score, indicating a high degree of consistency for these discussions.

On the other hand, the two movements exhibit different patterns concerning hashtags with high levels of active user participation. In the case of ALM, hashtags that receive significant contributions from highly active users tend to have lower consistency scores. These hashtags encompass a broader range of causes, including topics related to religion (#jesusmatters, #jesussaves), gender (#sexnotgender, #istandwithjkrowling), conspiracy theory (#obamagate), provocative speech (#blmterrorists), and animal rights (#adoptdontshop). Essentially, the analysis suggests that the sub-topics contributing to ALM's initial high cause diversity struggle to maintain a presence in the ongoing discussion and are typically driven by a small number of highly active users.

Conversely, in the case of the P-BLM dataset, the hashtags displaying substantial engagement from active users are notably fewer in number and predominantly revolve around the movement's core theme, which is centered on issues related to police officers. Interestingly, the hashtag#latinos also emerges as a notable one, drawing active user participation. In light of recent research highlighting instances of anti-Black sentiment within the Latino community (Haywood, 2017; Padgett, 2020), the presence of the #latinos hashtag can be interpreted as an indication of Latino support for PLM against BLM.

WLM exhibits a distinct pattern when compared to other countermovements. Unlike other countermovements, which feature hashtags consistently promoted by a large number of unique users, WLM hashtags tend to be concentrated in the low-consistency region, supported by a relatively smaller user base. This suggests that WLM lacks a

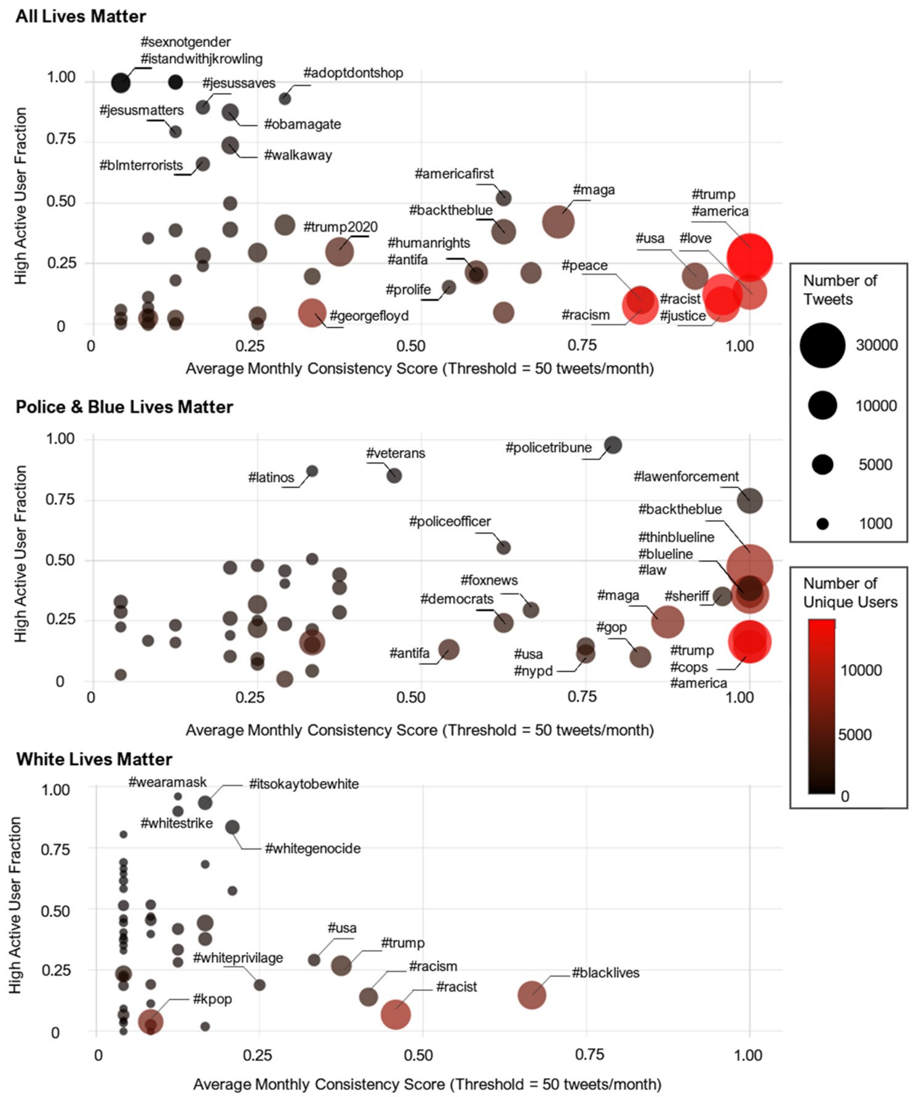

Fig. 2. Comparison of High Active User Fraction and Average Monthly Consistency Scores of top 50 hashtags for All Lives Matter and Police & Blue Lives Matter.

cohesive core discourse capable of consistently mobilizing its supporters. This also explains the having the lowest consistency scores among all counter-movements despite having a narrower movement definition in comparison to ALM. Notably, hashtags with the highest tweet counts for WLM include #blacklives, #racist, and #kpop, which are predominantly authored by opposing user groups, as evidenced by the analysis of corresponding tweets.

In a parallel comparison to ALM, WLM also features hashtags with a high active user fraction but limited consistency, such as #wearamask, #itsokaytobewhite, #whitegenocide, and #whitestrike. However, unlike the ALM case, these hashtags driven by highly active users do not encompass a broad spectrum of diverse issues. Instead, they are primarily focused on framing strategies associated with the WLM movement.

The analysis above reveals that the rich diversity resulting from a vaguer signifier does not necessarily translate into the consistency of these diverse claims. This lack of consistency becomes particularly evident when comparing the All Lives Matter and Police & Blue Lives Matter movements. However, in the context of social movements, the low consistency in addressing the causes of diverse groups within a movement might also result from frequently changing political and social agendas in society. The supporters might prioritize the messages from distinct groups depending on the prevailing agenda and shift their focus as circumstances dictate.

Nevertheless, such a situation requires these distinct groups to support one another when they remain on the agenda. Thus, a natural extension of this analysis is to assess whether these diverse sets of groups also lend support to each other and exhibit a cohesive structure within the movement, or if the discontinuity in their messages also results in isolation among the groups in terms of mutual support.

Given the aforementioned objective, we expanded our analysis to encompass the user interactions among the 50 most frequently used hashtags. A network representation as in Figure 3 is found to be useful for our purposes. In this visualization, each node represents a hashtag, and a weighted edge connects any pair of hashtags if they share at least one common author. Furthermore, the edges are weighted based on the number of shared supporters between each pair of hashtags. These visual representations were generated using Gephi, a widely employed network visualization software in scholarly research. Only a comparison of ALM and P-BLM is presented as they present a distinct comparison.

Figure 3 represents the resulting networks of hashtags for two movements. The thickness of the links represents the weight of the corresponding edge meaning that the thicker the edge the more authors supported both of the hashtags. The coloring of the edges is provided by the community detection of the Gephi which indicates the subgroups of hashtags that are mostly supported by common authors. To show the hashtags connected to the remaining network via low-weight edges, the edges having a weight of less than 50 are removed and isolated nodes are colored in black. The distribution of nodes along the two-dimensional space utilizes the built-in layout configuration of "Force Atlas 2" which considers the weights of the edges generating a view of nodes connected with stronger edges located in the center of the network and nodes connected via weaker links are spread around the center.

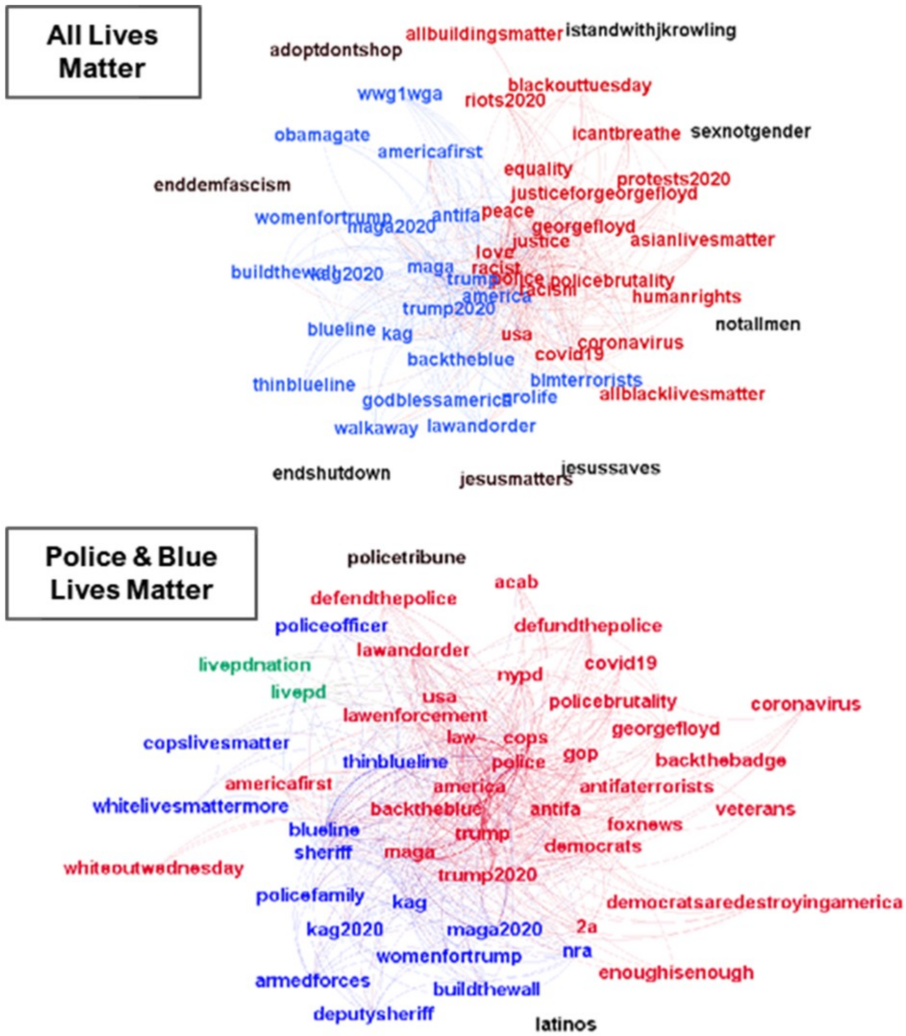

Fig. 3. Hashtag networks of common users.

Examining the ALM network in Figure 3, we observe that several hashtags remain isolated from the main connected network, particularly those with a high active user fraction as identified in the previous analysis. Additionally, numerous nodes are dispersed outside of the central network, only weakly connected by a few links.

In contrast, the network for Police and Blue Lives Matter exhibits a higher density of edges concentrated in the central region, with fewer isolated nodes. One way to quantitatively compare these networks is by using edge density as a metric. Edge density refers to the ratio of edges presented in the graph to all possible edges (Xu & et al., 2010). An edge density of 1 implies that there is an edge connecting every possible pair of nodes in the network. In our case, an edge density of 1 would signify that every pair of hashtags shares at least one common supporting author. However, it's important to note that edge density does not account for the weight of edges. Consequently, we filter all edges having less weight than a minimum threshold and iteratively increase the threshold to compare the network densities of each movement for different minimum threshold.

Resulting comparison for the network densities is presented in Figure 4. In parallel with our consistency comparison, it is worth noting that BLM serves as the reference case and exhibits the expected highest edge density. In this context, Police & Blue Lives Matter once again outperforms ALM in terms of garnering support from a common user base across multiple hashtags within our analysis. Conversely, WLM produces the lowest density in its hashtag networks. Consequently, our findings suggest that interactions within various sub-groups featuring diverse claims within ALM do not exhibit substantial mutual support, while P-BLM demonstrates a more cohesive structural framework. Lastly, in line with our findings on consistency, WLM faces challenges in establishing a common author base among different hashtags, reflecting its absence of a cohesive discourse to cultivate a consistent supporter base.

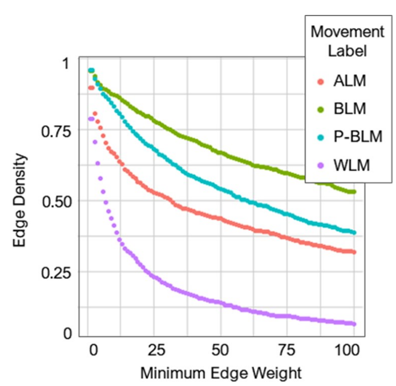

Fig. 4. Network edge-density comparison for different movements

4 Conclusion & Discussion

This paper examined the variation among countermovements, using BLM's countermovements — White Lives Matter, Blue Lives Matter, Police Lives Matter, and All Lives Matter— as case studies. Building on Laclau's concept of the floating signifier, we explored how the audience expands or contracts in response to the range of meanings that the adjective attached to the "Lives Matter" claim evokes. To conceptualize and empirically measure the resulting variation among countermovements, we proposed two novel concepts, cause diversity —the breadth of claims within countermovements— and consistency—the enduring nature of these claims over time. By applying network analysis and natural language processing techniques to a dataset of over 700,000 tweets from Twitter (January 2020 - December 2021), we tested the following argument. When countermovements' claims are more inclusive, eliciting more interpretations, they resonate with a wider array of groups, which is likely to result in high cause diversity but low claim consistency. Conversely, when countermovements' message is less inclusive and resonates with a narrower array of groups, it features a lower cause diversity but higher consistency. Our topic modeling results affirmed that ALM, carrying the most inclusive message, features the highest cause diversity, whereas P-BLM and WLM exhibit lower cause diversity. On the other hand, findings from our analysis confirmed that P-BLM has the highest consistency.

An important finding was the inverse relationship between cause diversity and consistency particularly present in the comparison of ALM and P-BLM. We hypothesized that countermovements characterized by high cause diversity would exhibit lower consistency. This happens because the inclusivity of the message resonates with a wide range of groups, leading them to seize the motto to further their particular agendas. Nevertheless, these groups' causes often do not align with the broader public's interests. As a result, even if they manage to briefly gain attention, they struggle to maintain the public's focus, resulting in lower consistency. Therefore, the prominence of their claims is reliant on the size of the group.

The connection between cause diversity and consistency carries substantial implications for a movement's unity and commitment, which Tilly defines as group cohesion and determination, respectively. When cause diversity is high, it encourages smaller groups to utilize the message for their own purposes, which, in turn, diminishes the internal coherence of countermovements' claims and group cohesion. With low group cohesion, each small group prioritizes its own objectives, often disregarding the causes championed by other small groups. This indifference results in low consistency. ALM has a broader user base, but a small number of highly active users tend to promote their own topics. However, they struggle to maintain the public's attention, causing their topics to fade into obscurity. Consequently, the movement experiences a decline in consistency.

In our research, we focused on countermovements that were mobilized in response to the main movement. This perspective allowed us to explore the dynamics of movements within a specific context. However, it's essential to acknowledge that our findings may have broader implications beyond countermovements alone. Further studies could extend the generalizability of our results to cover a wider range of social movements.

Indeed, the high volume of tweets and the figurative or allegoric nature of some of the content can present challenges in definitively determining users' positions regarding their support for a movement. This complexity underscores the need for more comprehensive and nuanced analysis in future studies. However, it is noteworthy that even in the face of these challenges, the use of randomly chosen samples during the analysis has proven to be a valuable approach. These samples generally provide a representative cross-section of the broader conversation, offering insights into prevailing sentiments and trends. For example, in the context of topics and hashtags related to the K-pop community, the consistent presence of criticism against countermovements suggests a noteworthy trend. While it may not provide a complete picture, this observation highlights the importance of considering these selected samples as indicative of broader sentiment.

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