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Framed Alliances: A Computational Peek Into the News in The
Guardian's World Section

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Abstract

With growing tensions in the current political landscape, international news has become an increasingly important source through which the public perceives conflicts. How military associations are framed through news discourse, and what signals these frames convey for current politics, therefore merit more attention. To address this gap, the study introduces framed alliances to capture the mediated status of military associations. As a structural frame, the framed alliances refer to the cognitive construction of alliances in media discourse and serve as a public benchmark for perceiving real-world politics. To model such structures, the study collected all news articles under *The Guardian's* World section during 2025, establishing a duplex network with nations as nodes and two types of framed ties as edges: issue similarities through topic modeling and cooperative relations captured through positive sentiment evaluation. The study further analyzes the interdependence between the two layers. Through social network analysis and duplex network analysis, framed alliances present a regionalized constellation of issues and a polycentric pattern of cooperation. The two layers are significantly correlated, with edges tending to be duplicated across layers, whereas nodes behave differently between layers. Small states are more active in sharing issues while becoming peripheral in cooperation relations. These findings indicate that nations with more shared issues are more likely to establish cooperative relations, while smaller states remain constrained by their resource capacities. The study contributes to alliance studies by introducing the mediated dimension of alliances, and to framing studies by supplementing structure-based approaches with an innovative computational framework.

Keywords: alliances, news frames, duplex network analysis, international relations

Zusammenfassung

Mit den zunehmenden Spannungen in der gegenwärtigen politischen Landschaft sind internationale Nachrichten zu einer immer wichtigeren Quelle geworden, durch die die Öffentlichkeit Konflikte wahrnimmt. Wie militärische Assoziationen durch den Nachrichtendiskurs gerahmt werden und welche Signale diese Rahmungen für die aktuelle Politik vermitteln, verdient daher größere Aufmerksamkeit. Um diese Forschungslücke zu schließen, führt die Studie das Konzept der framed alliances ein, um den medial vermittelten Status militärischer Assoziationen zu erfassen. Als struktureller Frame bezeichnet das Konzept der framed alliances die kognitive Konstruktion von Allianzen im Mediendiskurs und dient als öffentlicher Referenzrahmen für die Wahrnehmung realweltlicher Politik. Zur Modellierung solcher Strukturen sammelte die Studie alle Nachrichtenartikel aus der World-Sektion von *The Guardian* im Jahr 2025 und erstellte ein Duplex-Netzwerk mit Nationen als Knoten sowie zwei Arten gerahmter Verbindungen als Kanten: thematische Ähnlichkeiten mittels Topic Modeling und kooperative Beziehungen, erfasst durch die Bewertung positiver Sentiments. Darüber hinaus analysiert die Studie die Interdependenz zwischen den beiden Ebenen. Mithilfe sozialer Netzwerkanalyse und Duplex-Netzwerkanalyse zeigen framed alliances eine regionalisierte Konstellation von Themen sowie ein polyzentrisches Muster der Kooperation. Die beiden Ebenen sind signifikant korreliert, wobei Kanten dazu tendieren, sich über die Ebenen hinweg zu duplizieren, während sich die Knoten zwischen den Ebenen unterschiedlich verhalten. Kleine Staaten sind aktiver beim Teilen von Themen, werden jedoch in Kooperationsbeziehungen eher peripher. Diese Ergebnisse deuten darauf hin, dass Nationen mit stärker geteilten Themen eher kooperative Beziehungen etablieren, während kleinere Staaten weiterhin durch ihre Ressourcenbeschränkungen eingeschränkt bleiben. Die Studie leistet einen Beitrag zur Allianzforschung, indem sie die mediale Dimension von Allianzen einführt, sowie zur Framing-Forschung, indem sie strukturorientierte Ansätze durch ein innovatives computergestütztes Rahmenwerk ergänzt.

Schlüsselwörter: Allianzen, mediale Deutungsrahmen, Duplex-Netzwerkanalyse,
Internationale Beziehungen

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Framed Alliances: A Computational Peek Into the News in *The Guardian's* World Section

Introduction

With the increasing complexity of our world, we seem to be living more and more connected to global affairs, facing both rising commodity prices and deepening societal divisions, all because of wars unfolding thousands of miles away. This tremor is not a random butterfly effect, but a chain reaction caused by alliances. As formal agreements through which two or more sovereign states coordinate their military policies (Lanoszka, 2022), alliances bind distant peoples from multiple states into security communities, thereby shaping the destinies of not only the states but also individuals. Given this profound impact, states manage these alliances through treaties; however, for citizens, the media serve as the primary lens through which they perceive and make sense of these global commitments. News coverage describing conflicts, collaborations, revolutions, and state separations pictures a world landscape in the public mind, shaping the sense of place, informing political decisions, and in turn, influencing politics itself. In other words, media serve as “information systems vitally involved in maintenance, change, and conflict processes at the societal level” (Ball-Rokeach & DeFleur, 1976). Despite the significance of both alliances and media, existing scholarship has rarely linked them together. This gap limits explanations of citizens’ perceptions of international politics and obscures strategic frames of alliances in mass media. In this light, how alliances are represented through media becomes a critical yet underexplored question, calling for a systematic examination of media-constructed alliance structures.

Accordingly, the study introduces the concept of framed alliances to represent the mediated status of real-world military associations. Framed alliances are not plain reflections of reality but rather structured alliances within news discourse, influencing audiences’ perceptions of political situations. Specifically, this study revolves around the question of how alliances are framed in international news discourse, namely, what

structural attributes they reflect and what political signals they convey. Therefore, to further operationalize the concept, the study draws on previous alliance research (Bailes et al., 2016; Gowa & Mansfield, 1993; Liska, 1968; Mansfield & Bronson, 1997; Sprecher & Krause, 2006; Wallander, 2000), and conceptualizes alliances as a duplex network wherein states serve as nodes, connected by two distinct types of ties: one grounded in similarity of issues states are confronted with, and the other in positive cooperation. Guided by this framework, the study collected all articles published in *The Guardian*'s World section throughout 2025 as the raw dataset. Subsequently, the study constructed the positive interaction layer using automated sentiment analysis and the common issue layer using topic modeling. For analysis, the study applied social network analysis to each layer and duplex network analysis to the dependence between layers.

The results suggest that the common issue layer is a regionalized yet interconnected structure in which multiple small states take important structural roles. The positive interaction layer is a polycentric system with fragmented communities, with France nonetheless serving as a super hub in influencing, bridging, and disseminating across the whole network. Regarding the interdependence between the two layers, they exhibit highly similar patterns: states that confront similar issues are more likely to establish positive cooperative ties at the dyadic level. However, states whose issues are broadly similar to those of many others tend to be less active in establishing such cooperations.

The study's contributions span three aspects. First, the study advances current alliance scholarship by complementing treaty-based observations with a discursive perspective, measuring how alliances are constructed within news discourse. This allows for a systematic depiction of the framed world political landscape, bridging the gap between real-world politics, media processing, and public perception. Second, it enriches frame analysis by extending the operationalization of structural frames to military alliances. By employing semantic network analysis combining deductive and inductive approaches, the study analyzes the framed structure of alliances while maintaining a balance between

reliability and validity. Third, the study introduces an innovative computational framework to conceptualize framed alliances. In terms of data processing, the study integrates multiple language-processing models, with each step being validated for reliability and validity. In terms of analysis, the study applies social network analysis to interpret each dimension and duplex network analysis to evaluate interdependence between dimensions, resulting in a comprehensive quantification of alliances. All data and programs are openly accessible¹, ensuring transparency and reproducibility. In conclusion, this study serves as an interdisciplinary practice linking political science and computational communication, advancing our understanding of the media's socially constructive role in shaping alliance presentations.

Literature Review

Alliances

Alliance remains an elusive concept, while academic consensus confines it to the military-political context, distinguishing it from other types of international coalitions such as the European Economic Community (Fedder, 1968). As Liska (1968) defined, an alliance “associates like-minded actors in the hope of overcoming their rivals”, suggesting that alliance formation is first driven by common threats. In response, states make rational decisions to maximize members’ aggregate utilities (Altfeld, 1984) or to navigate the security-autonomy trade-off between larger and smaller states (Bennett, 1997). This asymmetry is reflected in a recurring pattern where great powers attract smaller allies (Liska, 1968). Beyond the pattern’s surface, both sides hold fears upon entering alliances, as smaller states worry about the erosion of their identities, while great powers fear overextending their commitments and resources (Liska, 1968). Only when common threats emerge, might smaller states seek protection, while great powers must also safeguard their own resources. Notably, existing alliance formation theories are not universally applicable,

¹ Accessible via the Google Drive link:

<https://drive.google.com/drive/folders/1DSfmlJ1nhRexlx0WL8R1KxyTY3sbQ91g?usp=sharing>

as theorists have primarily focused on great power-related alliances, rendering small states, namely those with less governing capabilities or resources, not well explored (Bailes et al., 2016). Such overgeneralization has resulted in imbalanced or incompatible analyses of alliances, leaving blind spots regarding small states in current scholarship. Despite these deficiencies, facing common threats remains a necessary condition for alliance formation.

Though the alliance formation is constrained within the military context, its influence extends across various domains of interaction. From an economic perspective, states are more inclined to trade with allies out of security externality concerns (Sprecher & Krause, 2006). Such security externalities stem from efficiency gains within intra-alliance trade, which allows more domestic resources to be devoted to enhancing military power (Gowa & Mansfield, 1993). Consequently, the internal trade strengthens the aggregate political-military power of the alliance (Mansfield & Bronson, 1997). More importantly, Wallander (2000) argues that alliances “are not always merely aggregations of national power and purpose, they can be security institutions as well,” where institutional assets are established to provide members with information and infrastructure to integrate military capabilities. For instance, within the North Atlantic Treaty Organization (NATO), the North Atlantic Council was founded for defense, finance, and production. Subsequently, through the Supreme Headquarters Allied Powers Europe, NATO developed common practices and procedures for consultation, as well as infrastructure for logistics and air defense. These influences generated by alliances permeate from the military domain into the daily governance of member states. Therefore, grounded in both theories and empirical accounts, alliances facilitate positive interactions across multiple domains within the alliance structure. However, beyond the military, economic, and diplomatic dimensions, such multidimensional interactions remain underexplored, largely due to the difficulty of measuring other dimensions, such as culture, and verifying their correlations with alliance formation. Nevertheless, the research above suggests that the alliance itself can be considered a sufficient condition for generating multidimensional positive interactions.

While a large volume of literature addresses the qualitative question of why states ally and what effects alliances bring, the question of with whom states ally remains comparatively understudied. To answer the latter, scholars first leveraged dyadic structures to model alliances, further exploring their correlations with variables such as democracy, regime similarity, and shared cultural groups (Gibler & Wolford, 2006; Lai & Reiter, 2000). However, the dyad cannot appropriately handle interdependence, which violates regression's prerequisite of independence. In the meantime, the dyad treats original multiparter alliances as collections of dyads (Dorobantu et al., 2020), resulting in the simplification of alliances' dynamic structure by splitting a complex into separate units. Therefore, network analysis has been introduced as an ideal toolkit for alliances, taking states as nodes and treaties as ties. For example, the Exponential Random Graph Model (ERGM) was applied to address interdependence between alliances (Cranmer et al., 2012). Similarly, the Stochastic Actor-Oriented Model was employed to reveal triadic interactions across amity and enmity (Warren, 2010). Additionally, scholars have utilized agent-based modeling to observe alliance dynamics under domestic shocks, capturing the evolving attributes of alliances (Maoz & Joyce, 2016).

Although models for alliances are advancing over time, the data underlying alliances have shown little change. This stagnation is due to the military nature of the alliance definition, which necessitates reliance on explicit agreements such as treaties (Snyder, 1997). Through agreements, both allies and adversaries can confirm a state's intention (Leeds, 2003), thereby committing to partners or deterring opponents. The two main data sources recording treaties, the Correlates of War project (Maoz et al., 2019) and the Alliance Treaty Obligations and Provisions (ATOP; Leeds et al., 2002), have not been updated in recent years, limiting their applicability for current scholarship. Furthermore, a question arises when scholars establish alliances based on published treaties: are there secret treaties known only to leaders and not disclosed to the public? Advocates of transparency might object to this assumption because they primarily focus on the benefits

of open-door political behavior, neglecting the rising audience costs (Stasavage, 2004). More specifically, leaders are assessed by political audiences on “whether the leadership is successful or unsuccessful at foreign policy” (Fearon, 1994), thus risking reputation damage or crisis escalation. To this end, there lies a considerable possibility that some treaties are negotiated behind closed doors, and never announced publicly, resulting in the incompleteness of existing tangible treaty-based alliances.

Given the insufficiency of current data sources, can non-treaty data approximate alliances? Some attempts have been made, for example, utilizing states’ attributes such as political similarity, economic development, geographic proximity to predict alliance formation (Cranmer et al., 2012; Herath et al., 2025). However, less attention has been paid to simulating alliance structures by examining their manifestations in other political vehicles, such as media coverage. To achieve this, a predefined model is necessary. Theoretical accounts posit that common threats necessitate the formation of alliances, which in turn amplify positive interactions (Gowa & Mansfield, 1993; Liska, 1968; Mansfield & Bronson, 1997; Sprecher & Krause, 2006; Wallander, 2000). Simultaneously, empirical accounts (Cranmer et al., 2012; Maoz & Joyce, 2016; Warren, 2010) have suggested network analysis as a powerful analytical tool, identifying alliances as latent patterns emerging from shared issues and dense cooperative ties. Moreover, the limitations reflected in existing scholarship call for more inclusive data sources, by incorporating small states’ behaviors as well as replacing treaty databases with more timely and publicly available databases, such as international daily news. These considerations lay the foundation for the concept and measure design of framed alliances.

Frames

Frame analysis has been approached from multiple paradigmatic perspectives, such as cognitive, critical, and constructivist paradigms (D’Angelo, 2002), each serving distinct theoretical goals. In this study, frames are employed to interpret the influence of media discourse on the public, and are therefore examined through a constructivist lens. Defined

by Gitlin (1980), frames are “persistent patterns of cognition, interpretation and presentation of selection, emphasis and exclusion by which symbol-handlers routinely organize discourse.” They function by providing an interpretive toolkit to “locate, perceive, identify, and label” otherwise ambiguous events (Goffman, 1974), thereby guiding the construction of social meanings for users. Consequently, frames are not straightforward reflections of reality; instead, they are “constructions that give meaning to reality, and shape the understanding of reality” (Verloo, 2016). Empirical studies further support this argument. For instance, scholars found that public opinion on nuclear power shifted in tandem with media reorientation, albeit with a slight lag, indirectly validating the constructive role of frames (Gamson & Modigliani, 1989).

Given this constructive role, the dimensionality of frames directly shapes their analytical scope and comparability across contexts. Regarding dimensionality, frames are widely classified as generic frames and issue-specific frames (Semetko & Valkenburg, 2000). The former are embedded across temporal or societal contexts, thereby contributing to broader topics, while the latter are “pertinent only to specific topics and events” (de Vreese, 2005). In particular, generic studies encounter limitations in capturing contextual nuances. Existing comprehensive resources include the five news frames (Semetko & Valkenburg, 2000), the policy frames codebook (Boydston et al., 2020) and the media frames corpus (Card et al., 2015). However, these resources are either too broad or too narrowly focused on specific topics or national contexts. Conversely, issue-specific frames can delve into issues within detailed contexts; however, they are limited in comparability, as different scholars have analyzed these frames using different criteria (Matthes, 2012). Consequently, this issue-based dimensionality remains inherently limited: generic frames sacrifice essential nuances, while issue-specific frames struggle with cross-contextual verification.

Alternatively, Van Gorp (2007) redefined frames from a structural perspective, proposing the frame package as “a cluster of logically organized devices that function as an identity kit for a frame.” Such a package requires three components: manifest framing

devices, reasoning devices, and an implicit cultural phenomenon. The first refers to conceivable text features, such as metaphors and word choices, while the second refers to the implicit logic chain from which readers can draw inferences (Van Gorp, 2010). The cultural phenomenon represents a cultural consensus, such as archetypes and narratives. In other words, Van Gorp advocated for regarding issues as structures, subsequently deconstructing them into textual fragments and applying specific logic to reorganize them, thereby unveiling specific social meanings beyond these structures. In practice, frame packages rely on predefined structural conditions as general criteria to select and organize information. Furthermore, these criteria are refined in light of contextual factors, thereby achieving a balance between specificity and generalization. Structural dimensionality thus addresses the limitations of issue-based approaches through its analytical strategies.

In addition, the structural dimensionality calls for a mixed approach. Traditionally, scholars have identified two primary strategies for frames (Semetko & Valkenburg, 2000): deductive and inductive. The deductive approach detects predefined frames within texts, while the inductive method derives frames from texts with few or no prior assumptions. With advances in computational methods, scholars have increasingly expanded both strategies to large-scale corpora. From a deductive perspective, the approach incorporates neural networks to determine the extent to which frames are embedded in contexts. For example, scholars fine-tuned BERT to detect generic frame distributions in a gun-violence corpus, achieving an accuracy of 0.84 (Liu et al., 2019). From an inductive perspective, topic modeling has been leveraged to track frame shifts in European refugee debates across 24 news outlets (Heidenreich et al., 2019) and to compare frame preferences in public discussions about COVID-19 on Twitter (Wicke & Bolognesi, 2020). The concept of frame package has offered a theoretical framework for integrating computational deductive and inductive approaches, which is further operationalized through semantic network analysis. Considering news discourse as a web of “issue depictions and interpretative repertoires” (Baden, 2018), semantic network analysis identifies frames by mapping not only which

devices appear but also where they appear, namely, whether they occupy central or peripheral positions as well as how they cluster. For example, Jiang et al. (2025) constructed frames by employing BERT and LDA to identify frames as “clusters of both topics and actors” through community detection in gun-violence news articles. Computational methods facilitate the application of the mixed approach across large-scale corpora, simultaneously enabling the assessment of both reliability and validity.

Frame analysis thus offers a powerful lens for examining how reality is constructed within news discourse. Issue-based dimensionality faces a tension between generalization and specificity, whereas structure-based dimensionality offers a viable solution through semantic network analysis, particularly with advances in computational methods. This study, therefore, adopts a semantic network analysis approach, operationalized through computational methods, to examine how alliances are constructed in media discourse.

Building on the literature, the study conceptualizes framed alliances as a network and poses the following questions:

RQ1: What structural features characterize framed alliances?

RQ1.1: What are the structural characteristics of the common issue network and the positive interaction network, respectively?

RQ1.2: To what extent are the common issue network associated with the positive interaction network?

RQ2: How do the structural patterns of framed alliances reflect the current global political landscape?

Research Design

Concept

In this study, framed alliances are defined as associations constructed within media discourse, serving as a proxy that captures how alliance structures are perceived through frames rather than directly mirroring real-world alliances. The concept rests on a fundamental assumption: the complete landscape of real-world alliances remains difficult

for the public to perceive, given the challenges of exhaustive data collection and the limited publicity of treaties. As a result, the public relies on international news discourse, constructing their understanding of alliances through frames. Therefore, rooted in inclusive international news corpora, framed alliances can be extracted as a network, taking states as nodes and their relationships as ties. More specifically, these relationships are identified based on two patterns: states encountering common issues and states maintaining positive interactions. In this vein, the study establishes a standardized network structure, which is further refined by semantic similarities of issues and sentiment scores across news contexts involving states.

Accordingly, framed alliances are structured as a duplex network. The positive interaction layer is a co-occurrence network, capturing whether two or more states appear simultaneously in positive news contexts. The common issue layer is a co-semantic network, capturing whether states are facing similar issues. However, states in similar situations can become either allies or adversaries, so the layer requires exclusion of adversary pairs, approximated by state pairs with significant negative co-occurrences. Together, the two layers interpret framed alliances from complementary perspectives and enable analysis of their interdependence.

Data

Data for this study were collected via *The Guardian*'s official API. As an independently owned British news outlet, *The Guardian* is backed by 1.3 million readers. Notably, its revenue outside the UK increased by 16.3% according to its 2024/2025 annual report (The Guardian, 2025), reflecting its growing international reach. The outlet also features a dedicated World section with subsections covering Africa, the Americas, Asia-Pacific, Australia, and the Middle East, ensuring broad geographical representation. More importantly, *The Guardian* was selected for its rare provision of full, free access to researchers, which ensures reproducibility and transparency.

In terms of temporal scope, this study adopted a one-year observation window

spanning 2025, focusing on articles published within the World section. By doing this, a one-year duration ensures relatively complete tracking of political events, as most transnational conferences and elections occur on an annual basis. Additionally, the one-year window avoids temporal fluctuations. While a relationship may remain stable for months, it could undergo significant shifts over the years. Given that the study is a static observation, the one-year window is intended to balance data stability with overall completeness.

Therefore, the study collected 7,384 articles published in *The Guardian's* World section between January 1 and December 31, 2025. According to the UN country list (United Nations, n.d.), which includes the two non-member observer states, 188 countries were identified in these articles and organized according to the framed alliances design. To achieve this, the study first utilized the Python package SpaCy (Montani et al., 2023) to identify geopolitical entities, then passed them to the Python package `country_converter` (Stadler, 2017) to determine whether these entities were UN members or observers. The combined pipeline has achieved a precision of 0.990, a recall of 0.906, and an F_1 score of 0.946 against a human benchmark (Appendix A).

Network Establishment

To construct the positive interaction layer, the study limited the unit of analysis to the sentence level, minimizing the influence of unrelated information on sentiment scoring. To this end, the study first extracted sentences that mention two or more states, then called the DeepSeek-V3 model to score each sentence on a scale of -1 (negative), 0 (neutral), and 1 (positive). The model yielded an arithmetic precision of 0.769, a recall of 0.808, an F_1 score of 0.784, and an accuracy of 0.814 based on a human benchmark in this study (Appendix B). Subsequently, the study identified state pairs from these sentences and produced state-level co-occurrence edges, with the average sentiment score for each pair as an attribute.

However, the data remained noisy due to stochasticity, in other terms: Do the

framed relations between state A and state B represent statistically significant co-occurrence, or just random linkages across massive data? The problem can be resolved by filtering techniques, highlighting core connections, and reducing measurement errors (Mukerjee et al., 2019). Therefore, the study utilized netbone (Yassin et al., 2023) to extract the skeleton of the co-occurrence layer using the disparity filter algorithm (Serrano et al., 2009), which preserved the layer’s local details while maximally removing unrelated nodes. Based on this skeleton, the study further classified edges as positive or negative depending on whether their sentiment attribute was greater than or less than 0. Accordingly, the positive interaction layer was constructed, while the negative interaction network was also established to inform the construction of the common issue layer.

To construct the common issue layer, the study first identified all issues involving identified states. Similarly, to reduce noise, the study defined constrained windows for analysis. Unlike the previous layer, issues can only be extracted from sufficient context; thus, each window was defined as a group of sentences comprising the target sentence that mentions states, along with its preceding and succeeding context (Völker & Saldivia Gonzatti, 2024). The study employed BERTopic to extract topics from all windows and manually aggregated them into 35 issues.

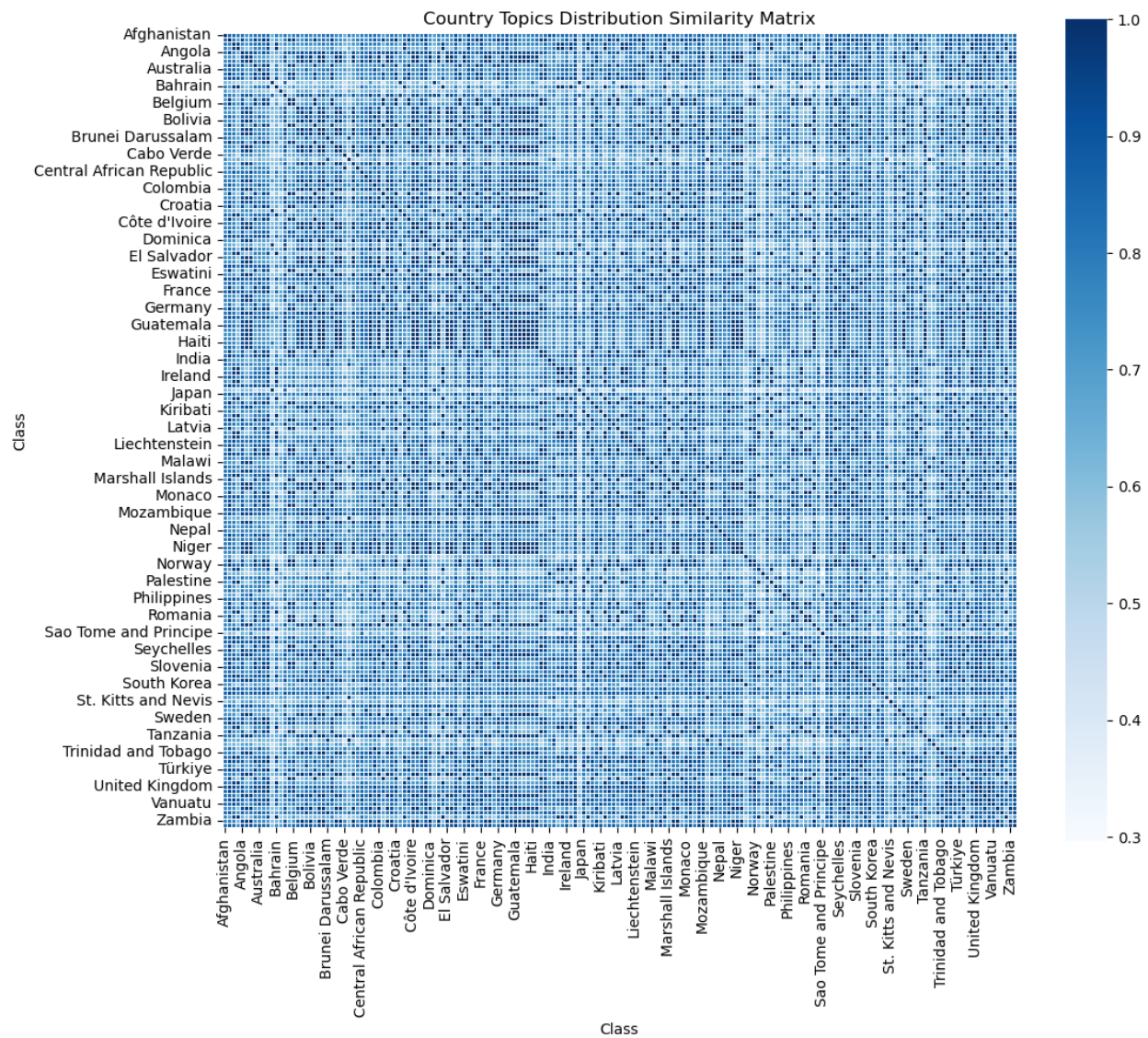
Drawing on the validation framework from Maier et al. (2018), the study utilized multiple methods to evaluate the results from the perspectives of reliability, interpretability, and validity. These include calculating a stability score (Niekler, 2016), vector-based coherence (C_v ; Röder et al., 2015), a manual review of topics, and Diversity (Dieng et al., 2020). In particular, the stability score measures the similarity of results from running the model multiple times at random, while C_v considers the co-occurrence probability of words relative to randomness, as well as the semantic similarity between words. Finally, Diversity considers the uniqueness of words within topics. Accordingly, the BERTopic model with the same parameters was rerun on the same dataset five times at random, yielding a mean reliability score of 0.601, indicating moderate reproducibility. Regarding C_v , the score is

0.694, showing a strong coherence within topics and, therefore, high interpretability for human interpretation. In addition, each topic was manually inspected through its keywords and the top three representative documents, and then assigned a realistic meaning (Appendix C). The 35 issues have moderate granularity, recognizing two worldwide issues, the Israel-Palestine war and the Russia-Ukraine war, while also preserving regional conflicts, such as the India-Pakistan conflict, showcasing a good intra-topic validity. Meanwhile, the mean Diversity is 0.898, indicating clear distinctions between topics and contributing to high inter-topic validity. To conclude, the results of the BERTopic modeling in this study demonstrate acceptable reliability, interpretability, and validity.

To measure issue similarity across states, the study calculated the probability distributions of these topics for each state and computed the cosine similarities between them (Figure 1).

The disparity filter algorithm was applied again to the similarity scores to extract the network backbone. Subsequently, adversary pairs identified in the negative interaction network were removed from this layer, thereby establishing the common issue layer.

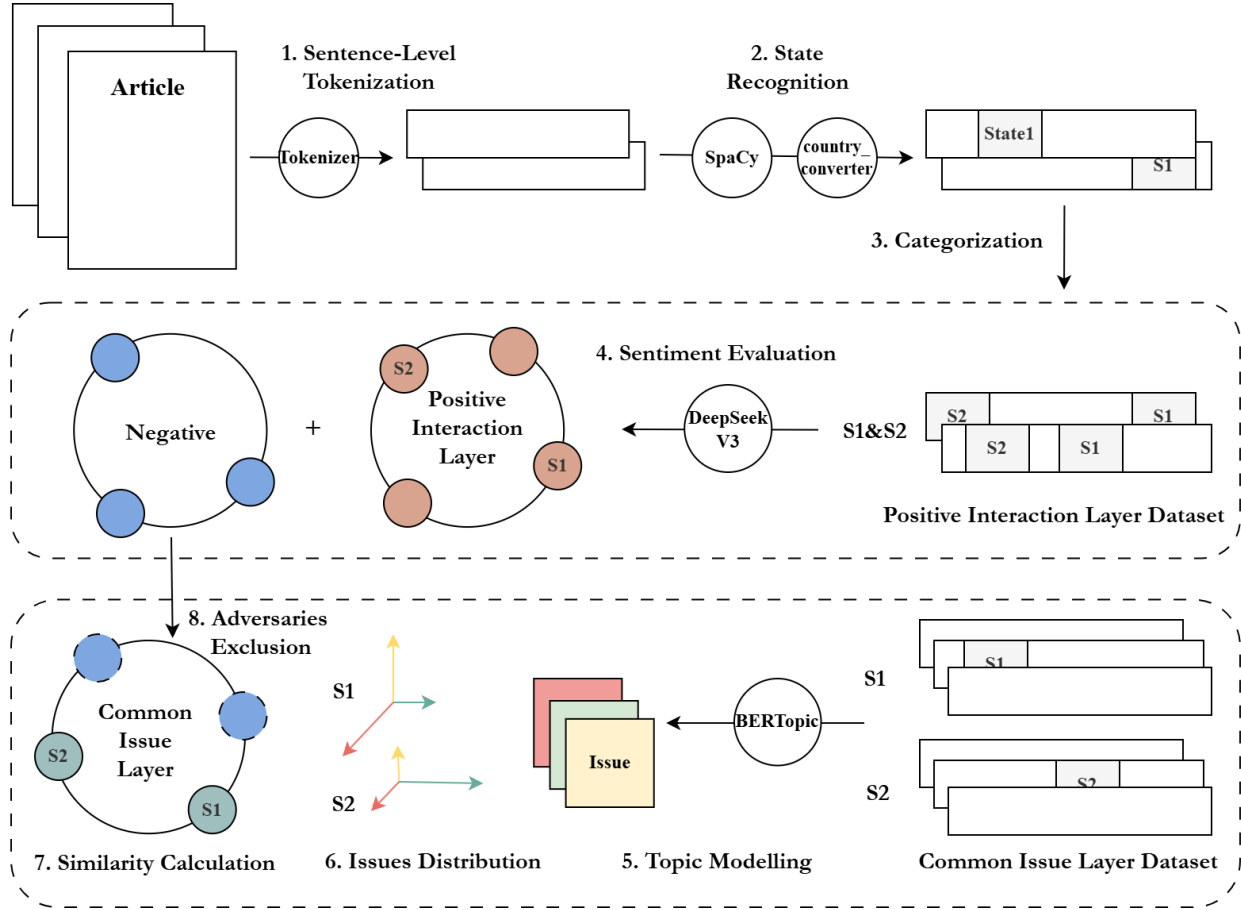
In summary, the network was established through eight steps. To reduce noise, news articles were first tokenized into sentences as research units. An NLP pipeline integrating SpaCy and country_converter was then employed to identify states within these sentences. Considering the data volume, sentences were categorized into two custom datasets for the two layers to save operation space. The positive interaction layer dataset comprised sentences that mention at least one state pair, which were then scored for sentiment by the DeepSeek-V3 model. Subsequently, average sentiment scores were calculated for each pair to establish both the positive and significant negative interaction layers. The common issue layer dataset was organized by individual states, with corresponding subsets of all windows mentioning them. BERTopic extracted issues across all windows, and calculated issue distributions per state subset. Next, issue distribution similarity between states was computed and used as edges for the raw common issue layer. Finally, state pairs with

Figure 1*Country Issues Similarity Matrix*

significant negative interactions were subtracted to construct the common issue layer. The complete workflow is shown in Figure 2.

Social Network Analysis

The study employed social network analysis as the primary toolkit for each layer's structural features (RQ1.1). The framework offers not only descriptive metrics to evaluate

Figure 2*Framed Alliances Establishment Workflow*

cohesion and efficiency, but also exploratory approaches for community detection and leader identification. In this vein, the study first characterized each layer through density, transitivity, mean distance, diameter, and global efficiency.

Density indicates the average strength of ties within a network (Wasserman & Faust, 1994), serving as a direct measure of cohesion. However, it has a fundamental limitation in terms of comparability, as no universal standards exist for evaluating densities across different networks (Scott, 2012). Therefore, the study utilized the most recent ATOP alliance data as a benchmark to contextualize the observed values². Additionally,

² As the ATOP records alliance data only up to 2018, the benchmark density was calculated based on the

the study applies transitivity to capture the tendency of “the friend of my friend becomes my friend” (Wasserman & Faust, 1994). This property evaluates the quality of cohesion by revealing whether connections follow a hub-and-spoke pattern or are distributed in mutual connections. In terms of efficiency, geodesic distance is a foundational concept measuring the shortest path between two nodes. Mean distance represents the average geodesic distance across an entire network, while diameter represents the longest geodesic distance, indicating the most extreme connecting path between nodes. Although the two metrics are intuitive and straightforward, they are sensitive to extreme values, a limitation addressed by global efficiency (Latora & Marchiori, 2001). As the value approaches 1, nodes become more reachable to one another through existing edges. Together, the three indices measure efficiency from average, extreme, and comprehensive perspectives. For all metrics above except density, permutation tests against configuration models (Newman et al., 2001) are conducted to assess statistical significance, as density is constrained to match observed values in configuration models.

Second, the study detects potential communities within each layer to reveal underlying alliance groups. Given that real alliance networks are based on multiple treaties, framed alliances should also exhibit distinct groups within the network structure. Accordingly, the study identifies potential partitions based on the Louvain Algorithm (Blondel et al., 2008), which is particularly suitable as it requires no assumptions about initial community structures and supports weighted calculations (Crooks et al., 2014). Within communities, nodes are densely connected and edges carry greater weight, while between communities, nodes are loosely connected and edges carry lower weight. To evaluate community quality, the study also reports the Modularity (Q; Newman & Girvan, 2004) and External-Internal Index (E-I Index; Krackhardt & Stern, 1988). A strong

alliance network as it existed in that year. Therefore, other direct structural comparisons were not conducted due to the temporal gap between the ATOP’s data (2018) and the current study’s observation window (2025).

community structure typically yields a Q ranging from 0.3 to 0.7, with higher values being rare. The E-I Index reflects a community's insularity and openness by comparing its external edges and internal edges. As the index approaches -1, the corresponding community becomes increasingly inward-cohesive. By revealing internal divisions and identifying specific alliance groupings from the broader network, community detection is pivotal for understanding polarization and homogenization among states.

Third, the study computes four centrality measures: degree, eigenvector, betweenness, and closeness, which assist in identifying nodes with different roles. For a single node, degree reflects its influence through the number of its ties (Wasserman & Faust, 1994), while eigenvector also considers tie quality by incorporating the importance of neighboring nodes. Closeness captures a node's reachability through its mean shortest path to all other nodes (Tabassum et al., 2018), while betweenness reflects a node's gatekeeper role through the proportion of shortest paths between node pairs that pass through it (Tabassum et al., 2018). Together, the four centrality measures capture nodes' structural roles from complementary perspectives: local influence, relational quality, reachability, and brokerage.

Multiplex Network Analysis

To further examine the research questions, the study then analyzes the interdependence between the common issue layer and the positive interaction layer (RQ1.2). Modeled as a multiplex network, framed alliances consist of a set of real-world actors linked by different types of ties, each type existing on corresponding layers (Chen, 2021). However, in network-based inference, interdependence is an inevitable consideration. More specifically, the tie between two actors is also influenced by their ties to a third actor due to common sources, shared pathways, and resource capacities (Frank & Strauss, 1986). In each layer of framed alliances, this feature is evident in the high transitivity, whereby two states sharing a common partner, are inclined to establish a direct connection. Importantly, this inescapable dependence can be modeled through the ERGM. The model

utilizes multilateral statistics such as transitivity to simulate the full network, as these statistics are inherently edge-dependent; the model automatically accounts for dependence (Frank & Strauss, 1986), which can be briefly expressed as:

$$P(Y = y) \propto \exp \left(\sum_n \theta_n g_n(y) \right) \quad (1)$$

Where Y is the observed network, $g_n(y)$ is the network statistic, θ_n is the corresponding coefficient. Furthermore, scholars have extended such models into multiplex networks by introducing cross-layer statistics and joint probabilities (Krivitsky et al., 2020). Take a duplex network as an example:

$$P(Y_A = y_A, Y_B = y_B) \propto \exp \left(\sum_n \theta_n g_n(y_A, y_B) \right) \quad (2)$$

Where the network Y is constituted of layers Y_A and Y_B , $g_n(y_A, y_B)$ is the network statistic including both intralayer and interlayer statistics, and θ_n is the coefficient to $g_n(y_A, y_B)$.

Accordingly, the study drew on these frameworks to examine interdependence within framed alliances from both edge and node perspectives. Specifically, the study utilizes the Conway-Maxwell-Binomial (CMB) Model, Conjunction Model, and Cross-Layer Two-Star Model.

The statistic in the CMB model is defined to evaluate the extent to which edges overlap across layers. By assessing edge overlap, the model reflects how interlayer dependence influences edge pattern similarity. When the coefficient is 0, the two layers are independent, whereas a coefficient greater than 0 indicates positive dependence in overall edge overlap. Put differently, the two layers tend to exhibit similar link combinations across the same set of nodes. Although the CMB model verifies whether edge patterns are interdependent, the specific types of patterns require further clarification. There are three categories of patterns: conjunction (an edge in one layer facilitates its appearance in another layer), mutual exclusivity (an edge in one layer inhibits its appearance in another

layer), and substitutability (an edge in one layer offsets the default increase of its appearance in another layer). For framed alliances, conjunction is particularly relevant as it explains the direct effect of the common issue layer on the positive interaction layer; that is, whether two states facing common issues are more likely to engage in positive interactions with each other. When the coefficient is 0, two states' positive interactions are independent of their issue similarity, whereas when the coefficient is above 0, positive interactions are positively conditioned on issue similarity. Apart from edges, nodal degrees also capture inter-layer dependence. The statistic in the Cross-Layer Two-Star Model evaluates the likelihood that a node with ties in one layer also maintains ties in another layer. A negative coefficient indicates that nodes exhibit functional differentiation across layers; that is, nodes highly active in one layer tend to play a peripheral role in the other, rather than maintaining a consistent hub status across the multiplex system.

In this study, the original layers were first simplified into unweighted layers, based on two considerations. First, weights increase the risk of model degeneracy during simulation; second, connection existence better captures topological dependence than connection intensity. Subsequently, the study combined the two layers into a duplex structure and utilized the R package `ergm.multi` (Krivitsky et al., 2020, 2023) to implement the model simulation. Goodness of fit is evaluated through in-model statistics, degree distribution, edge-wise shared partners, and minimum geodesic distance. The first metric assesses the model's ability to reproduce the specific configurations included in the formula, while the last three metrics reflect sociality, clustering, and diffusion of the simulated network, respectively (Goodreau et al., 2009). The fitting is also assessed using diagnostic tools provided by `ergm.multi`.

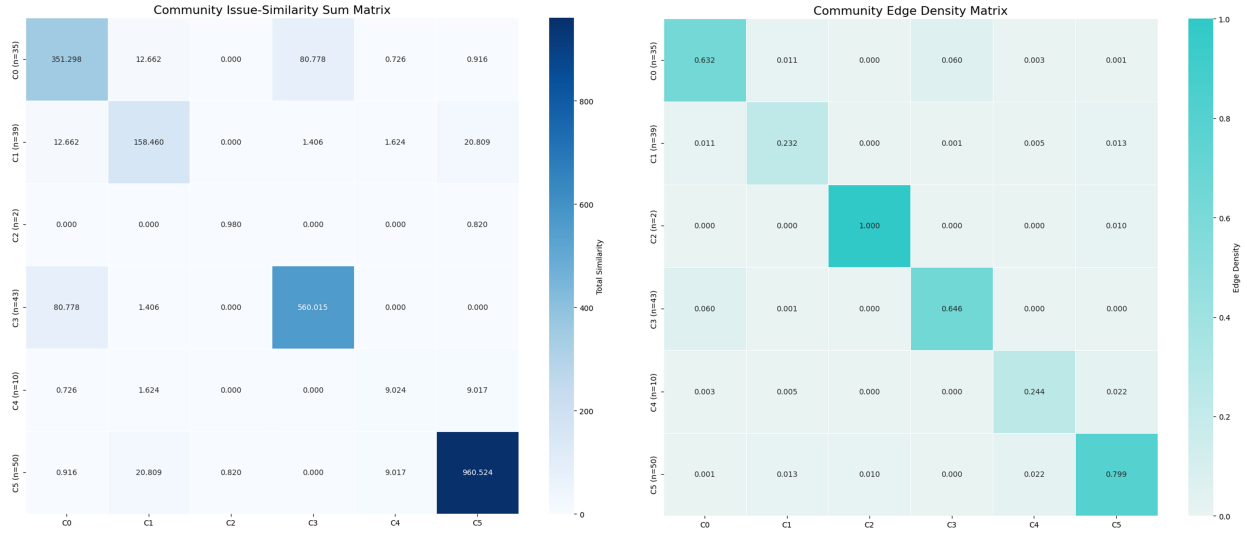
Notably, given that framed alliances represent a novel construct, the study adopted an exploratory orientation, wherein theoretical interpretations of the structural findings are developed inductively in the discussion, drawing on established frameworks in international relations as they become relevant to the observed patterns (RQ2).

Results

Common Issue Layer

The common issue layer contains 179 states and 2,271 edges. Between state pairs, the average issue similarity reaches 0.955 on a scale from 0 to 1, indicating a high degree of issue commonality across states. With regard to cohesion, the layer pattern presents a low density ($D_{obs} = 0.143$) compared to ATOP alliances ($D_{ATOP} = 0.246$) while exhibiting a high transitivity ($T_{obs} = 0.794$, $T_{exp} = 0.206$, $p < 0.001$). In terms of efficiency, the layer exhibits a long mean distance ($Md_{obs} = 3.589$, $Md_{exp} = 2.091$, $p < 0.001$), a long diameter ($D_{obs} = 10.000$, $Dia_{exp} = 4.309$, $p < 0.001$), and a low global efficiency ($G_{obs} = 0.387$, $G_{exp} = 0.527$, $p < 0.001$). In summary, the pattern reflects the diversity and regionalization of issues across states. The detected communities further quantify and reinforce this conclusion. A total of six communities (Appendix D) constitute the entire network with a modularity of 0.621, suggesting a strong community structure. Within communities, nodes are closely connected, and edges carry higher issue similarity, as illustrated in Figure 3. However, between communities, states are rarely linked, as further evidenced by the weighted E-I Index. The global index is -0.881, while each community's index ranges from -0.936 to -0.115, suggesting a high degree of issue insularity.

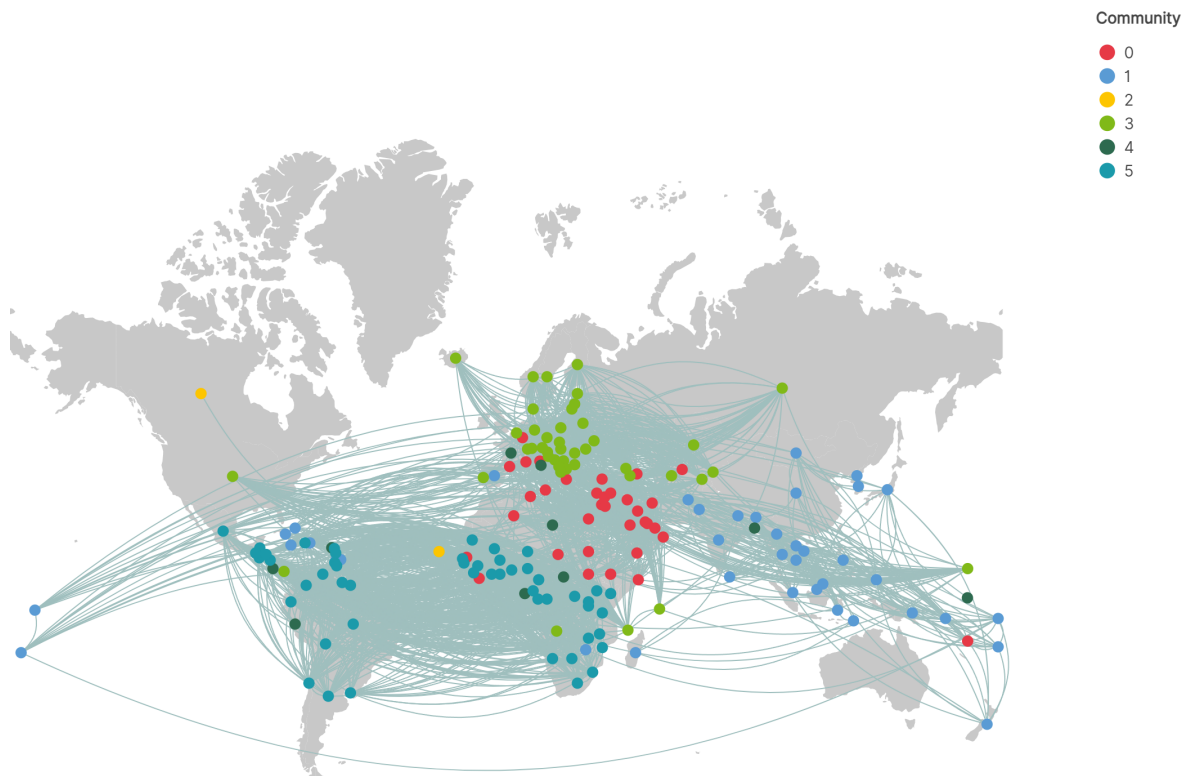
Regarding leader identification, different states occupy prominent positions within the common issue layer. More importantly, these states are often absent from political research. For example, Grenada possesses the highest degree and eigenvector centrality, suggesting that it is the most extensively and influentially connected actor in the network through shared issues. Portugal possesses the highest betweenness centrality, functioning as a broker bridging issue similarities across states. Regarding closeness, Jamaica ranks the highest, indicating that it is the most efficiently connected to all other states through shared issues. In other words, Jamaica may not directly share issues with most states, but it can reach all other states most efficiently as a potential global mediator.

Figure 3*Community Matrices in the Common Issue Layer*

Overall, the common issue layer (Figure 4) reveals a regionalized yet interconnected landscape, where small states serve as structurally vital actors.

Positive Interaction Layer

The positive interaction layer encompasses 100 states out of 195 member states and observer states, with 148 edges and a total positive sentiment score of 54.566. The average sentiment score of 0.369 indicates that interactions among states in news discourses are moderately positive overall. Compared to the common issue layer, both the density ($D_{obs} = 0.030$) and the transitivity ($D_{obs} = 0.1705$, $D_{exp} = 0.042$, $p < 0.001$) are markedly lower in the positive interaction layer. In other words, only 3% of all possible state cooperative links are realized; those that do exist tend to cluster in triangles. Similarly, efficiency is also lower in this layer, with a mean distance of 4.826 ($md_{exp} = 4.067$, $p < 0.001$), a diameter of 12 ($Dia_{exp} = 9.372$, $p < 0.033$), and a global efficiency of 0.243 ($G_{exp} = 0.265$,

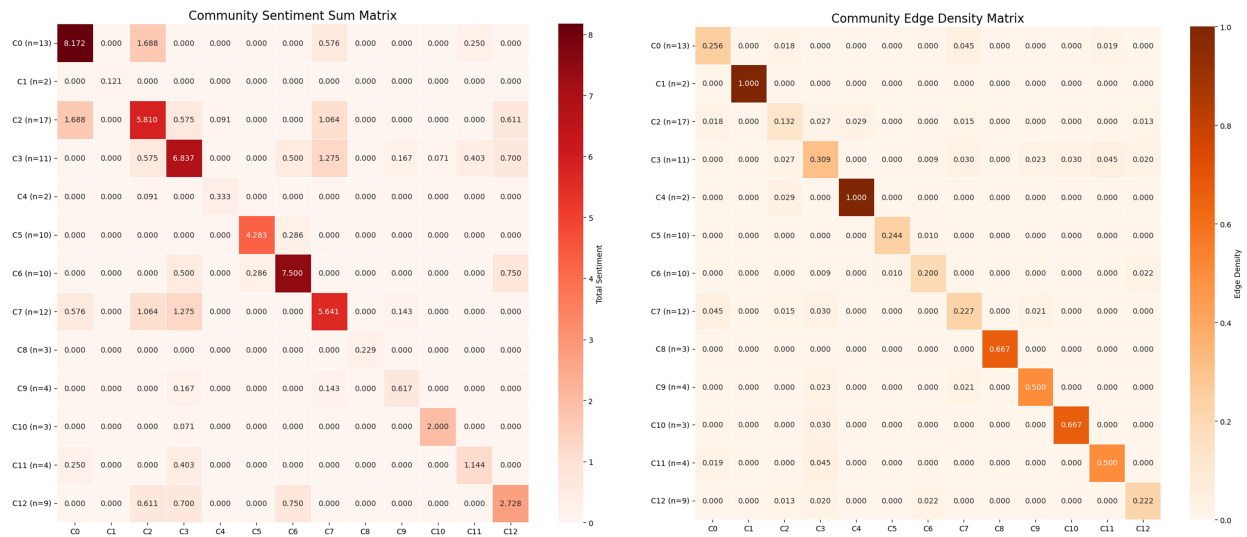
Figure 4*Common Issue Layer Landscape*

$p < 0.053$). In conclusion, the layer is globally fragmented yet closely connected within local triangular clusters, at the cost of overall efficiency and connectivity. In addition, 13 communities (Appendix E) were identified, with a total modularity of 0.703, suggesting a well-defined community structure characterized by higher density and positive sentiment within communities (Figure 5). The global E-I Index of -0.665 indicates pervasive inward cohesiveness across all communities, with individual community indices ranging from -0.139 to -1.000. From a structural perspective, the positive interaction layer aligns with a polycentric pattern (Kim, 2020), characterized by high modularity and multiple

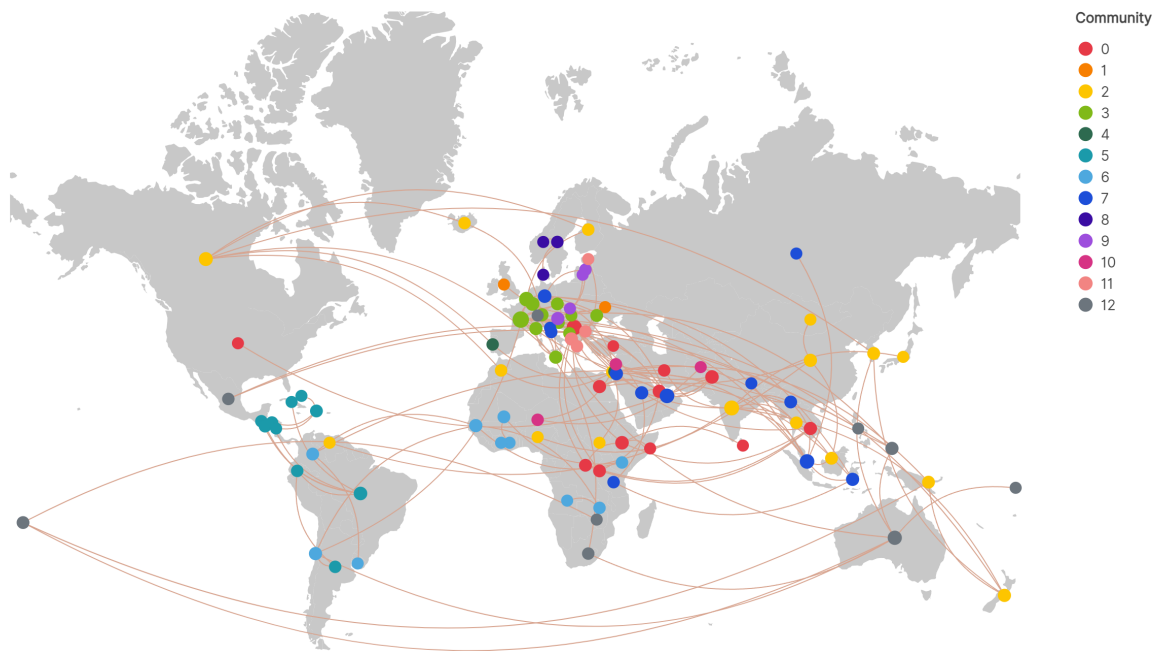
fragmented communities. At the actor level, in contrast to the multi-leader pattern observed in the common issue layer, France emerges as the dominant hub, with the highest scores across all four centrality measures. France not only maintains the most connections within the network but also engages extensively with other influential states. In addition, it also governs the flow of framed cooperation across the entire network in terms of availability and efficiency.

Figure 5

Community Matrices in the Positive Interaction Layer



To conclude, the positive interaction layer (Figure 6) is characterized by a polycentric system that is inwardly cohesive yet outwardly sparse, with a monocentric node controlling the entire network.

Figure 6*Positive Interaction Layer Landscape*

Duplex Network

Structurally, framed alliances constitute an unaligned duplex network, sharing the same set of nodes across layers, while the number of active nodes differs between layers (Figure 7). As revealed by the preceding analyses, the two layers are distinct across multiple metrics, for example, the common issue layer is denser while the positive interaction layer is sparser, and they also differ in community numbers and key actors. However, the CMB, conjunction, and cross-layer two-star models unveil the interdependence disguised by these differences (Table 1).

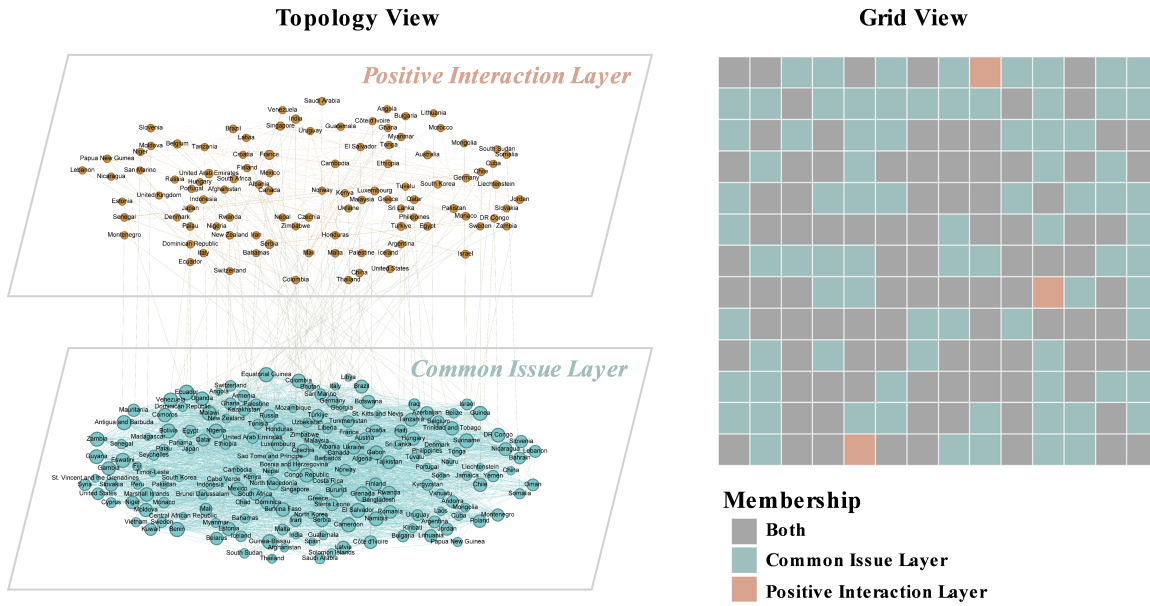
As the results show, the overall patterns of the two layers are strongly and significantly dependent, as reflected by the CMB statistic. In other words, within framed alliances, states partially replicate their issue-based connection and disconnections when

Table 1*Duplex Network Model Results*

	Estimate	Std. Error
CMB Model		
Edges (Layer c)	-1.384***	0.094
Edges (Layer p)	-4.425***	0.093
CMB-Statistic	0.664***	0.135
AIC=14887, BIC=14912, sample size=10000		
Conjunction Model		
Edges (Layer c)	-1.844***	0.022
Edges (Layer p)	-4.886***	0.098
Conjunction-Statistic	0.912***	0.180
AIC: 14886, BIC: 14912, sample size=10000		
Cross-Layer Two-Star Model		
Total Edges	-1.635***	0.021
Conjunction-Statistic	1.157***	0.002
Two-Star-Statistic	-0.069***	0.186
AIC: 14832, BIC: 14857, sample size=10000		

Note. Layer c: common issue layer, Layer p: positive interaction layer, ***: $p < 0.001$, AIC: Akaike Information Criterion, BIC: Bayesian Information Criterion.

Figure 7
Framed Alliances



establishing positive interactions. Unlike the divergence of top nodes in single-layer analyses, the CMB model detects an overall overlap across layers by including non-top nodes. When states regionalize their issues and form local alliances, their interactions are also constrained within these issue-based systems. Within these systems, regional centers may emerge, contributing to the polycentric structure observed in positive interactions. Similarly, states that do not share common issues tend not to establish cooperative links.

Having established macro-level interdependence, the study further examined the specific type of interlayer relationship at the dyadic level. The conjunction model reveals that two states that establish a link in the common issue layer are also more inclined to connect in the positive layer. Therefore, beyond the conservative tendency to collaborate with neighbors, states' collaborations are also significantly shaped by situational similarities. This finding is consistent with traditional alliance theory, suggesting that states facing similar issues are more likely to form alliances, thereby fostering internal

cooperation. However, given the discrepancy in active states across layers (Figure 7), not all issue-based connections translate into positive interactions, suggesting an underlying selection process through which states choose their cooperation partners, though common issues still remain a significant consideration.

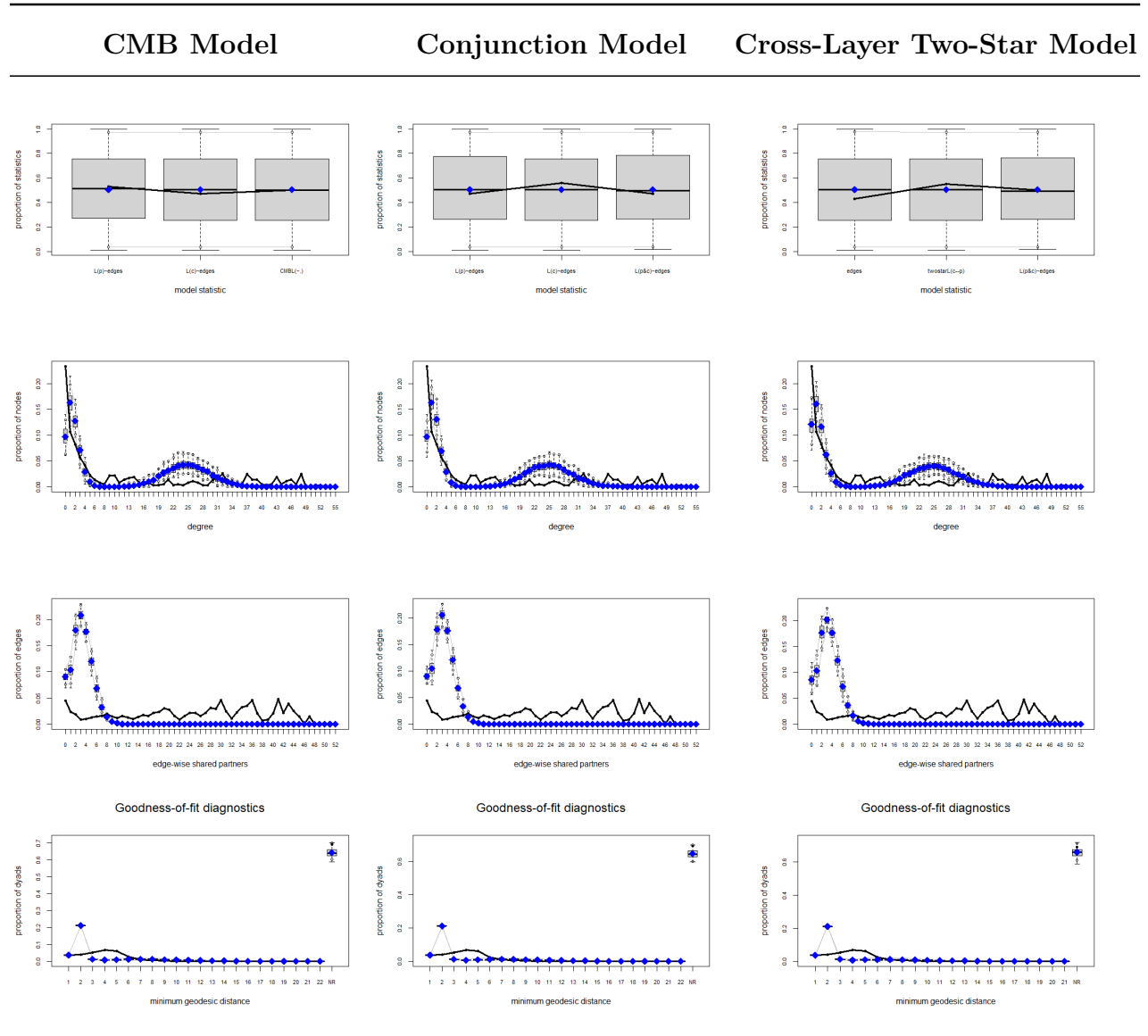
Nevertheless, the cross-layer two-star model reveals a significant negative coefficient. States that share more issues with other states tend to engage in fewer positive interactions. As shown by the common issue layer, small states occupy important structural positions because they are not locked into regional issues as major powers are. However, lacking sufficient resources to lead regional cooperation, they are ultimately relegated to peripheral roles in actual interactions. Regarding the models' explanatory power, the goodness of fit of the three models (Figure 8) suggests some deficiencies. At the global structural level, these models fit well, while local details, particularly clustering, are less effectively captured due to the complex topology of the multiplex system. The models' fit could be enhanced by incorporating more parameters; however, this would result in overfitting. Despite these limitations, the strong significance of the coefficients ensures the robustness of the primary findings.

Discussion

As a mediated status, framed alliances function as both a cognitive construction of international relations and a regular benchmark for the public to perceive. Consequently, they are not merely a discourse network, but a supplement to real-world politics, where their patterns serve as an infrastructure of the current political landscape. Therefore, the study delves into the signals conveyed by the framed structure, from each layer to the interdependence between layers.

Common Issue Layer

The pattern of the common issue layer can be conceptualized through the classical Regional Security Complex Theory (RSCT; Buzan & Wæver, 2003). It defines a complex where states' primary security concerns are sufficiently interlinked to distinguish them from

Figure 8*Goodness of fit for the Three Models*

surrounding states. Consequently, security interactions are more likely to appear within complexes rather than across them. In doing so, the theory offers a valuable regional-level aspect of the political landscape, in contrast to globalization trends. More specifically, states in this layer are not united by shared global issues; instead, they are more preoccupied with regional conflicts or issues. The localization of issues, on the one hand, leads to a more stable structure in which disruptions remain locally contained. On the

other hand, it also limits opportunities for states to form alliances with those facing different regional issues. This phenomenon of regionalization further supports the RSCT. However, the original theory relies on geographical proximity to set boundaries for complexes, a criterion not strictly observed in the communities detected in this layer. For example, states such as Austria and Kazakhstan are assigned to the same community, owing to the introduction of non-territorial issues and the global calculation of issue similarities. Therefore, the findings here push the RSCT beyond its original geographical boundaries, suggesting that issue-based similarities can transcend territorial proximity in defining security complexes.

Notably, why do small states emerge as central actors in the common issue layer rather than powers? The RSCT offers a potential explanation: within specific complexes, major powers are locked in due to their capacity to alter the situation, making them subject to greater political scrutiny, while small states are compelled to navigate across complexes in search of greater flexibility. Hence, small states become engaged with a broader range of regional issues, elevating their centrality within the common issue layer. This finding supports the call for more inclusive alliance research that extends beyond great power dynamics, as small states play a structurally significant role in shaping issue-based alliance landscapes.

Positive Interaction Layer

The endogeneity in news discourse reflected by high transitivity is explained by Kinne (2013) as a mechanism for reducing risks and increasing gains. For any two states, a shared partner provides information to both, while creating a more durable and stable club through triadic structures. Accordingly, the generally sparse yet locally cohesive layer reflects states' cautious and conservative approach to positive interactions. Although low efficiency hinders states' connections through cooperations, it protects collaborations by impeding infiltrators entering clusters and disrupting existing collaborations, thereby reducing the risk of betrayal by unfamiliar members (Cassar, 2007). From a polycentric

structural perspective, communities operate as autonomous units while remaining responsive to others through multiple forms of interaction, such as cooperation (Carlisle & Gruby, 2019). The polycentric system is characterized by communities with “overlapping mandates, ambiguous hierarchies of authority, and no ultimate arbiter”; nevertheless, it can function fluidly in an ordered chaos (Koinova et al., 2021), a feature attributable to its structural redundancy. This feature is also associated with high transitivity, which offers alternative paths for cooperation to circumvent disruptions across the entire network, enhancing its resilience to risks (Carlisle & Gruby, 2019). The polycentricity reflected by these communities captures emerging tendencies in the world political landscape, while corresponding to its macrostructural properties such as low density and high transitivity. However, France, as a monocentric node, is the Achilles’ heel in this subtly balanced polycentric system. On the one hand, it provides shortcuts for global cooperation that would otherwise rely on redundant paths. On the other hand, it represents the most vulnerable point in the network; should it be disrupted, the entire network could be severely destabilized. Therefore, the co-existence of a monocentric node and a polycentric network reveals the vulnerability of the current interaction landscape. This seemingly paradoxical structure reflects a notable tension, with France emerging to improve the low efficiency inherent in the polycentric system, yet simultaneously introducing risk to what was previously a stable and balanced structure.

In brief, this layer is robust overall, relying on redundant cooperation paths yet fragile should its monocentric node be disrupted.

Framed Alliances

Within the duplex network, the two layers share dependent patterns, exhibiting similar connection preferences but divergent nodal roles. Specifically, small states significantly shape the fundamental landscape of issues, whereas major powers ultimately lead cooperation within framed alliances. However, how does this unique duplex structure emerge? The concept of structural power (Strange, 2004) may shed light on this question.

Although originally developed for political economy, this theory is also applicable to the global political system in this study. Different from the power that coerces states through direct commands, structural power defines the framework by setting the agenda for discussions and international regimes of rules and customs, where other states have to operate. Accordingly, major powers predefine issues and discussion paths, according to which small states have to perform on the front stage, while the actual rule creators remain backstage to oversee the evolving landscape. As states allocate their resources to practical collaborations, small states step back due to capability constraints, while more capable states become more active. This suggests that while both layers follow the same predefined patterns, the actual engagement within each layer is determined by a state's operational capacity. In the common issues layer, participation costs are comparatively low, as small states can engage with issues in multiple forms. Conversely, the interaction layer requires high-level commitments and resource exchanges, which effectively obstruct the mobility of small states.

Conclusion

The study defines and measures framed alliances to bridge the gap between treaty observations and mediated statuses. Conceptually, framed alliances are proximate military associations constructed through cognitive media discourse, which influences public perceptions. Methodologically, framed alliances are operationalized as a duplex network in which states serve as nodes, with issue similarities and positive interactions in news discourse as ties across two respective layers. The study addresses two main research questions: the structural features of framed alliances, and the global political landscape they reflect. Specifically, the author interprets these questions from the perspective of each individual layer as well as the interlayer dependence.

The study finds that both layers reflect features of low density, high transitivity, long mean distance, long diameter, low global efficiency, and high modularity. Moreover, there is a significant positive correlation in both overall patterns and dyadic links across

the two layers. Yet states behave quite differently between layers, with divergent key actors in each. In the common issue layer, various small states occupy structurally significant positions across degree, eigenvector, betweenness, and closeness centrality. In contrast, France emerges as the center across all centrality measures in the positive interaction layer.

Based on these observations, the study contends that the common issue layer reflects the regionalization of issues; similarly, the positive interaction layer is characterized by a polycentric system that ensures network robustness at the expense of efficiency. Regarding interdependence, the study proposes that major powers predefine a macro framework for both issues and interactions, thereby establishing implicit rules for other states to follow. Nevertheless, due to varying capacities to operate within this framework, small states are confined to the common issue layer while withdrawing from actual cooperative interactions, which demand greater resources.

The findings carry implications across theoretical, methodological, and practical dimensions. The central contribution lies in the concept of framed alliances as a replicable, media-grounded framework for studying international relations. Drawing on the concept of frame packages, the study demonstrates how to construct alliances through a semantic network, providing a replicable template for future studies adopting similar approaches. In addition, the study synthesizes alliance literature and derives common issue engagement and positive interaction as two layers for future alliance detection. Regarding research design, the study employs a duplex network to approximate alliances, examining the mechanisms underlying alliance formation through interlayer dependence, and provides a reproducible example with openly accessible data and code. Through the lens of framed alliances, the study interprets the current world political system as a polycentric interaction system shaped by regional issues, offering a snapshot of the current global political landscape. Moreover, framed alliances can serve as a mediating structure in political communication research. This structure can reveal how the media frames news narratives to shape public opinions on wars and conflicts. Meanwhile, it can also be used to

explore public perceptions of alliances, serving as an important lens for understanding how the political landscape is socially constructed.

The limitations of this study lie in several aspects. Conceptually, although the study draws on frame analysis, it does not examine its actual function in constructing alliances among audiences, nor does it empirically explain the linkage between framed and real-world alliances. These gaps are acknowledged as boundary conditions of the current study rather than oversights; the primary aim is to identify structural patterns in news discourse and offer theoretical interpretations of the observed statistics. Methodologically, several models exhibit different deficiencies. The sentiment scoring model operates on a scale of -1, 0, and 1, which cannot further distinguish sentiment intensity, thereby limiting its granularity. The BERTopic demonstrates instability in topic extraction, with a reliability score of 0.601, which may raise concerns for reproducibility. In the meantime, the duplex network model captures overall structure but lacks sensitivity to local details, which weakens its explanatory power. Regarding the data source, the study relies on a single media outlet, which may affect the representativeness of framed alliances. As a British private news outlet, *The Guardian* has specific reporting preferences towards states and political events, a factor that should be considered when assessing the validity of the findings.

Future research might examine how framed alliances relate to treaty-based alliances, and how media reporting styles and political affiliations shape these representations. On the audience side, further research could explore how individuals perceive alliances through framing, the specific psychological processes involved, and how these perceptions ultimately inform political attitudes and decisions. In addition, this study also advocates for a more comprehensive paradigm in alliance studies and international relations. Rather than viewing political interactions as a single-layer plan, a topological perspective may better capture their complexity. States' interactions are also constituted by multiple types of relationships, such as economic, military, and cultural, which should be incorporated as covariates in empirical analysis rather than focusing solely on actor attributes. Moreover,

how these relationships interact and what social meanings emerge from such complex systems remain underexplored. The duplex network model presented here serves as an initial step toward such topological modeling, and it is hoped that future research will build on this foundation to further unpack the complexity of international political relations.

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Appendix A

Validation for the States Recognition Pipeline

Since accurate and complete state identification is a prerequisite for the study, the NLP pipeline’s results require verification to ensure reliability. The study employed the Cochran’s Modified Sample Size Formula ($e = 0.05$, $p = 0.5$, $Z = 1.645$ for a 90% confidence interval, $N = 7,384$) for a finite population, and thus sampled 261 articles from the shuffled dataset. The results were evaluated using precision, recall, and F_1 score through manual annotation of erroneous ($N_{mistake}$) and missing entities ($N_{missing}$), which were then compared with the number of identified states ($N_{identified}$).

$$n_0 = \frac{Z^2 \cdot p \cdot (1 - p)}{e^2} \quad (A1)$$

$$n = \frac{n_0}{1 + \frac{n_0 - 1}{N}} \quad (A2)$$

Precision: evaluates how accurately the identified entities refer to states in articles. For example, “Georgia” may refer to a country, but it can also refer to a person’s name or the U.S. state.

Recall: evaluates how completely states were retrieved during the identification.

F_1 score: a balance score between Precision and Recall.

$$Precision = \frac{N_{identified} - N_{mistake}}{N_{identified}} \quad (A3)$$

$$Recall = \frac{N_{identified} - N_{mistake}}{N_{identified} - N_{mistake} + N_{missing}} \quad (A4)$$

$$F_1 \text{ score} = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (A5)$$

Appendix B

Validation for the Sentiment Scoring Model

According to the Cochran's formula, the project sampled 269 items ($e = 0.05$, $p = 0.5$, $Z = 1.645$ for a 90% confidence interval, $N = 38,688$) from the dataset, and categorized the samples into Positive, Negative, and Neutral sentiments manually. By comparing the results of the human annotation with those of the model, a 3*3 multi-class confusion matrix was generated. Furthermore, the study also calculated Precision, Recall, and F_1 score for each category and the overall performance. Take the positive category as an example:

TP: Sentences classified as positive by both the model and the human annotator.

FP: Sentences classified as positive by the model but identified as non-positive by the human.

TN: Sentences classified as non-positive by both the model and the human.

FN: Sentences classified as non-positive by the model but identified as positive by the human.

$$Precision = \frac{TP}{TP + FP} \quad (B1)$$

$$Recall = \frac{TP}{TP + FN} \quad (B2)$$

$$F_1 \text{ score} = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (B3)$$

The overall model metrics were calculated as the arithmetic mean of the three categories.

Appendix C

Keywords-Issue Mapping List

The full list with representative documents is available via the Google Drive link

(<https://drive.google.com/drive/folders/1DSfmlJ1nhRexlx0WL8R1KxyTY3sbQ91g?usp=sharing>).

Table C1 only shows the keywords.

Table C1

Keywords-Issue Mapping List

Topic	Top 10 Keywords	Issue Label
0	gaza, israeli, said, hamas, palestinian, aid, cease-fire, people, killed, hostages	Israel-Palestine war
1	russian, said, ukrainian, zelenskyy, trump, putin, peace, war, european, president	Russia-Ukraine war
2	uk, chinese, tariffs, eu, trade, taiwan, said, new, trump, beijing	Trade friction
3	maduro, bolsonaro, president, trump, said, country, south, africa, government, drug	Latin American turmoil
4	thai, earthquake, people, border, said, cambodian, junta, military, country, bangkok	Southeast Asia crisis
5	indian, kashmir, pakistani, military, border, said, attack, strikes, administered kashmir	India-Pakistan conflict
6	greenland, danish, trump, canal, said, modi, greenlandic, oil, arctic, vance	Pax Americana
7	hurricane, melissa, storm, tsunami, winds, wildfires, people, temperatures, said	Nature disaster

Continued on next page

Table C1 (Continued)

Topic	Top 10 Keywords	Issue Label
8	carney, canadian, trump, trudeau, trade, canadians, tariffs, election, mark carney	Canada-US conflict
9	french, le, macron, le pen, pen, sarkozy, bayrou, lecornu, budget, political	Macron crisis
10	korea, north, north korea, korean, south korea, south, kim, yoon, pyongyang	Russo-Korean cooperation
11	new zealand, zealand, new, animal, animals, uk, species, year, bird, welfare	Environment
12	pope, francis, leo, church, catholic, vatican, prevost, pope francis, pope leo	Religion
13	abortion, abortions, najim, government, libyan, court, detention, people, refugees	Human rights
14	england, cricket, football, cup, sport, world cup, rugby, world, pages, win	Sports competitions
15	aucus, submarines, submarine, nuclear, class, review, nuclear powered, virginia class	Aucus Pact
16	rsf, uae, darfur, sudanese, fasher, el fasher, support forces, war, rapid support	Sudan-UAE conflict
17	museum, louvre, tapestry, paris, bayeux, art, cultural, jewels, franco, stolen	Art
18	swedish, police, shooting, graz, said, attack, people, örebro, right, school	Swedish domestic violence
Continued on next page		

Table C1 (Continued)

Topic	Top 10 Keywords	Issue Label
19	crash, plane, flight, ahmedabad, air, aviation, boeing, investigation, uk, indian	Air accidents
20	afghans, taliban, afghan, couple, women, family, kabul, barbie, british, uk	Taliban activities
21	power, blackout, operator, outage, grid, electricity, energy, power cut, iberian	Power cut-off
22	abramovich, uk, chelsea, jersey, bvi, tax, money, government, oligarch, companies	War aids
23	irish, connolly, dublin, catherine, catherine connolly, taoiseach, dáil, election	Election
24	turkey, mamoglu, istanbul, erdoğan, turkish, protests, mayor, whatsapp, chp	Turkish domestic turmoil
25	eurovision, contest, song, song contest, participation, broadcaster, competition, ebu	BDS
26	hasina, siddiq, yunus, sheikh hasina, aunt, dhaka, sheikh, corruption, sir, tulip	UK-Bangladesh friction
27	wilders, party, pvv, dutch, d66, geert, geert wilders, election, right, far right	Domestic election
28	prabowo, protests, suharto, protesters, gen, government, military, corruption, young	South Asia revolutions
29	microsoft, 8200, unit 8200, unit, azure, surveillance, cloud, ai, technology, used	Spywares

Continued on next page

Table C1 (Continued)

Topic	Top 10 Keywords	Issue Label
30	body, kenyan, british, wanjiru, search, family, police, missing, case, murder	Kenyan crime case
31	saudi, arabia, saudi arabia, prince, crown prince, bin, khashoggi, salman, trump	US–Saudi ties
32	border, controls, polish, border controls, migration, tusk, irregular, asylum	Immigrants
33	meloni, trump, italian, prime, giorgia, leader, european, giorgia meloni, far right	Italian domestic disputes
34	ivanishvili, georgian, bachiashvili, georgian dream, dream, tbilisi, hunnewell	Bachiashvili-Ivanishvili Vendetta

Appendix D

Communities in the Common Issue Layer

Table D1

Community Composition and Size Distribution

Community	Size	States
0	35	Algeria, Andorra, Azerbaijan, Bahrain, Chad, Cyprus, Egypt, Ethiopia, Greece, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Liberia, Luxembourg, Malta, Monaco, Oman, Palestine, Qatar, San Marino, Saudi Arabia, Senegal, Somalia, South Sudan, Sudan, Syria, Tunisia, Türkiye, United Arab Emirates, Uzbekistan, Vanuatu, Yemen
1	39	Afghanistan, Bahamas, Barbados, Bhutan, Brunei Darussalam, Cambodia, China, Cuba, Dominican Republic, Fiji, India, Indonesia, Jamaica, Japan, Kiribati, Laos, Madagascar, Malaysia, Mongolia, Myanmar, Nepal, New Zealand, North Korea, Pakistan, Palau, Papua New Guinea, Philippines, Singapore, Solomon Islands, South Korea, Spain, Sri Lanka, St. Vincent and the Grenadines, Thailand, Timor-Leste, Tonga, Tuvalu, Vietnam, Zimbabwe
2	2	Cabo Verde, Canada

Continued on next page

Table D1 (Continued)

Community	Size	States
3	43	Albania, Angola, Armenia, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Comoros, Croatia, Czechia, Denmark, Estonia, Finland, Georgia, Germany, Hungary, Iceland, Kazakhstan, Kyrgyzstan, Latvia, Liechtenstein, Lithuania, Marshall Islands, Moldova, Montenegro, North Macedonia, Norway, Panama, Poland, Portugal, Romania, Russia, Serbia, Seychelles, Slovakia, Slovenia, Sweden, Switzerland, Tajikistan, Turkmenistan, Ukraine, United States
4	10	Bangladesh, Central African Republic, Costa Rica, France, Italy, Libya, Nauru, Peru, Sao Tome and Principe, St. Kitts and Nevis
5	50	Antigua and Barbuda, Argentina, Belize, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, Chile, Colombia, Congo Republic, Côte d'Ivoire, DR Congo, Dominica, Ecuador, El Salvador, Equatorial Guinea, Eswatini, Gabon, Gambia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Kenya, Malawi, Mali, Mauritania, Mexico, Mozambique, Namibia, Nicaragua, Niger, Nigeria, Rwanda, Sierra Leone, South Africa, Suriname, Tanzania, Trinidad and Tobago, Uganda, Uruguay, Venezuela, Zambia

Appendix E

Communities in the Positive Interaction Layer

Table E1

Community Composition and Size Distribution

Community	Size	States
0	13	Cambodia, DR Congo, Egypt, Ethiopia, Iran, Pakistan, Qatar, Rwanda, Serbia, Somalia, Sri Lanka, Türkiye, United States
1	2	Ukraine, United Kingdom
2	17	Canada, China, Finland, Iceland, India, Israel, Japan, Malaysia, Mongolia, Morocco, New Zealand, Nigeria, Papua New Guinea, South Korea, South Sudan, Thailand, Venezuela
3	11	Belgium, Croatia, Czechia, France, Hungary, Liechtenstein, Luxembourg, Malta, Moldova, Monaco, Montenegro
4	2	Palestine, Portugal
5	10	Argentina, Bahamas, Brazil, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Nicaragua
6	10	Angola, Chile, Colombia, Côte d'Ivoire, Ghana, Kenya, Mali, Senegal, Uruguay, Zambia
7	12	Germany, Indonesia, Italy, Jordan, Myanmar, Nepal, Russia, San Marino, Saudi Arabia, Singapore, Tanzania, United Arab Emirates
8	3	Denmark, Norway, Sweden
9	4	Latvia, Lithuania, Slovakia, Slovenia

Continued on next page

Table E1 (Continued)

Community	Size	States
10	3	Afghanistan, Lebanon, Niger
11	4	Albania, Bulgaria, Estonia, Greece
12	9	Australia, Mexico, Palau, Philippines, South Africa, Switzerland, Tonga, Tuvalu, Zimbabwe