Fighting Words: A computational text analysis of affective salience in national security strategies*

J Andrés Gannon

April 6, 2025

States produce detailed public accounts of their defense priorities through NSS documents and white papers. But do these reveal meaningful insights into interstate relations or are these merely bureaucratic rhetoric? This paper redefines NSS documents as dynamic, performative texts constructing state social intimacy. Using large language models, sentiment analysis, and advanced stance detection, I develop an asymmetric index of affective salience capturing both the prominence of states in NSS texts (salience) and their evaluative orientations (affinity). An analysis of over 400 documents from 92 countries (1962–2024) shows that salience is best explained by economic interdependence, that affinity mirrors traditional indicators of alliance and rivalry, and that affective salience predicts international crises as well as interstate diplomacy. Ultimately, the study challenges the cheap talk narrative and offers a robust framework for anticipating emerging security dynamics.

*I gratefully acknowledge the research assistance provided by members of the Vanderbilt University's Laboratory for Research on Conflict and Collective Action (ROCCA); Sorin Caldararu, Claire Cho, Jacqueline Huang, Junhao Luo, Emerson McCarthy, Blaire Richards, Anthony Rodas, Simon Rosenbaum, Allie Sniezek, Harmony Wang, Nikki Weitzenhoffer, Ethan Xu, and Jenny Yang. I am especially grateful for the research assistance of Isabel Arvelo, who led the data processing and preparation. I also thank Andrew Coe, Nadiya Kostyuk, Stephen Long, and Ryan Shandler for providing feedback on earlier drafts.

1 Introduction

States have long relied on public declarations to articulate their security priorities and strategic intentions. The first time Taiwan was mentioned in a "National Security Strategy of the United States" (1991, 9), the US devoted an entire paragraph to describing its "strong, unofficial, substantive relations" with the island as well as indicating the US objective was "constructive and peaceful interchange across the Taiwan Strait". President Biden (2022, 24) echoed this interest in peace and stability more than two decades later, but this time conveyed a stronger US commitment to "support Taiwan's self-defense and to maintain our capacity to resist any resort to force or coercion against Taiwan". In both cases, these statements spurned much debate and deliberation across national capitals, in 1991 in signaling that Taiwan was on the US radar so soon after the end of the Cold War, and in 2022 because the language of support and resistance to coercion mattered for the perceived credibility of US extended deterrence (Mastro 2023).

Recent history includes even starker examples of states signaling changes in the salience of and stance toward other actors. Russia's invasion of Ukraine in 2022 was an escalation of its gray zone incursion in Crimea in 2014, which itself was a marked shift from Russian's more positive relations with Ukraine following the end of the Cold War (Gannon et al. 2024). Yet, only a year before the incursion, the Ministry of Defence of Ukraine (2013, 51) commended their country's focus on "developing a strategic partnership with the Russian Federation, the United States of America, and the People's Republic of China on the basis of effective and mutually beneficial cooperation". And while soon after, the Ministry of Defence of Ukraine (2015, 70) noted that their relationship with the US had "changed from the crisis response policy to the stable long-term strategic partnership", that very same year the only mention of Ukraine in the US National Security Strategy was in the context of a general promotion of international norms and universal values.

These examples all come from states' National Security Strategy (NSS) documents. The articulation of a state's national security strategy is a fundamental exercise in statecraft, reflecting how states prioritize defense policies, assess threats, and communicate their strategic intentions to both domestic and international audiences (Tritten 1991; Chin, Skinner, and Yoo 2023). Drawing an analogy with social media, where users publicly curate and rank friendships, I argue that NSS documents function as digital galleries of state social intimacy. NSS documents serve as public manifestations of states' relational hierarchies in the international system and serve both as articulations of security priorities and performative acts that publicly rank and evaluate interstate relationships. I introduce a novel concept of *affective salience* that captures two interrelated but distinct dimensions: (1) salience, which reflects the prominence of a given actor in a state's NSS discourse, and (2) affinity, which denotes the state's evaluative stance—positive, negative, or neutral—toward that actor. I combine these concepts to theorize affective salience as an asymmetric, relational measure to assess the intensity and direction of a state's publicly articulated ties. States not only declare who matters to them but also, through carefully crafted language, display an ordered hierarchy of relationships.

Methodologically, the study leverages large language models (LLMs) and machine learning techniques to analyze the content and structure of the most comprehensive known collection of these documents to construct a novel index of affective salience at the directed-dyad level. While scholars code political relevance and affinity using observable behavioral markers, states themselves 'code' and publicly broadcast their own sense of these relationships. Empirical analysis reveals that geography and great power status are weaker predictors of expressed salience in NSS documents than economic exports to the target and the target's military spending, and that the affinity expressed in NSS documents accurately match both formal practitioner labels like alliance co-membership as well as informal scholastic labels like rivalry and warm peace. Application of this measure to observed instances of conflict and cooperation suggests that a state's publicly expressed affective salience toward another state can robustly predict

the presence of an international crisis and the number of diplomatic visits in the following year. These findings challenge the notion that public statements are simply bureaucratically-oriented cheap talk. Instead, they are dynamic, public performances that reflect, shape, and help predict international relations.

This study makes three important contributions. First, it theoretically re-conceptualizes public strategic discourse as a performance of state social intimacy, moving beyond signaling theories focused on credibility. Unlike private communications, which are transient and audience-specific, NSS documents, despite being produced through domestic bureaucratic processes, are dynamic public performances that serve as both signals and records of a state's relational hierarchy. Second, it introduces a novel methodological framework for measuring affective salience that captures both the intensity and directionality of interstate predispositions, advancing our understanding of how states communicate their own conceptions of political relevance and security affinities. Third, it demonstrates how computational text analysis can reveal patterns in how actors perceive and prioritize relationships over time, providing a new methodological approach that can be generalized to other political contexts.

2 Existing explanations for signaling interstate relations

The challenges of identifying intentions and motives notwithstanding, what states say and how they interpret what others say is an important feature of international relations (Krebs and Jackson 2007; Yarhi-Milo 2013). Much in international relations is, and has always been, telegraphed. The study of signaling in international relations has a similarly long history, with scholars examining how states communicate their intentions and capabilities to other states to avoid conflict, build trust, and manage crises (Schelling 1960; Jervis 1976). States regularly send each other signals that serve multiple functions: they can enhance coercive

bargaining with adversaries by communicating capabilities or resolve, coordinate expectations with allies and adversaries alike, or even mislead opponents by obscuring intentions. These signals can be sent through a variety of verbal channels and material actions, with the means of communication used – along with characteristics of the speaker, target audience, and intended purpose – impacting whether a signal is costly or cheap and credible or not. In turn, this determines the role of signaling in shaping future international interactions.

Traditional perspectives on signaling in world politics focus on their communicative inefficiency or instrumental function (Gartzke et al. 2017). Rationalist theories often view public strategic statements as low-cost cheap talk with little impact on state behavior, favoring costly signals like military deployments, alliance commitments, or economic sanctions (Schelling 1966; Fearon 1994, 1997; Kydd 2000; Fuhrmann and Sechser 2014). when talking matters, it is often private or during conflict negotiations (Katagiri and Min 2019; Carson, Min, and Nuys 2024; Sukin and Lanoszka 2024; Min 2025). In contrast, some constructivist accounts emphasize the role of discourse in shaping international norms and identities (Onuf 1989; Wendt 1999), but they often treat public documents as expressions of pre-existing ideational structures rather than as dynamic, strategic performances.

Public statements, when considered at all, are treated as significant under relatively narrow conditions. For example, they may be seen as credible when they are transparent (Yoder and Spaniel 2022), involve specific threats or promises (McManus 2014; Tucker 2023; Takei 2024), are half-hearted (McManus and Sendinç 2024), occur during early interactions (Lupton 2018), reveal an actor's highest priority (Joseph 2021), or when contributions to collective action may be marginally worthless (Kenkel 2019). Comparatively less attention is paid to how states publicly signal their relational priorities, especially in the content of national security. Even then, credibility is often assumed to flow from the content or accompanying material actions rather than the speech act itself. This skepticism extends to strategic documents

at the highest levels of government like NSS documents, which are frequently dismissed as bureaucratic artifacts or aspirational expressions rather than genuine signals of state intentions and relations (Snider 1995; DuMont 2019; Logan and Friedman 2022). And when they have been analyzed, previous research has largely focused on US NSS documents (Flournoy 2006; Caudle and Spiegeleire 2010; Tama 2017), often treating NSS texts from other countries only qualitatively and in isolation (Bogdanov 2022; Chin, Skinner, and Yoo 2023). These efforts provided fragmented insights, leaving a gap in comprehensive comparative analysis (Doyle 2007; Grieco 2018; Golubović and Saković 2023).

Parallel debates about political relevance and affinity further underscore the importance of recognizing relational dynamics among states, as well as how they are communicated by states themselves (Chirot and Hall 1982; Bremer 1992; Maoz 2010). Foundational research identifies a state's politically relevant international environment (PRIE) and those with whom the state was most likely to interact (Weede 1976; Lemke 1995; Maoz 1996). The identification of these politically relevant dyads has traditionally been based on structural attributes like geographic proximity, great power status, and the capacity to project force, with subsequent refinements – such as "dangerous dyads" (Bremer 1992; Klein, Goertz, and Diehl 2006) and "politically active dyads" (Quackenbush 2006, 2024) – trying to capture when and why specific interstate relationships become consequential. However, these measures often treat relevance as binary, bidirectional, and static, failing to capture how political relevance changes over time and is often asymmetric.[1]

A state can be salient to another state's security policy because they constitute a potential threat or a potential partner.[2] So, affinity has similarly been reduced to observable cooperation or conflict, reflected in measures such as formal alliance and defense cooperation (Leeds et al.

[1]For debates about the characteristics that make a given dyad relevant for specific topics, see Lemke (1995), Lemke and Reed (2001), Benson (2005), Bennett (2006), Xiang (2010), and Braumoeller and Carson (2011).

[2]Or both (Weitsman 1997; Long, Nordstrom, and Baek 2007). Examples of formally allied states with antagonistic relations include Greece and Turkey in NATO, India and Pakistan in the Shanghai Cooperation Organisation (SCO), and Armenia and Azerbaijan in the Commonwealth of Independent States (CIS).

2002; Gibler 2009; Kinne 2020), rivalries (Thompson 2001; Terechshenko 2020; Thompson, Sakuwa, and Suhas 2021), or voting alignment in international organizations (Gartzke 1998; Bailey, Strezhnev, and Voeten 2017). Others have theorized that affinities can be inferred from similarity of alliance portfolios (Signorino and Ritter 1999; Leeds and Savun 2007), regime type and economic contact (Markowitz and Fariss 2018), and the presence or absence of militarized foreign policies (Corbetta 2013; Diehl, Goertz, and Gallegos 2021). These measures are widespread for good reason; the data have been carefully collected, they often have wide geographic and temporal scope, and findings using these data are consistent with much of what we intuitively suspect about international interactions.

While empirically tractable, these approaches also assume symmetry and relative stability, eliding the nuanced, directional nature of how states evaluate each other.[3] States' expressions of affinity and salience are often asymmetric, context-specific, and subject to change. Some allies may be indispensable while others are peripheral; some adversaries dominate security planning while others are ignored. Even within alliances like NATO, states maintain differentiated expectations of actual trust or perceived reliability that is not reflected in the uniformity and consistency of formal alliance membership (Gartzke and Weisiger 2013a; Gartzke and Gleditsch 2022). Meanwhile, rivalries like the US and China fluctuate in intensity and relevance, with some periods of hostility punctuated by cooperation in ways that are not reflected in data that consistently identifies that dyad as a hostile rivalry. UN voting patterns face similar critiques for masking strategic abstentions (Bailey, Strezhnev, and Voeten 2017), inflated consensus (Häge and Hug 2016), and statistical difficulties accounting for chance agreement (Häge 2011).

This is not simply a problem of measurement error in quantitative assessments of interstate salience and affinity. Policymakers also face a problem in that the motivations behind changes

[3]There are exceptions. Alliances have been studied as varying in their depth, reliability, and reliance (Mattes 2012; Alley 2021; Gannon 2025a). Rivalries similarly vary in being severe or lesser (Diehl, Goertz, and Gallegos 2021).

to a state's security policy are not always clear. New missiles could be developed in preparation for an attack on a neighboring state, but they could also be developed to deter a third state from attacking an ally. The same is true of increases in defense spending, which could be driven by a desire to protect against a rising adversary or to signal resolve to an ally. Because of this, states can fall prey to main character syndrome, where they think every change in another state's military power is about them. The assumption shared by both scholars and practitioners is that because states' public declarations of friendship, enmity, and salience cannot be trusted, they are not worth analyzing. This study challenges that assumption by evaluating an important method by which states openly communicate their perception of what actors are politically relevant for their national security considerations, and how.

3 A theory of the public performance of interstate relations

States are active producers of their international relationships. Far from passive reactors to material constraints or static alignments, states subjectively curate their relations with other actors based on evolving perceptions of relevance and alignment. I argue that NSS documents are a critical site of this curation, functioning not merely as declarations of policy but as deliberate public performances of interstate relationships. Through these documents, states perform relational hierarchies, projecting how they position others within their strategic worldview.

I conceptualize a state's relative position in the international environment using a spatial utility function where a state determines both which states bear relevance for their own foreign policy decisions as well as the degree to which they feel other states share a compatible or incompatible foreign policy orientation (Morrow 1986). A state can be relevant to an actor because there is a high expectation of future interaction or because decisions made by that state are likely to bear

strategic consequences for the state in question. Distinct from relevance, a state holds some set of beliefs about other states' preferences over international issues as well as those states' strategies for actualizing those preferences. These beliefs determine the extent to which a state feels another state's foreign policy orientation departs from its own preferred ideal point.

To systematically analyze how states publicly signal these beliefs, I introduce the concept of *affective salience*, which integrates two related but distinct dimensions of interstate relations: salience and affinity. Salience reflects a state's judgment of another state's relevance to its security concerns. Affinity captures the evaluative valence of that relationship — ranging on a continuum of negative (rival, threat) to neutral to positive (ally, partner). States thus view other actors in the international system through hierarchies of relevance and preference alignment. These dimensions are inherently asymmetric and dynamic; a state may assign high salience to a rival while remaining peripheral in that rival's own strategic discourse.

Scholars have long debated the utility and sincerity of public documents like NSS that communicate state relations — whether they represent genuine strategic signaling or serve primarily as tools of internal bureaucratic coherence — so their potential as a data source for understanding broader patterns of interstate relations and the structure of the international system has been under-explored (Snider and Nagl 2001; Mohr et al. 2013; DuMont 2019). But for policymakers, these documents are incredibly significant and their production involves much time, effort, and personnel meticulously crafting specific language to further individual, bureaucratic, or national aims. As Chin, Skinner, and Yoo (2023, 104) put it, "if any words matter, the words in [national security strategy documents] do".

I argue that NSS documents serve a dual purpose for an issuing state: they articulate a state's security relations and simultaneously perform those relations publicly in a way that itself constitutes these relationships (Albert, Kessler, and Stetter 2008; Trager 2012). NSS documents have long been recognized by practitioners for their *relational* insight - that is, "as

strategies for relating enemies and allies" (Burke 1941, 304). Because these documents describe the way a state "imagines the world of entities and actions involved in national security", they should consequently be understood as performative acts that publicly construct and curate a state's relational hierarchy in the international system (Mohr et al. 2013, 675).

Drawing from performance theory and research on digital social network curation, I argue that NSS documents express affective salience because they function as public manifestations of state social intimacy, in which states selectively display and rank their relational ties much like individuals curate their networks on social media platforms (Goffman 1956; Alexander 2004; Alexander, Giesen, and Mast 2006; Kaplan 2021, 2024).[4] A social media user's top friends lists and tagged interactions serve as public performances of relational intimacy and status (Donath and Boyd 2004; Ellison and Vitak 2015). This performance of intimacy goes beyond simply listing allies and adversaries; it involves nuanced expressions of closeness, distance, and ambivalence. Just as social media users highlight some friendships while ignoring others, states strategically curate relational hierarchies in NSS documents to display social closeness and enmity. Conversely, states can perform detachment by omitting or distancing from particular friends or downplaying particular rivals to convey relative irrelevance.

The public, universal, and costless nature of NSS documents differentiates it from other ways states signal their relationships. These persistent and widely disseminated public records function like digital galleries, where states act as curators of their own relational networks. And unlike private communications, which are tailored to specific audiences, NSS documents are designed for maximal exposure - creating an enduring record of social capital to domestic publics, allies, adversaries, and neutral third parties simultaneously. This "content collapse" magnifies the performative stakes because multiple, typically distinct audiences are aggregated into one generalized audience in a way that prevents states from varying the representation of

[4]For related dramaturgical theories of international politics see Carson (2016), Carson and Yarhi-Milo (2017), McManus and Yarhi-Milo (2017), and Hall (2017).

their social network to different audiences (Hogan 2010; Ellison and Boyd 2013, 156). As with costlier public signals like summits and treaty signings, the curation of interstate relations in NSS documents is performative acts that shape political reality rather than merely reflecting it (Austin 1962; Ramsay 2011). Despite being cheap talk toward a homogenized global audience, NSS documents function as a form of diplomacy performed by state representatives to influence international events (Trager 2016, 206).

This has several implications for international politics that will be empirically tested in Section 5. First, by strategically choosing who to reference in NSS documents, governments publicly establish relational hierarchies, akin to how social media users structure friend lists, with some connections prominently displayed and others downplayed or omitted. The content of these documents is a strategic choice to foreground certain relationships, often elevating or diminishing ties beyond what material interactions might suggest. Much like states demonstrate resolve on one issue by admitting lack of resolve on a different issue (Trager 2011), a state may signal the prominence of one ally or adversary by concurrently downplaying the significance of others.

Second, just as individuals manage their reputations by aligning with high-status peers, states use NSS documents to associate themselves with key allies and position themselves against undesirable adversaries. These public performances of affinity can serve as signals of commitment or hostility that complement, substitute, or forecast more costly signals like military deployments or economic sanctions. By publicly declaring their affinity for certain states, governments create expectations about future behavior that can be difficult to reverse without reputational costs. This is especially important for states managing complex alliance networks, where public expressions of differential affinity can help manage expectations about the reliability of security guarantees without formally altering alliance treaties.

Third, NSS documents function as a thermostat for interstate relations, allowing states to

adjust the temperature of their expressed affinities in response to changing geopolitical conditions. NSS documents are not mere reflections of pre-existing realities but actively participate in producing them. A state elevating a partner or labeling a rival reshapes perceptions. Much like social media platforms allow users to redefine friendships and priorities in real time, NSS documents are a strategy for dynamically updating a state's public alignments which is particularly valuable during periods of potential, but yet uncertain, strategic realignment. Unlike formal treaties and military mobilizations, which are costly to undertake and reverse, NSS documents provide a flexible mechanism for states to signal shifts in their relational priorities and public alignments. A state can warm a cooling relationship by increasing the affective salience expressed toward another actor, or cool an overheating rivalry by reducing negative public rhetoric.

This approach bridges rationalist and constructivist theories by conceptualizing NSS documents as strategic performances that simultaneously reflect, constitute, and contest relational hierarchies. Public statements of affinity and salience are neither mere noise nor determinative scripts; they are tools through which states navigate complex international landscapes. Empirically, approaching public state discourse as active curation provides a direct window into how states themselves conceptualize their security environment, rather than relying on researcher-imposed metrics of political relevance or similarity in observable foreign policy decisions. The affective salience expressed in NSS documents reveals not just who states consider important and whether those relationships constitute threats, opportunities or something in between, but also how they use public rhetoric to change those relationships. This approach complements traditional measures of alignment while adding crucial information about perception and self-expressed priority that is often missing from theories that discount public signals of relational ties as cheap talk or as static manifestations of identity originating from elsewhere.

4 Data and measurement

The proposed method leverages NSS documents to provide a direct lens into the relational hierarchies of social intimacy conveyed by states. Specifically, I produce and validate a directed measure of affective salience in international security. Existing measurement strategies focused on sentiment analysis that are often trained on general corpora and convey how an actor feels, but not toward whom and to what extent. I instead leverage improvements in stance detection to augment advanced sentiment analysis using large language models as well as salience detection which is a novel contribution to the literature. This approach also detects more subtle changes in how states perceive their allies and adversaries, which might not be immediately evident in conventional measures of material power or formal alignment declarations like written defense pacts or declarations of war.

4.1 National Security Strategy (NSS) documents

I define an NSS as a public text written by a state in a given year outlining some aspect of their foreign policy as it pertains to security or defense. Their primary purpose is to guide and/or describe national security decisions by connecting ends and means and conveying intended national priorities in the security realm (Caudle 2009; Ettinger 2017).[5] They may also serve domestic purposes in conveying foreign policy goals to domestic audiences, coordinating fragmented bureaucracies, and building consensus (Goldgeier and Suri 2015; Tama 2015; Lettow 2021).

Not all states produce these documents, and states that do produce these often do so in some years, but not others. This could occur because a state produces these documents once per administration or at some other regular temporal interval, because there are strategic reasons

[5]For a dissenting, less optimistic take on whether these documents serve any purpose, see Logan and Friedman (2022).

to keep such information secret, or because a state has insufficient bureaucratic capacity to produce them or even insufficient concern for national security. Alternatively, states may produce more than one type of NSS and may even do so in the same year.[6] Comparability across space and time cannot be assumed and must instead be theoretically informed by knowledge of the specific context of the document(s) in question (Stolberg 2012).

The first stage involved gathering NSS documents from open and public sources, building on efforts by Becker and Malesky (2017), Razeto and Jenne (2021), Becker, Jee, et al. (2024), and Neal and Gardner (2024).[7] Documents focused exclusively on specific aspects like cyber policy or counter-terrorism as well as those generally covering diplomacy or foreign policy were excluded. Combined, I analyze 449 documents produced by a total of 92 countries from 1962 to 2024.[8]

The documents were gathered and stored as pdf files and then converted to text and csv format using PyMuPDF4LLM (Smith 2023; McKie 2024) and Marker (Paruchuri 2024). Unlike existing analyses of NSS documents that rely on a bag of words assumption or sentence-level analysis, this data processing pipeline preserves the order of the texts and separates them into chunks using an MPNet tokenizer from 'sentence-transformers/all-mpnet-base-v2' (Song et al. 2020).[9] This has the benefit of capturing natural linguistic boundaries like section headings and paragraph breaks which preserves the context of the text. Consequently, the csv

[6]For example, the United States publishes a National Security Strategy (NSS) as its primary document, but also publishes a National Defense Strategy (NDS), National Military Strategy (NMS), Nuclear Posture Review (NPR), National Homeland Security Strategy (NHSS), and National Intelligence Strategy (NIS) (Bogdanov 2022).

[7]As the theoretical motivation concerns public texts, the omission of NSS documents that states do not publicly release should not bias inferences. Nonetheless, it remains possible that there are NSS documents that were public when they were produced, but are no longer available, or that are publicly available and known to state officials but were not found by my research team or other scholars who have engaged in similar efforts.

[8]The full list of documents this paper makes available includes over 800 documents. In the subsections that follow, I apply the computational text analysis techniques to a subsample of all English language NSS that are at the general defense/security level of analysis.

[9]Instead of chunking, much existing research pre-processes texts, which fails to capture contextual information (Lahoti, Garimella, and Gionis 2018; Burnham 2024; Overbeck et al. 2025) and has recognized downsides with the computational models use here (Palomino et al. 2017; Denny and Spirling 2018; Miyajiwala et al. 2022).

version is formatted with each row as a page from the document and columns provide identifier information about the country, year, document name, doctrine type, and sentence number.

4.2 Measurement

For each state in the Correlates of War Project (2017) state membership list, I create a list of aliases and synonyms that include variations of the country name, capital city, and demonyms. I then use these lists to identify the chunks where at least one state is mentioned in the NSS documents. The chunks are then pruned into sentences using spaCy's sentence tokenizer to identify sentences where State B is mentioned as well as the sentence immediately before and after that reference (Montani et al. 2023). This process allows me to identify all mentions of each state in the NSS documents, even if they are not explicitly labeled as such, and their immediate semantic context.

Using these data, I measure the salience and affinity that each state conveys in their NSS toward each other state using text-based machine learning techniques. I then combine those measures of salience and affinity to create a directed-dyad measure of affective salience. This procedure is summarized in Figure 1 and explained in the sections that follow.

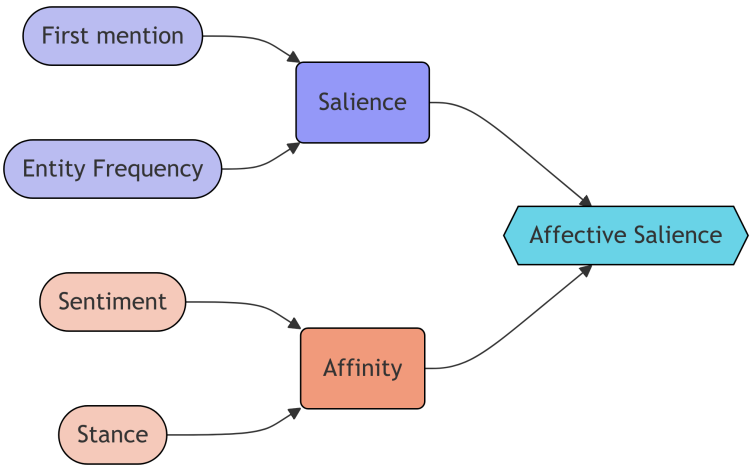

Figure 1: Components of affective salience and their measurements.

4.2.1 Measuring salience

First, I measure *salience*, defined as the degree to which a state's security apparatus thinks about another state, using the mentions of other actors in a state's NSS text chunks. Salience is identified using two indices that are commonly used both independently and in combination in computational models for search engine optimization (SEO) and salient named entity extraction (SNEE); *first-mention* and *entity-frequency* (Dunietz and Gillick 2014; Wu et al. 2020; Grönberg 2021).[10]

First-mention is the document chunk index m_e for each entity e where it is first mentioned. I then identify the total number of chunks N where at least one entity is mentioned and invert and normalize the measure as $S_{first} = \frac{N-m_e+1}{N}$ so that entities mentioned in the first chunk have a score of 1 and entities mentioned in the last chunk $m_e = N$ have a score strictly greater

[10]Other salience detection models like SWAT (Ponza, Ferragina, and Piccinno 2019), SEL (Trani et al. 2018), and transformer models (Asgarieh, Thadani, and O'Hare 2024; Bullough et al. 2024) could improve precision and recall, but produce only binary outputs and are very sensitive to fine-tuning, which impacts replicability and external validity (Bhowmik et al. 2024).

than, but approaching zero.[11] This normalization adjusts for the fact that NSS documents vary greatly in length and some states mention other actors frequently and while some states mention others infrequently.

Entity-frequency is measured as the total number of chunks f_e where entity e is mentioned. This is calculated as $S_{freq}(e) = \frac{f_e}{f_{max}}$ where f_{max} is the highest number of chunks where any entity appears. This normalization similarly adjusts for the fact that some issuing states mention many states in their NSS and others mention relatively few. And because the data are processed in pruned chunks rather than individual words or sentences, multiple references to a country within the same contextual chunk does not bias the measure.

Salience is then measuring by linearly combining first-mention and entity-frequency as $S_{salience} = \alpha S_{first} + (1 - \alpha) S_{freq}$ where $\alpha = 0.5$ is a hyper-parameter equally weighing the two components and maintaining the original scale. Both components are bounded $(0, 1]$ with higher values indicating higher salience. For robustness, I also calculate, and then similarly scale a multiplicative combination $S_{salience} = S_{first} \times S_{freq}$ which provides a higher penalty for low values on either dimension.

4.2.2 Measuring affinity

Second, I measure *affinity*, defined as an affective or attitudinal position toward a particular entity, which in this case is the target state. Although many computational text analysis models have used sentiment to measure relational affinity, recent work has demonstrated that sentiment conveys something sufficiently distinct from stance that the former cannot accurately proxy for the latter (Mohammad et al. 2016; Rauh 2018; Boukes et al. 2020; Chan et al. 2021;

[11] An alternate measure using $S_{first} = \frac{N - m_e}{N}$ would mean that states first mentioned in the last chunk of a text would have a first-mentioned score of 0. The use of $m_e + 1$ allows me to differentiate these states from those that are not mentioned at all, as the latter are more appropriately measured as having a salience of 0 than the former.

Küçük and Can 2021; van Atteveldt, van der Velden, and Boukes 2021; Bestvater and Monroe 2023). However, current state of the art stance metrics produce only binary measures, and measurement uncertainty cannot be easily aggregated across multiple text chunks mentioning the same target entity. Consequently, I calculate affinity using a combination of *sentiment* and *stance*.

For *sentiment*, the text chunks that mention each target state are extracted from the NSS documents and processed using VADER, a well-established rule-based sentiment analyzer that assigns an initial continuous score [-1, 1] for each text chunk mentioning a given target state along with a mean and standard deviation (Hutto and Gilbert 2014).

Then, *stance* is measured by leveraging recent advances in few-shot learning and target-aware opinion classification to capture sentiment directed toward distinct states rather than overall affect. In the context of NSS documents, the issuing state conveys a stance toward particular states which may be distinct from the general sentiment being expressed in a particular document chunk (Biber and Finegan 1988; Du Bois 2007; AlDayel and Magdy 2019). This form of stance detection can be done using natural language inference (NLI), also known as textual entailment, which uses language models as pre-trained universal classifiers to identify the stance of a text toward a particular entity (Burnham 2024).[12] Stance detection is computed using a classification model defining a directional relationship between a text and a hypothesis about whether a human reading the text T would infer that hypothesis H is true (AlDayel and Magdy 2021). The model calculates stance classification as a true or false response to the proposed hypothesis that the stance toward a given entity is positive, negative, or neutral. So

[12]I use a few-shot classification approach by fine-tuning the Political DEBATE large model (based on DeBERTa V3) on a small set of hand-coded documents from our corpus for NLI classification (A. Wang et al. 2020; Burnham et al. 2024; Laurer et al. 2024). DeBERTaV3 is an LLM based on BERTopic that has been shown to outperform other models in stance detection tasks and topic modeling (Egger and Yu 2022; Qi 2023; Burnham 2024). Political DEBATE (DeBERTa Algorithm for Textual Entailment) is an NLI classifier specifically trained for political text analysis across four classification categories: stance detection, hate speech detection, event extraction, and topic classification (Burnham et al. 2024). For similar work using active learning to fine-tune models like RoBERTa to a specific local task, see Bonikowski, Luo, and Stuhler (2022) and Card et al. (2022).

for a given text chunk T, one proposes the hypothesis H, 'the author of this text expresses support or alliance with Ukraine' and based on its reading of the text, the model would then respond 'true' or 'false'. A text with a generally negative sentiment but positive stance toward a mentioned entity can consequently be identified as an expression of positive affinity, as an actor expressing 'the death and destruction of innocent civilians in Ukraine is a tragedy' is indicative of support for Ukraine, *because of* the negative sentiment expressed in the text. This appropriately captures the fundamentally semantic relationship between the expression and target in a directional manner composed of an evaluated recognizable objective H, an expression T containing a negative or positive evaluation, and a relation true/false that attributes the expressed valuation to the object in question (Fogel-Dror et al. 2019; Overbeck et al. 2025). As NLI produces a binary true/false response, the model is run separately for each hypothesis H (threat, neutral, or support) and selects the one with the highest probability. These results produce a stance score $\epsilon(-1, 0, 1)$, for each target state in each chunk.

From this, I calculate affinity by combining the sentiment and stance detection scores. First, I calibrate the sentiment scores by aligning their valence with the predicted stance: support/alliance predictions become positive, threat/rival predictions become negative, and neutral predictions remain unchanged. This adjustment accounts for cases where emotionally charged words appear in contexts contrary to their typical connotation. but this does not leverage the additional benefit of semantic understanding we get from Political DEBATE. The scores are then scaled so that those with negative stances fall between -1 and -0.5, those with neutral stances fall between -0.5 and 0.5, and those with positive stances fall between 0.5 and 1. I then scale the scores into three distinct ranges: negative stances fall between -1 and -0.5, neutral stances between -0.5 and 0.5, and positive stances between 0.5 and 1. This scaling preserves the categorical stance information while allowing for differences in intensity within each category to produce a continuous measure that reflects both the direction and strength of the affinity.

To refine these estimates of affinity, I incorporate a gold-standard calibration process using Best-Worst Scaling (BWS) where four coders were each presented with randomized sets of four text chunks and asked to identify the chunks where the writer expressed the most positive and the least positive sentiment toward a given target state (Finn and Louviere 1992; Louviere 2015; Kiritchenko and Mohammad 2016, 2017).[13] This yields multiple pairwise comparisons from which I derive a relative ranking of sentiment across the corpus. These rankings are then aggregated and linearly mapped onto the [-1, 1] scale. This design-based supervised learning (DSL) approach statistically validates the sentiment scores and calibrates them to the context of the unique corpus, reducing bias (Egami et al. 2024a; Egami et al. 2024b).

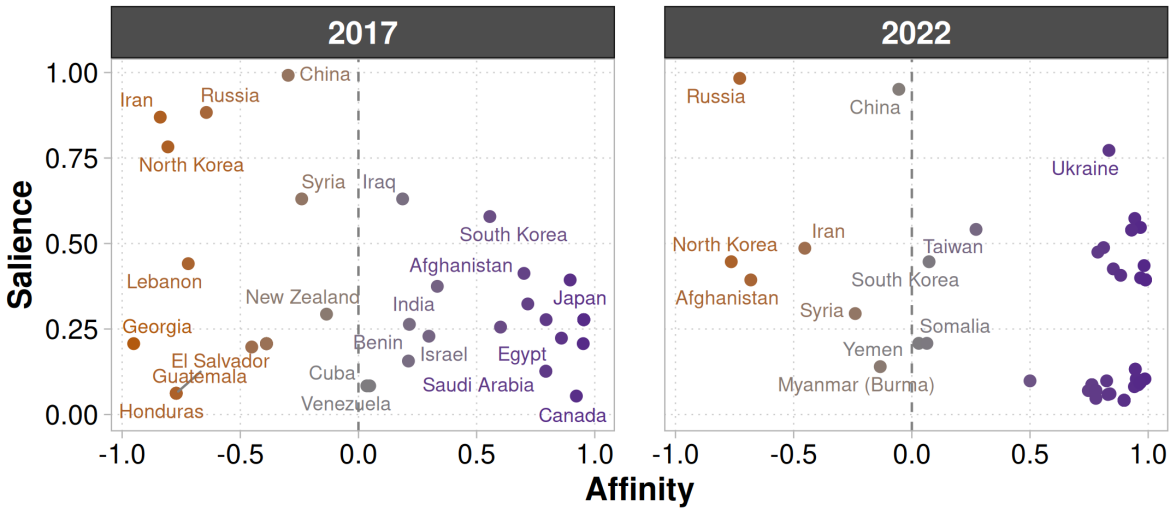

Figure 2: Affinity and salience scores for states mentioned in the US NSS. Colors refer to each state's value for affinity. Closely clustered states are unlabeled to simplify visual interpretation.

To illustrate the face validity of the measures of salience and affinity, Figure 2 shows the scores for states mentioned in President Trump's 2017 NSS and President Biden's 2022 NSS.

[13]Since many chunks mention more than one state, the coders were told the target state to code for that particular entry. Coders were instructed to make their evaluation using only information in the chunk.

The data are consistent with the Trump administration's "America First" strategy warning of great power competition with Russia and China as well as rogue states like Iran and North Korea, alongside his dissatisfaction with US allies in Europe (Landler and Sanger 2017). This is contrasted with Biden's 2022 NSS that identifies US security priorities as long-term competition with China and an immediate threat from Russia, as well as a stronger emphasis on positive multilateral ties with traditional US allies (McDonald 2023). And although the US affinity toward Ukraine is positive in both documents, Ukraine's salience in the 2022 NSS (0.77) is higher than in the 2017 NSS (0.21), reflecting a shift in how the US communicated the centrality of Ukraine in national security planning.

4.2.3 Measuring affective salience

Finally, I multiply salience and affinity to measure *affective salience* as the intensity and direction of a state's stance toward another state. Affective salience is comprised of (1) a positive or negative stance toward an actor, (2) weighted by the strength of the sentiment expressed in that stance, and (3) weighted by the salience of that country in an issuing state's national security strategy. Put more specifically, this measure explains how much a state thinks about another state and how it feels about that state, with more extreme values indicating stronger affective salience and values closer to 0 indicating the target state is relatively peripheral. This measure is calculated as $S_{affective} = S_{salience} \times S_{affinity}$ where the product of the two scores is bounded by $[-1, 1]$ with higher values indicating higher affective salience. This measure is particularly useful for identifying cases where a state is highly salient to another state but the affective valence of that relationship is low, or vice versa. For example, a state may mention another state frequently in its NSS documents but express negative sentiment toward that state, indicating that the relationship is characterized by rivalry or hostility. Conversely, a state may mention another state infrequently but express positive sentiment toward that state,

Table 1: Sample of measures for Ukraine (2017) showing the 10 countries with the highest salience. Higher values indicate higher values for all columns. The theoretical range of salience values is [0, 1] and for affinity and affective salience values is [-1, 1].

	Salience			Affinity			Affective Salience
Target Country	First Mention	Entity Frequency	Salience	Sentiment	Stance	Affinity	
Russia	0.99	1.00	1.00	-0.02	-0.94	-0.78	-0.77
Poland	0.92	0.78	0.85	0.68	0.43	0.55	0.47
United Kingdom	0.97	0.61	0.79	0.70	0.36	0.53	0.42
United States	0.88	0.56	0.72	0.60	0.60	0.60	0.43
Lithuania	0.92	0.44	0.68	0.67	0.38	0.52	0.36
Belarus	1.00	0.28	0.64	0.51	0.40	0.45	0.29
Germany	0.77	0.44	0.61	0.31	0.50	0.40	0.25
Norway	0.86	0.33	0.60	0.88	0.83	0.86	0.51
Denmark	0.95	0.17	0.56	0.37	0.00	0.18	0.10
Netherlands	0.97	0.06	0.51	0.76	1.00	0.88	0.45

indicating that the relationship is characterized by support or alliance.

Table 1 provides an illustrative example of all three measures – salience, affinity, affective salience, and their components – for states mentioned in Ukraine's 2017 NSS. The table shows the 10 countries that were most salient to Ukraine as well as their scores on all metrics. Not surprisingly, Russia has the highest salience score for Ukraine, as it is the first country Ukraine mentions in their NSS and is also mentioned more than any other country. The United States, by comparison, is in the 88th percentile in terms of how early it is mentioned, and Ukraine only mentions the US a little more than half as often as it mentions Russia. As expected, Ukraine's lowest affective salience is toward Russia (-0.77), reflecting Russia's high salience (1) and highly negative affinity (-0.78).

Together, these techniques allow for a more comprehensive and nuanced analysis of affective salience than has previously been possible.[14] First, the salience detection method provides a

[14]The utility and consequences of LLM models to social science questions and methods is the subject of ongoing discussion (Bisbee et al. 2024; Laurer et al. 2024; Y. Wang 2024; Caballero and Jenkins 2025; Ornstein, Blasingame, and Truscott 2025; Thapa et al. 2025). My approach expands upon recent applications in political science of similar models for classification (Burnham et al. 2024), dictionary creation (Häffner et al. 2023), event extraction (Arslan, Munawar, and Cruz 2024), named entity recognition (Balluff, Boomgaarden,

novel way to quantify the relative importance of different actors in a state's strategic discourse. Second, LLMs can capture nuanced semantic relationships and contextual meanings that might be missed by simpler keyword-based approaches. And third, the combination of sentiment analysis and stance detection allows for a more fine-grained understanding of how states express their relationships, going beyond simple positive or negative categorizations.

5 Research design and results

The empirical models that follow demonstrate that states actively communicate the salience and affinity of their relations with other states through their NSS documents. In some cases, the findings validate existing scholarly measures of these concepts, and in other cases they provide new insights into the structure of international relations to motivate future research. I separate the data into the three conceptual categories described above to model (1) the factors that explain NSS salience, (2) how affinity in NSS documents compares with and augments existing measures of foreign policy similarity and alignment, and (3) how affective salience can help predict significant state interactions in crisis and diplomacy.

5.1 Explaining salience

NSS documents provide a unique window into how states perceive their own security environment and the factors that drive their foreign policy decisions. By varying the salience of states in NSS documents, governments communicate the political relevance of other actors when it comes to security issues and in doing so they publicly establish relational hierarchies of relevance. Scholars have theorized salient interstate relationships as analogous to the gravity model of trade; political relevance is seen as a function of perceived motive and opportunity.

and Waldherr 2024), and stance detection (Burnham 2024).

Empirically, many measures of PRIE and political relevance use some variation of great power status (Morgenthau 1948; Maoz 2010) and geographic distance (Boulding 1962) to identify the other states that are most relevant to a given actor. I use NSS documents to identify whether states themselves see political relevance in the same way.

I model salience as a dependent variable and identify the variables that best predict which states are most salient in a given country's NSS. I train the model on a set of variables that existing research has argued matter for a state's politically relevant international environment (PRIE) and politically relevant dyads, including the target's status as a great power (Correlates of War Project 2017), the target's military expenditure as well as the difference in military expenditure between the target and issuing state (Mansfield 1993), the presence of an ongoing militarized interstate dispute (MIDs) and the onset of one in the previous year (Palmer et al. 2021), geographic distance measured as contiguity, capital to capital distance, and a third measure coded as 0 for contiguous states and logged capital to capital distance otherwise (Lemke 1995; Markowitz and Fariss 2013), trade flows measures as smoothed bilateral exports and imports (Barbieri, Keshk, and Pollins 2009), the presence of a ATOP defense pact (Leeds et al. 2002), shared regime type using the UDS measure of democracy (Marquez 2016; Pemstein, Meserve, and Melton 2017), number of intergovernmental organizations (IGOs) where the two states share full membership (Pevehouse et al. 2020), the target state's GDP and difference in GDP for the target and issuing state (Markowitz and Fariss 2013), foreign policy similarity using kappa-corrected alliance s-scores and kappa-corrected UN voting s-scores (Gibler 2009; Häge 2011; Bailey, Strezhnev, and Voeten 2017), ordinal (1-5) peace scale coding of positive and negative peace (Diehl, Goertz, and Gallegos 2021), and strategic rivalry (Thompson and Dreyer 2012).

I fit an extreme gradient boosting (XGBoost) machine learning model that uses a greedy function approximator to iteratively fit new individual models based on the errors in the

preceding models for each observation in the test set, adjusting the relative weights of each variable to improve model fit (Chen and Guestrin 2016). To minimize data leakage problems inherent in machine learning models with panel data (Cerqua, Letta, and Pinto 2024), the model is split using grouped k-fold cross-validation by dyad with 5 folds, meaning each dyad is randomly assigned to either the training or validation set. When predicting salience for dyads the model has not seen during training (within that fold), the average prediction error magnitude is 0.15, suggesting a reasonably strong ability to predict salience for an unseen directed dyad year based on the covariates in the model.

Analysis of the final model trained on all data reveals the most influential variables driving these predictions, shown in Figure 3 as SHAP values (Liu and Just 2020). The results indicate that the salience of a target state in NSS documents is best predicted by exports to the target state, the target state's CINC score, and the distance between the two states' capitals. Consistent with existing theories of political relevance, higher CINC scores and lower capital to capital distance are generally associated with higher salience. However, exports to the target state is the strongest predictor, with a SHAP value suggesting it is almost twice as important at capital to capital distance, and geographic contiguity is the least influential variable in the model. The high x-axis dispersion for these values, particularly geographic distance, also suggests that the relationship between these variables and salience is non-linear, providing avenues for future research.

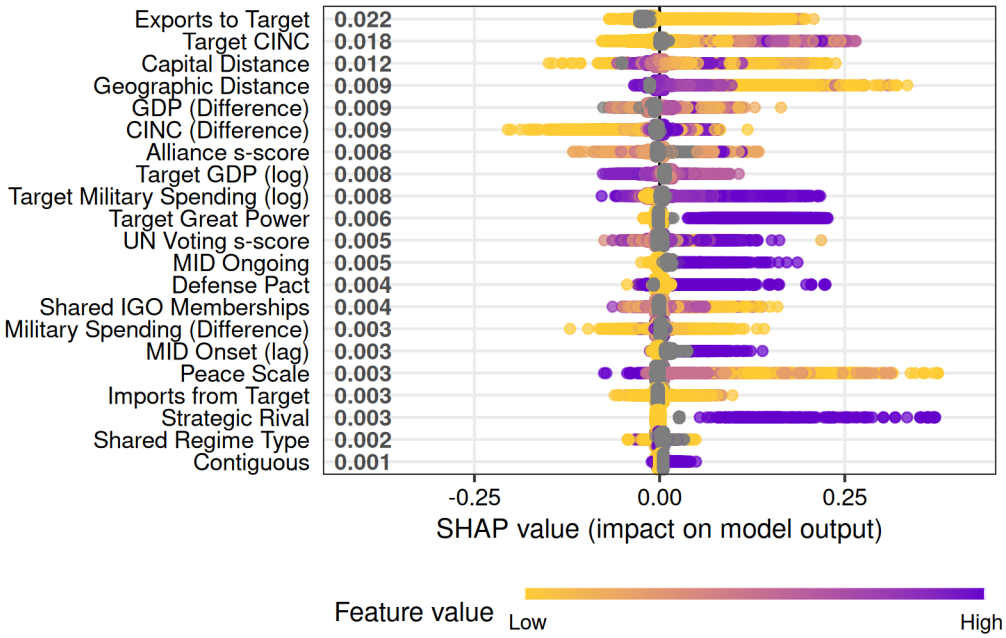

Figure 3: SHAP values indicating feature importance in the model. Higher y-axis values indicate higher variable influence in predicting salience. The points shows SHAP values for each variable for each observation. The further the points are from zero, the greater the impact of that feature on the prediction, with positive (negative) values indicating a positive (negative) association and a larger x-axis dispersion suggesting the feature has a non-linear effect.

5.2 Validating affinity

To validate the measure of affinity, I next compare what NSS documents convey about the alignment of states with existing measures of positive and negative interstate ties. Just as individuals manage their social media reputations and network positions by conveying positive or negative affinity toward certain peers, states use NSS documents to associate themselves with certain allies and communicate their distance themselves from undesirable enemies (Gartzke and Weisiger 2013a, 2013b).

I first identify the correlation between affinity in NSS documents and well-regarded measures of

foreign policy similarity using Kappa-corrected s-score measures of alliance portfolio similarity and UN voting data (Cohen 1960; Gibler 2009; Häge 2011; Bailey, Strezhnev, and Voeten 2017). The NSS measure has a positive and statistically significant correlation with both measures (alliance portfolios = 0.12 and UN voting = 0.09). For comparison, the correlation between alliance and UN voting s-scores is 0.22. This suggests that while states speak more positively about those sharing defense partners or similar UNGA voting patterns, there is notable variation likely explained by a different underlying data generating process.

Second, I show the distribution of the NSS affinity index across varying categorical measures of affinity from formal defense pact membership (Leeds et al. 2002), peace levels (Diehl, Goertz, and Gallegos 2021), and strategic rivalries (Thompson 2001; Thompson, Sakuwa, and Suhas 2021). The results in Figure 4 show that, consistent with expectations, dyads in a defense pact have, on average, a higher NSS affinity than dyads without a defense pact, and that rival dyads have a lower NSS affinity than non-rival dyads. Interestingly, the five ordered categories in the peace level data show a clear and consistent pattern of higher peace levels having higher levels of NSS affinity *except for* the highest peace level – security community – which has a median NSS affinity in between that of negative peace and lesser rivalry. This reflects the fact that in the peace level data, many of the security community dyads are categorized as such because of their shared EU membership. In many cases, these states otherwise have little positive security cooperation with one another, and they consequently have less intensely positive expressions toward each other in their NSS documents. As a final observation, with the exception of serious rivalries and rival dyads, the median affinity expressed in NSS documents is positive. This is consistent with theories that states put on cooperative public façades to increase the credibility of assurances (Yoder and Spaniel 2022).

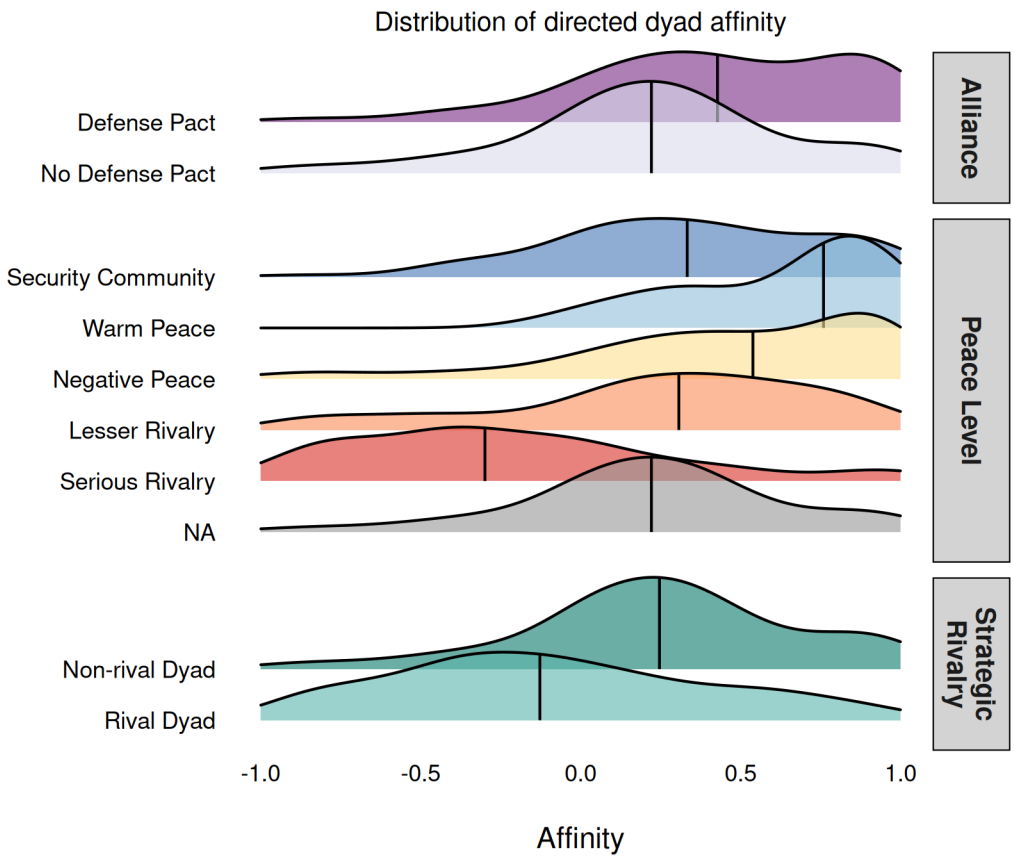

Figure 4: Distribution of the NSS affinity index across varying levels of existing measures of affinity. Vertical lines represent median values.

Third, I provide suggestive evidence that the granularity in the continuous measure of NSS affinity more than simply statistical noise, and instead captures known variation in expressed interstate relations. Figure 5 focuses on NATO alliance members in 2017 and shows that these dyads vary in how much positive affinity is expressed toward each other. The figure highlights the NATO directed dyads with the most positive, least positive, and median affinity scores. The data reflect significant negativity in France's expressed affinity toward Turkey, which was well recognized at the time due to historical animosity and sharp political differences (Jabbour

2022), Lithuania's highly positive affinity toward the US followed reassuring visits from senior US officials like Senator John McCain and Secretary of Defense James Mattis in light of expanding defense cooperation (Harris 2017). And Norway's affinity toward the US represents the median case within NATO as they have long been an involved NATO member with a strong defense relationship with the West, but they have been comparatively more cautious in their public rhetoric about Russia given their economic and military activity in the High North (Lindgren and Græger 2017). More broadly, the dispersion of affinity values across members of the same alliance and imbalanced nature in which some are more or less reciprocated than others provides important insight about how public communications of affinity can help us understand the causes and consequences of trust, and mistrust, in an alliance (Becker, Kreps, et al. 2024; Gannon 2025b).

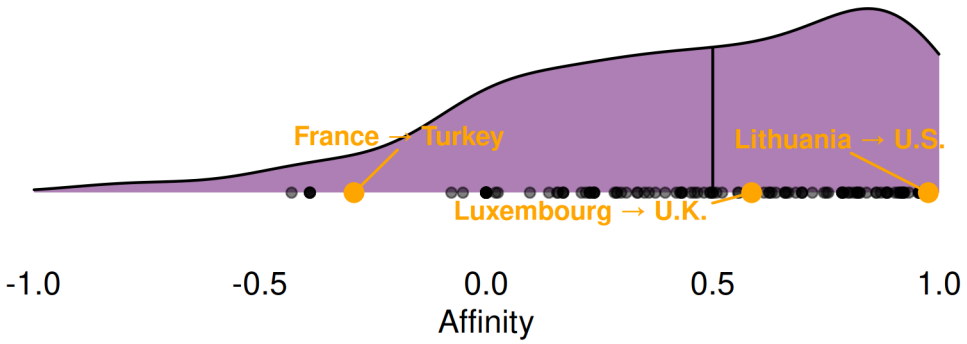

Figure 5: Distribution of affinity scores across NATO allies (2017). The ridge shows the distribution of all interstate dyads in 2017 and the points highlight dyads where both states belong to NATO. The lowest and high NATO dyads are highlighted in addition to the median dyad and its inverse.

5.3 Prediction with affective salience

The dynamic character of affective salience renders it a under-explored predictive tool. NSS documents are regularly updated to reflect evolving geopolitical contexts, meaning that shifts

in affective salience can serve as early warnings of impending crises or realignments as states telegraph their relationship status prior to more costly action. For example, an escalating negative affective salience toward a rival may predate more overt acts of aggression, while a surge in positive salience could signal conditions for deepening cooperation I demonstrate how these public performances of relational ties can predict both cooperative and coercive interactions between states. The theory of public performance of relational hierarchies would predict that these signals in the lead up to hostility or engagement are meaningful; states do not just costlessly signal positive or negative affective salience regardless of their true underlying beliefs. These statements are predictive of actual latent interstate relations that correlate with observable behavior.

To systematically test this, I quantitatively model the relationship between affective salience and two dependent variables: (1) the onset of international crises and (2) diplomatic visits. The explanatory variable is the affective salience that state A expressed toward state B in years where state A issues an NSS. I use the International Crisis Behavior (ICB) dataset (Brecher and Wilkenfeld 1997; Brecher et al. 2023) to identify the onset of crises, which is defined as an international event with hostile interactions and a heightened probability of military escalation (@ Brecher and Wilkenfeld 1997, 4–5). I also use the COLT dataset (Moyer et al. 2025) to identify diplomatic visits, which are defined as high-level official visits between heads of state or government. Both dependent variables are analyzed at the directed dyad-year level, with crisis coded as a binary indicator of whether the two states are on opposing sides in a crisis that begins and diplomatic visits coded as the number of visits from state A to state B. Both dependent variables are coded for the year following the NSS document release. The binary crisis onset models are fit using logistic regression, while the diplomatic visit count models are fit using Poisson regression.

For each dependent variable, I first fit a simple bivariate model with only the affective salience

Table 2: Coefficient estimates for regression models.

	Crisis onset			Diplomatic visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Affective salience	0.005**	0.004**	0.347+	2.694**	1.393**	0.764**
	(0.003)	(0.003)	(0.217)	(0.079)	(0.095)	(0.150)
Num.Obs.	14508	10413	212	13902	10030	5971
Controls	-	Y	-	-	Y	-
Dyad FE	-	-	Y	-	-	Y
AIC	411.5	293.3	201.6	16158.3	10600.3	11024.7
BIC	426.7	329.5	262.0	16173.4	10636.4	18335.2
RMSE	0.05	0.05	0.35	0.64	0.61	0.62

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$
Log odds coefficients shown for crisis onset models.

variable to mitigate the risk of post-treatment bias and over-adjustment (Montgomery, Nyhan, and Torres 2018; Clarke, Kenkel, and Rueda 2018; Dworschak 2023; Hünermund and Louw 2025). I then include covariates that existing theories posit could predict the dependent variables of interest; the balance of military power measured as difference in CINC scores for the crisis model and great power status of state B in the diplomacy model (Singer 1988; Lebovic and Saunders 2016), the geographic distance between the two states' capitals (Miller 2022), and whether both states are of the same regime type (Markowitz and Fariss 2018). Finally, I fit a fixed effects model to account for unobserved dyad-level heterogeneity.

Shown in Table 2, the results of the regression models show that affective salience is a statistically significant predictor of both crisis onset and diplomatic visits. The findings suggest that states are less likely to experience crises with an actor with whom they express positive affective salience and states are more likely to send diplomats to countries toward whom they express higher levels of positive affective salience. This supports the hypothesis that public performances of relational ties can serve as early indicators of interstate behavior.

6 Conclusion

This study re-positions National Security Strategy documents as more than mere administrative outputs—they are vibrant, performative texts that encapsulate a state's public curation of its relational landscape. By developing an asymmetric index of affective salience that combines measures of salience and affinity, the paper reveals that NSS documents convey subtle yet consequential signals about how states perceive and prioritize their international relationships. The findings demonstrate that key geopolitical variables – such as military expenditure and great power status – play a critical role in determining the extent to which one state features in another's strategic discourse. Moreover, the dynamic shifts captured in NSS rhetoric, particularly in the context of international crises and diplomacy, underscore the method's potential as an early warning system for emerging international crises.

The theoretical contribution of this research is significant. By drawing on analogies to digital social curation, the study re-frames NSS documents as public performances of state social intimacy. This perspective challenges the traditional view that dismisses such texts as cheap talk or mere bureaucratic records. Instead, it posits that through their persistent and public nature, NSS documents serve as enduring signals that shape expectations, influence behavior, and even act as a form of diplomacy. They create a structured ordering of interstate relationships that reflects both current strategic priorities and anticipated future behaviors. In this light, the performative aspect of NSS documents is not only a reflection of internal policy debates but also a strategic tool that has real-world consequences.

On the empirical front, the integration of computational techniques with traditional geopolitical analysis offers a robust framework for measuring and predicting state behavior that complements existing formal theories (Gartzke et al. 2017). I provide a unique form of evidence about who states want to publicly convey they are thinking about and how, as well

as the factors that might explain or predict that. States decide their own politically relevant dyads, and NSS documents offer a more nuanced and temporally sensitive view of security salience – capturing not just who matters to a state's security apparatus, but how much and under what conditions. The results underscore that public strategic discourse is inherently dynamic, capturing not only who states consider important but also the intensity with which they express their evaluations. Furthermore, this research has demonstrated the significant advantages of combining textual analysis with traditional material measures of power. The asymmetric affinity index developed through the analysis of NSS documents represents a critical advancement in measuring the intensity and directionality of state-to-state relations. By highlighting the limitations of symmetrical and static approaches, this paper provides a more accurate framework for understanding how states navigate their complex webs of alliances, rivalries, and shifting global power dynamics.

The affective salience measure developed in this paper offers policymakers a new tool for anticipating shifts in the global security environment. By tracking changes in how states discuss their relationships over time, it may be possible to identify emerging tensions or alignments before they manifest in more traditional measures. For scholars, this work opens up new avenues for research on the dynamics of interstate relationships. Further work could extend the analysis to incorporate internal policy documents like President's Daily Briefs (Goldfien and Joseph 2023; Carson, Min, and Nuys 2024), thereby examining the divergence between public signaling and private deliberations (McManus 2016), as well as public but audience-specific statements like diplomatic communiqués (Connelly et al. 2021), legislative debates (Kim, Londregan, and Ratkovic 2018), international agreements (Baturo, Dasandi, and Mikhaylov 2017), and domain-specific texts like cyber or climate change (Craig, Johnson, and Gallop 2022; Vogler 2023). Furthermore, these data offer a valuable opportunity to explore how states justify expressing high versus low affinity, as such variations can be indicative of strategic considerations to avoid perceptions of hypocrisy (McManus and Yarhi-Milo 2017) or to

signal potential for deeper alliances (Gannon and Kent 2021). Additionally, the data may reveal whether individual heads of state influence the tone of NSS documents (Lupton 2020, 2024), thereby linking public rhetoric to broader patterns of international behavior. And while I here focused only on affective salience, NSS documents contain a vast array of information that could be systematically analyzed like their use (or non-use) of emotional and moral language (Hall 2015; Post 2023; Yoon 2025) and different communicative mediums like persuasion (Walsh 2005) and resolve (Trager 2010; McManus 2017). Lastly, although the original corpus includes almost 200 documents written in non-English, existing computational limitations only allow the calculation of affective salience index to English texts. Given the speed at which advances in these computational techniques is occurring, I have no doubt that will be doable by the time this article is in print.

References

Albert, Mathias, Oliver Kessler, and Stephan Stetter. 2008. "On Order and Conflict: International Relations and the 'Communicative Turn'." *Review of International Studies* 34 (S1): 43–67. https://doi.org/10.1017/S0260210508007791.

AlDayel, Abeer, and Walid Magdy. 2019. "Assessing Sentiment of the Expressed Stance on Social Media." In *Social Informatics: 11th International Conference, SocInfo 2019, Doha, Qatar, November 18–21, 2019, Proceedings*, 277–86. Berlin, Heidelberg: Springer-Verlag. https://doi.org/10.1007/978-3-030-34971-4_19.

———. 2021. "Stance Detection on Social Media: State of the Art and Trends." arXiv. https://doi.org/10.48550/arXiv.2006.03644.

Alexander, Jeffrey C. 2004. "Cultural Pragmatics: Social Performance Between Ritual and Strategy." *Sociological Theory* 22 (4): 527–73. https://doi.org/10.1111/j.0735-2751.2004.00233.x.

Alexander, Jeffrey C., Bernhard Giesen, and Jason L. Mast, eds. 2006. *Social Performance: Symbolic Action, Cultural Pragmatics, and Ritual*. Cambridge Cultural Social Studies. Cambridge, UK ; New York: Cambridge University Press.

Alley, Joshua. 2021. "Alliance Participation, Treaty Depth, and Military Spending." *International Studies Quarterly* 65 (4): 929–43. https://doi.org/10.1093/isq/sqab077.

Arslan, Muhammad, Saba Munawar, and Christophe Cruz. 2024. "Political-RAG: Using Generative AI to Extract Political Information from Media Content." *Journal of Information Technology & Politics* 0 (0): 1–16. https://doi.org/10.1080/19331681.2024.2417263.

Asgarieh, Eliyar, Kapil Thadani, and Neil O'Hare. 2024. "Scalable Detection of Salient Entities in News Articles." arXiv. https://doi.org/10.48550/arXiv.2405.20461.

Austin, J. L. 1962. *How to Do Things with Words*. Harvard University Press.

Bailey, Michael A., Anton Strezhnev, and Erik Voeten. 2017. "Estimating Dynamic State

Preferences from United Nations Voting Data." *Journal of Conflict Resolution* 61 (2): 430–56. https://doi.org/10.1177/0022002715595700.

Balluff, Paul, Hajo G. Boomgaarden, and Annie Waldherr. 2024. "Automatically Finding Actors in Texts: A Performance Review of Multilingual Named Entity Recognition Tools." *Communication Methods and Measures* 18 (4): 371–89. https://doi.org/10.1080/19312458.2024.2324789.

Barbieri, Katherine, Omar M. G. Keshk, and Brian M. Pollins. 2009. "Trading Data: Evaluating Our Assumptions and Coding Rules." *Conflict Management and Peace Science* 26 (5): 471–91. https://doi.org/10.1177/0738894209343887.

Baturo, Alexander, Niheer Dasandi, and Slava J. Mikhaylov. 2017. "Understanding State Preferences with Text as Data: Introducing the UN General Debate Corpus." *Research & Politics* 4 (2): 2053168017712821. https://doi.org/10.1177/2053168017712821.

Becker, Jordan, Haemin Jee, Andreea Budeanu, Maxwell Love, and Seth Benson. 2024. "European Strategies in the Shadow of Sino-American Competition: A Text-as-Data Approach." In *United States Military Academy, West Point*. Rochester, NY. https://doi.org/10.2139/ssrn.4758032.

Becker, Jordan, Sarah E Kreps, Paul Poast, and Rochelle Terman. 2024. "Transatlantic Shakedown: Presidential Shaming and NATO Burden Sharing." *Journal of Conflict Resolution* 68 (2-3): 195–229. https://doi.org/10.1177/00220027231167840.

Becker, Jordan, and Edmund Malesky. 2017. "The Continent or the 'Grand Large'? Strategic Culture and Operational Burden-Sharing in NATO." *International Studies Quarterly* 61 (1): 163–80. https://doi.org/10.1093/isq/sqw039.

Bennett, D. Scott. 2006. "Exploring Operationalizations of Political Relevance." *Conflict Management and Peace Science* 23 (3): 245–61. https://doi.org/10.1080/07388940600837748.

Benson, Michelle A. 2005. "The Relevance of Politically Relevant Dyads in the Study of

Interdependence and Dyadic Disputes." *Conflict Management and Peace Science* 22 (2): 113–33. https://doi.org/10.1080/07388940590948556.

Bestvater, Samuel E., and Burt L. Monroe. 2023. "Sentiment Is Not Stance: Target-Aware Opinion Classification for Political Text Analysis." *Political Analysis* 31 (2): 235–56. https://doi.org/10/g72d6x.

Bhowmik, Rajarshi, Marco Ponza, Atharva Tendle, Anant Gupta, Rebecca Jiang, Xingyu Lu, Qian Zhao, and Daniel Preotiuc-Pietro. 2024. "Leveraging Contextual Information for Effective Entity Salience Detection." arXiv. https://doi.org/10.48550/arXiv.2309.07990.

Biber, Douglas, and Edward Finegan. 1988. "Adverbial Stance Types in English." *Discourse Processes* 11 (1): 1–34. https://doi.org/10.1080/01638538809544689.

Bisbee, James, Joshua D. Clinton, Cassy Dorff, Brenton Kenkel, and Jennifer M. Larson. 2024. "Synthetic Replacements for Human Survey Data? The Perils of Large Language Models." *Political Analysis* 32 (4): 401–16. https://doi.org/10.1017/pan.2024.5.

Bogdanov, Plamen Nikolov. 2022. "The Role of the National Security Strategy in the National Security of the United States of America." In *Romanian Military Thinking International Scientific Conference Proceedings*, 42–57. Centrul tehnic-editorial al armatei.

Bonikowski, Bart, Yuchen Luo, and Oscar Stuhler. 2022. "Politics as Usual? Measuring Populism, Nationalism, and Authoritarianism in U.S. Presidential Campaigns (1952–2020) with Neural Language Models." *Sociological Methods & Research* 51 (4): 1721–87. https://doi.org/10/grzg7s.

Boukes, Mark, Bob van de Velde, Theo Araujo, and Rens Vliegenthart. 2020. "What's the Tone? Easy Doesn't Do It: Analyzing Performance and Agreement Between Off-the-Shelf Sentiment Analysis Tools." *Communication Methods and Measures* 14 (2): 83–104. https://doi.org/10.1080/19312458.2019.1671966.

Boulding, Kenneth. 1962. *Conflict and Defense: A General Theory*. New York: Harper.

Braumoeller, Bear F., and Austin Carson. 2011. "Political Irrelevance, Democracy, and the

Limits of Militarized Conflict." *Journal of Conflict Resolution* 55 (2): 292–320. https://doi.org/10.1177/0022002710393918.

Brecher, Michael, and Jonathan Wilkenfeld. 1997. *A Study of Crisis*. Ann Arbor: University of Michigan Press.

Brecher, Michael, Jonathan Wilkenfeld, Kyle C. Beardsley, Patrick James, and David Quinn. 2023. "International Crisis Behavior Data Codebook." Codebook Version 15.

Bremer, Stuart A. 1992. "Dangerous Dyads: Conditions Affecting the Likelihood of Interstate War, 1816-1965." *Journal of Conflict Resolution* 36 (2): 309–41. https://www.jstor.org/stable/174478.

Bullough, Benjamin, Harrison Lundberg, Chen Hu, and Weihang Xiao. 2024. "Predicting Entity Salience in Extremely Short Documents." In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing: Industry Track*, edited by Franck Dernoncourt, Daniel Preoţiuc-Pietro, and Anastasia Shimorina, 50–64. Miami, Florida, US: Association for Computational Linguistics. https://doi.org/10.18653/v1/2024.emnlp-industry.5.

Burke, Kenneth. 1941. *The Philosophy of Literary Form*. Univ of California Press.

Burnham, Michael. 2024. "Stance Detection: A Practical Guide to Classifying Political Beliefs in Text." *Political Science Research and Methods*, 1–18. https://doi.org/10.1017/psrm.2024.35.

Burnham, Michael, Kayla Kahn, Ryan Yank Wang, and Rachel X. Peng. 2024. "Political DEBATE: Efficient Zero-shot and Few-shot Classifiers for Political Text." arXiv. https://doi.org/10.48550/arXiv.2409.02078.

Caballero, William N., and Phillip R. Jenkins. 2025. "On Large Language Models in National Security Applications." *Stat* 14 (2): e70057. https://doi.org/10.1002/sta4.70057.

Card, Dallas, Serina Chang, Chris Becker, Julia Mendelsohn, Rob Voigt, Leah Boustan, Ran Abramitzky, and Dan Jurafsky. 2022. "Computational Analysis of 140 Years of

US Political Speeches Reveals More Positive but Increasingly Polarized Framing of Immigration." *Proceedings of the National Academy of Sciences* 119 (31): e2120510119. https://doi.org/10/gqkxwz.

Carson, Austin. 2016. "Facing Off and Saving Face: Covert Intervention and Escalation Management in the Korean War." *International Organization* 70 (1): 103–31. https://doi.org/10.1017/S0020818315000284.

Carson, Austin, Eric Min, and Maya Van Nuys. 2024. "Racial Tropes in the Foreign Policy Bureaucracy: A Computational Text Analysis." *International Organization* 78 (2): 189–223. https://doi.org/10/gvhs28.

Carson, Austin, and Keren Yarhi-Milo. 2017. "Covert Communication: The Intelligibility and Credibility of Signaling in Secret." *Security Studies* 26 (1): 124–56. https://doi.org/10.1080/09636412.2017.1243921.

Caudle, Sharon L. 2009. "National Security Strategies: Security from What, for Whom, and by What Means." *Journal of Homeland Security and Emergency Management* 6 (1). https://doi.org/10/fgnxvr.

Caudle, Sharon L., and Stephan de Spiegeleire. 2010. "A New Generation of National Security Strategies: Early Findings from the Netherlands and the United Kingdom." *Journal of Homeland Security and Emergency Management* 7 (1). https://doi.org/10/dxkqmn.

Cerqua, Augusto, Marco Letta, and Gabriele Pinto. 2024. "On the (Mis)Use of Machine Learning with Panel Data." arXiv. https://doi.org/10.48550/arXiv.2411.09218.

Chan, Chung-hong, Joseph Bajjalieh, Loretta Auvil, Hartmut Wessler, Scott Althaus, Kasper Welbers, Wouter van Atteveldt, and Marc Jungblut. 2021. "Four Best Practices for Measuring News Sentiment Using 'Off-the-Shelf' Dictionaries: A Large-Scale p-Hacking Experiment." *Computational Communication Research* 3 (1): 1–27.

Chen, Tianqi, and Carlos Guestrin. 2016. "XGBoost: A Scalable Tree Boosting System." In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery*

and Data Mining, 785–94. https://doi.org/10.1145/2939672.2939785.

Chin, John J., Kiron K. Skinner, and Clay Yoo. 2023. "Understanding National Security Strategies Through Time." *Texas National Security Review* 6 (4): 103–24. https://doi.org/10.26153/tsw/48842.

Chirot, Daniel, and Thomas D. Hall. 1982. "World-System Theory." *Annual Review of Sociology* 8: 81–106. https://www.jstor.org/stable/2945989.

Clarke, Kevin A., Brenton Kenkel, and Miguel R. Rueda. 2018. "Omitted Variables, Countervailing Effects, and the Possibility of Overadjustment." *Political Science Research and Methods* 6 (2): 343–54. https://doi.org/10/gf5hbn.

Cohen, Jacob. 1960. "A Coefficient of Agreement for Nominal Scales." *Educational and Psychological Measurement* 20 (1): 37–46. https://doi.org/10/dghsrr.

Connelly, Matthew J, Raymond Hicks, Robert Jervis, Arthur Spirling, and Clara H Suong. 2021. "Diplomatic Documents Data for International Relations: The Freedom of Information Archive Database." *Conflict Management and Peace Science* 38 (6): 762–81. https://doi.org/10.1177/0738894220930326.

Corbetta, Renato. 2013. "Cooperative and Antagonistic Networks: Multidimensional Affinity and Intervention in Ongoing Conflicts, 1946–2001." *International Studies Quarterly* 57 (2): 370–84. https://doi.org/10.1111/isqu.12020.

Correlates of War Project. 2017. "State System Membership List, V2016."

Craig, Anthony J. S., Richard A. I. Johnson, and Max Gallop. 2022. "Building Cybersecurity Capacity: A Framework of Analysis for National Cybersecurity Strategies." *Journal of Cyber Policy* 7 (3): 375–98. https://doi.org/10.1080/23738871.2023.2178318.

Denny, Matthew J., and Arthur Spirling. 2018. "Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It." *Political Analysis* 26 (2): 168–89. https://doi.org/10/gdjsqk.

Diehl, Paul F., Gary Goertz, and Yahve Gallegos. 2021. "Peace Data: Concept, Measurement,

Patterns, and Research Agenda." *Conflict Management and Peace Science* 38 (5): 605–24. https://doi.org/10.1177/0738894219870288.

Donath, J., and D. Boyd. 2004. "Public Displays of Connection." *BT Technology Journal* 22 (4): 71–82. https://doi.org/10.1023/B:BTTJ.0000047585.06264.cc.

Doyle, Richard B. 2007. "The U.S. National Security Strategy: Policy, Process, Problems." *Public Administration Review* 67 (4): 624–29. https://www.jstor.org/stable/4624613.

Du Bois, J. W. 2007. "The Stance Triangle." In *Stancetaking in Discourse: Subjectivity, Evaluation, Interaction*, edited by Robert Englebretson, 139–82. John Benjamins Publishing.

DuMont, Malia. 2019. "Elements of National Security Strategy." Washington, DC: Atlantic Council.

Dunietz, Jesse, and Daniel Gillick. 2014. "A New Entity Salience Task with Millions of Training Examples." In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, Volume 2: Short Papers*, edited by Shuly Wintner, Stefan Riezler, and Sharon Goldwater, 205–9. Gothenburg, Sweden: Association for Computational Linguistics. https://doi.org/10.3115/v1/E14-4040.

Dworschak, Christoph. 2023. "Bias Mitigation in Empirical Peace and Conflict Studies: A Short Primer on Posttreatment Variables." *Journal of Peace Research* 61 (3): 462–76. https://doi.org/10.1177/00223433221145531.

Egami, Naoki, Musashi Hinck, Brandon M. Stewart, and Hanying Wei. 2024a. "Using Imperfect Surrogates for Downstream Inference: Design-based Supervised Learning for Social Science Applications of Large Language Models." arXiv. https://doi.org/10.48550/arXiv.2306.04746.

Egami, Naoki, Musashi Hinck, Brandon M Stewart, and Hanying Wei. 2024b. "Using Large Language Model Annotations for the Social Sciences: A General Framework of Using Predicted Variables in Downstream Analyses."

Egger, Roman, and Joanne Yu. 2022. "A Topic Modeling Comparison Between LDA, NMF,

Top2Vec, and BERTopic to Demystify Twitter Posts." *Frontiers in Sociology* 7. https://doi.org/10.3389/fsoc.2022.886498.

Ellison, Nicole B., and Danah M. Boyd. 2013. "Sociality Through Social Network Sites." In *The Oxford Handbook of Internet Studies*, edited by William H. Dutton, 151–72. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199589074.013.0008.

Ellison, Nicole B., and Jessica Vitak. 2015. "Social Network Site Affordances and Their Relationship to Social Capital Processes." In *The Handbook of the Psychology of Communication Technology*, 205–27. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118426456.ch9.

Ettinger, Aaron. 2017. "U.S. National Security Strategies: Patterns of Continuity and Change, 1987–2015." *Comparative Strategy* 36 (2): 115–28. https://doi.org/10.1080/01495933.2017.1317538.

Fearon, James D. 1994. "Domestic Political Audiences and the Escalation of International Disputes." *American Political Science Review* 88 (3): 577–92. https://doi.org/10.2307/2944796.

———. 1997. "Signaling Foreign Policy Interests Tying Hands Versus Sinking Costs." *Journal of Conflict Resolution* 41 (1): 68–90. https://doi.org/10.1177/0022002797041001004.

Finn, Adam, and Jordan J. Louviere. 1992. "Determining the Appropriate Response to Evidence of Public Concern: The Case of Food Safety." *Journal of Public Policy & Marketing* 11 (2): 12–25.

Flournoy, Michèle A. 2006. "Did the Pentagon Get the Quadrennial Defense Review Right?" *The Washington Quarterly* 29 (2): 67–84. https://doi.org/10.1162/wash.2006.29.2.67.

Fogel-Dror, Yair, Shaul R. Shenhav, Tamir Sheafer, and Wouter Van Atteveldt. 2019. "Role-Based Association of Verbs, Actions, and Sentiments with Entities in Political Discourse." *Communication Methods and Measures* 13 (2): 69–82. https://doi.org/10.1080/19312458.2018.1536973.

Fuhrmann, Matthew, and Todd S. Sechser. 2014. "Signaling Alliance Commitments: Hand-

Tying and Sunk Costs in Extended Nuclear Deterrence." *American Journal of Political Science* 58 (4): 919–35. https://doi.org/10.1111/ajps.12082.

Gannon, J Andrés. 2025a. "Allies as Armaments: Explaining the Specialization of State Military Capabilities." *Security Studies* 34 (1). https://doi.org/10.1080/09636412.2025.2467140.

———. 2025b. "Complementarity in Alliances: How Strategic Compatibility and Hierarchy Promote Efficient Cooperation in International Security." *American Journal of Political Science*.

Gannon, J Andrés, Erik A. Gartzke, Jon R. Lindsay, and Peter Schram. 2024. "The Shadow of Deterrence: Why Capable Actors Engage in Contests Short of War." *Journal of Conflict Resolution* 68 (2-3): 230–68. https://doi.org/10.1177/00220027231166345.

Gannon, J Andrés, and Daniel Kent. 2021. "Keeping Your Friends Close, but Acquaintances Closer: Why Weakly Allied States Make Committed Coalition Partners." *Journal of Conflict Resolution* 65 (5): 889–918. https://doi.org/10.1177/0022002720978800.

Gartzke, Erik A. 1998. "Kant We All Just Get Along? Opportunity, Willingness, and the Origins of the Democratic Peace." *American Journal of Political Science* 42 (1): 1–27. https://doi.org/10.2307/2991745.

Gartzke, Erik A., Shannon Carcelli, J Andrés Gannon, and Jiakun Jack Zhang. 2017. "Signaling in Foreign Policy." *Oxford Encyclopedia of Foreign Policy Analysis*.

Gartzke, Erik A., and Kristian Skrede Gleditsch. 2022. "Ties That Bias in International Conflict: A Spatial Approach to Dyadic Dependence from Alliance Ties and Inbetweenness." *International Studies Quarterly* 66 (1): 1–13. https://doi.org/10/gtvhjc.

Gartzke, Erik A., and Alex Weisiger. 2013a. "Fading Friendships: Alliances, Affinities and the Activation of International Identities." *British Journal of Political Science* 43 (1): 25–52. https://doi.org/10.1017/S0007123412000208.

———. 2013b. "Permanent Friends? Dynamic Difference and the Democratic Peace." *Inter-*

national Studies Quarterly 57 (1): 171–85. https://doi.org/10.1111/isqu.12046.

Gibler, Douglas M. 2009. *International Military Alliances, 1648-2008*. CQ Press.

Goffman, Erving. 1956. *The Presentation of Self in Everyday Life*. Edinburgh: Penguin Books.

Goldfien, Michael A., and Michael F. Joseph. 2023. "Perceptions of Leadership Importance: Evidence from the CIA's President's Daily Brief." *Security Studies* 32 (2): 205–38. https://doi.org/10.1080/09636412.2023.2200203.

Goldgeier, James, and Jeremi Suri. 2015. "Revitalizing the U.S. National Security Strategy." *The Washington Quarterly* 38 (4): 35–55. https://doi.org/10/gt9g4g.

Golubović, Marko, and Radiša Saković. 2023. "The Comparative Analysis of the State Strategic Documents in the Field of Security." *Vojno Delo* 75 (1): 1–17. https://doi.org/10/gt9g4f.

Grieco, Kelly A. 2018. "The 2018 National Defense Strategy: Continuity and Competition." *Strategic Studies Quarterly* 12 (2): 3–8. https://www.jstor.org/stable/26430813.

Grönberg, David. 2021. "Extracting Salient Named Entities from Financial News Articles." Master's thesis, Linköping University.

Häffner, Sonja, Martin Hofer, Maximilian Nagl, and Julian Walterskirchen. 2023. "Introducing an Interpretable Deep Learning Approach to Domain-Specific Dictionary Creation: A Use Case for Conflict Prediction." *Political Analysis* 31 (4): 481–99. https://doi.org/10/gtkcqc.

Häge, Frank M. 2011. "Choice or Circumstance? Adjusting Measures of Foreign Policy Similarity for Chance Agreement." *Political Analysis* 19 (3): 287–305. https://www.jstor.org/stable/23011439.

Häge, Frank M., and Simon Hug. 2016. "Consensus Decisions and Similarity Measures in International Organizations." *International Interactions* 42 (3): 503–29. https://doi.org/10/gtv3zr.

Hall, Todd H. 2015. *Emotional Diplomacy: Official Emotion on the International Stage*.

Cornell University Press.

———. 2017. "On Provocation: Outrage, International Relations, and the Franco–Prussian War." *Security Studies* 26 (1): 1–29. https://doi.org/10.1080/09636412.2017.1243897.

Harris, Gardiner. 2017. "Jim Mattis, in Lithuania, Reaffirms U.S. Commitment to NATO." *The New York Times*, May, A6.

Hogan, Bernie. 2010. "The Presentation of Self in the Age of Social Media: Distinguishing Performances and Exhibitions Online." *Bulletin of Science, Technology & Society* 30 (6): 377–86. https://doi.org/10.1177/0270467610385893.

Hünermund, Paul, and Beyers Louw. 2025. "On the Nuisance of Control Variables in Causal Regression Analysis." *Organizational Research Methods* 28 (1): 138–51. https://doi.org/10.1177/10944281231219274.

Hutto, C., and Eric Gilbert. 2014. "VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text." *Proceedings of the International AAAI Conference on Web and Social Media* 8 (1): 216–25. https://doi.org/10.1609/icwsm.v8i1.14550.

Jabbour, Jana J. 2022. "Turkey–France Political and Diplomatic Relations: Contemporary Issues and Future Perspectives." In *Turkish-French Relations: History, Present, and the Future*, edited by Aurélien Denizeau and Ozan Örmeci, 117–50. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-07988-7_5.

Jervis, Robert. 1976. *Perception and Misperception in International Politics*. Vol. 49. Princeton, N.J: Princeton University Press.

Joseph, Michael F. 2021. "A Little Bit of Cheap-Talk Is a Dangerous Thing: States Can Communicate Intentions Persuasively and Raise the Risk of War in the Processes." *The Journal of Politics* 83 (1): 166–81. https://doi.org/10.1086/709145.

Kaplan, Danny. 2021. "Public Intimacy in Social Media: The Mass Audience as a Third Party." *Media, Culture & Society* 43 (4): 595–612. https://doi.org/10.1177/0163443721991087.

———. 2024. "Performing Identity or Performing Relationships? Rethinking Performance

Theory in Social Media Studies." *Cultural Sociology* 18 (4): 441–63. https://doi.org/10.1177/17499755221149184.

Katagiri, Azusa, and Eric Min. 2019. "The Credibility of Public and Private Signals: A Document-Based Approach." *American Political Science Review* 113 (1): 156–72. https://doi.org/10.1017/S0003055418000643.

Kenkel, Brenton. 2019. "The Efficacy of Cheap Talk in Collective Action Problems." *Journal of Theoretical Politics* 31 (3): 370–402. https://doi.org/10.1177/0951629819850625.

Kim, In Song, John Londregan, and Marc Ratkovic. 2018. "Estimating Spatial Preferences from Votes and Text." *Political Analysis* 26 (2): 210–29. https://doi.org/10.1017/pan.2018.7.

Kinne, Brandon J. 2020. "The Defense Cooperation Agreement Dataset (DCAD)." *Journal of Conflict Resolution* 64 (4): 729–55. https://doi.org/10.1177/0022002719857796.

Kiritchenko, Svetlana, and Saif M. Mohammad. 2016. "Capturing Reliable Fine-Grained Sentiment Associations by Crowdsourcing and Best–Worst Scaling." In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, edited by Kevin Knight, Ani Nenkova, and Owen Rambow, 811–17. San Diego, California: Association for Computational Linguistics. https://doi.org/10.18653/v1/N16-1095.

———. 2017. "Best-Worst Scaling More Reliable Than Rating Scales: A Case Study on Sentiment Intensity Annotation." In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, edited by Regina Barzilay and Min-Yen Kan, 465–70. Vancouver, Canada: Association for Computational Linguistics. https://doi.org/10.18653/v1/P17-2074.

Klein, James P., Gary Goertz, and Paul F. Diehl. 2006. "The New Rivalry Dataset: Procedures and Patterns." *Journal of Peace Research* 43 (3): 331–48. https://doi.org/10.1177/0022343306063935.

Krebs, Ronald R., and Patrick Thaddeus Jackson. 2007. "Twisting Tongues and Twisting Arms: The Power of Political Rhetoric." *European Journal of International Relations* 13 (1): 35–66. https://doi.org/10.1177/1354066107074284.

Küçük, Dilek, and Fazli Can. 2021. "Stance Detection: Concepts, Approaches, Resources, and Outstanding Issues." In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2673–76. SIGIR '21. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3404835.3462815.

Kydd, Andrew. 2000. "Trust, Reassurance, and Cooperation." *International Organization* 54 (2): 325–57. https://www.jstor.org/stable/2601300.

Lahoti, Preethi, Kiran Garimella, and Aristides Gionis. 2018. "Joint Non-negative Matrix Factorization for Learning Ideological Leaning on Twitter." In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*, 351–59. WSDM '18. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3159652.3159669.

Landler, Mark, and David E. Sanger. 2017. "Trump Delivers a Mixed Message on His National Security Approach." *The New York Times*, December, A1.

Laurer, Moritz, Wouter van Atteveldt, Andreu Casas, and Kasper Welbers. 2024. "On Measurement Validity and Language Models: Increasing Validity and Decreasing Bias with Instructions." *Communication Methods and Measures* 19 (1): 46–62. https://doi.org/10.1080/19312458.2024.2378690.

Lebovic, James H., and Elizabeth N. Saunders. 2016. "The Diplomatic Core: The Determinants of High-Level US Diplomatic Visits, 1946–2010." *International Studies Quarterly* 60 (1): 107–23. https://doi.org/10.1093/isq/sqv008.

Leeds, Brett Ashley, Jeffrey Ritter, Sara Mitchell, and Andrew Long. 2002. "Alliance Treaty Obligations and Provisions, 1815-1944." *International Interactions* 28 (3): 237–60. https://doi.org/10.1080/03050620213653.

Leeds, Brett Ashley, and Burcu Savun. 2007. "Terminating Alliances: Why Do States Abrogate Agreements?" *The Journal of Politics* 69 (4): 1118–32. https://doi.org/10.1111/j.1468-2508.2007.00612.x.

Lemke, Douglas. 1995. "The Tyranny of Distance: Redefining Relevant Dyads." *International Interactions* 21 (1): 23–38. https://doi.org/10.1080/03050629508434858.

Lemke, Douglas, and William Reed. 2001. "The Relevance of Politically Relevant Dyads." *Journal of Conflict Resolution* 45 (1): 126–44. https://doi.org/10.1177/0022002701045001006.

Lettow, Paul. 2021. "U.S. National Security Strategy: Lessons Learned." *Texas National Security Review* 4 (2): 117–54. https://doi.org/10/gt9g4h.

Lindgren, Wrenn Yennie, and Nina Græger. 2017. "The Challenges and Dynamics of Alliance Policies: Norway, NATO and the High North." In *Global Allies*, edited by Michael Wesley, 91–114. Comparing US Alliances in the 21st Century. ANU Press. https://www.jstor.org/stable/j.ctt1sq5twz.10.

Liu, Yang, and Allan Just. 2020. "SHAPforxgboost: SHAP Plots for 'Xgboost'."

Logan, Justin, and Benjamin H. Friedman. 2022. "The Case for Getting Rid of the National Security Strategy." *War on the Rocks*. https://warontherocks.com/2022/11/the-case-for-getting-rid-of-the-national-security-strategy/.

Long, Andrew G., Timothy Nordstrom, and Kyeonghi Baek. 2007. "Allying for Peace: Treaty Obligations and Conflict Between Allies." *The Journal of Politics* 69 (4): 1103–17. https://doi.org/10.1111/j.1468-2508.2007.00611.x.

Louviere, Jordan J. 2015. *Best-Worst Scaling: Theory, Methods and Applications*. 1st ed. Cambridge: Cambridge University Press.

Lupton, Danielle L. 2018. "Signaling Resolve: Leaders, Reputations, and the Importance of Early Interactions." *International Interactions* 44 (1): 59–87. https://doi.org/10.1080/03050629.2017.1316268.

———. 2020. *Reputation for Resolve: How Leaders Signal Determination in International Politics*. Cornell University Press.

———. 2024. "Threat Construction and Coercive Credibility." *Security Studies* 33 (3): 407–38. https://doi.org/10.1080/09636412.2024.2307058.

Mansfield, Edward D. 1993. "Concentration, Polarity, and the Distribution of Power." *International Studies Quarterly* 37 (1): 105–28. https://doi.org/10.2307/2600833.

Maoz, Zeev. 1996. *Domestic Sources of Global Change*. Ann Arbor, MI: University of Michigan Press. https://doi.org/10.3998/mpub.14663.

———. 2010. *Networks of Nations: The Evolution, Structure, and Impact of International Networks, 1816–2001*. Cambridge University Press.

Markowitz, Jonathan N., and Christopher J. Fariss. 2013. "Going the Distance: The Price of Projecting Power." *International Interactions* 39 (2): 119–43. https://doi.org/10.1080/03050629.2013.768458.

———. 2018. "Power, Proximity, and Democracy: Geopolitical Competition in the International System." *Journal of Peace Research* 55 (1): 78–93. https://doi.org/10.1177/0022343317727328.

Marquez, Xavier. 2016. "A Quick Method for Extending the Unified Democracy Scores." {{SSRN Scholarly Paper}}. Rochester, NY. https://doi.org/10.2139/ssrn.2753830.

Mastro, Oriana Skylar. 2023. "The Challenges of Deterrence in the Taiwan Strait: Recommendations for U.S. Policy."

Mattes, Michaela. 2012. "Reputation, Symmetry, and Alliance Design." *International Organization* 66 (4): 679–707. https://doi.org/10.1017/S002081831200029X.

McDonald, Gloria. 2023. "Defining National Security: A Comparison of the Trump and Biden Administration's National Security Strategies." Research {{Report}}. Washington DC: America First Policy Institute.

McKie, Jorj. 2024. "Pymupdf4llm: PyMuPDF Utilities for LLM/RAG."

McManus, Roseanne W. 2014. "Fighting Words The Effectiveness of Statements of Resolve in International Conflict." *Journal of Peace Research* 51 (6): 726–40. https://doi.org/10.1177/0022343314539826.

———. 2016. "The Impact of Context on the Ability of Leaders to Signal Resolve." *International Interactions* 43 (3): 453–79. https://doi.org/10.1080/03050629.2016.1171764.

———. 2017. *Statements of Resolve: Achieving Coercive Credibility in International Conflict*. Cambridge University Press.

McManus, Roseanne W., and Tuba Sendinç. 2024. "Sending the B Team: The Impact of Lesser Signals of Resolve." *Journal of Peace Research* 0 (0): 1–15. https://doi.org/10/gtv3rj.

McManus, Roseanne W., and Keren Yarhi-Milo. 2017. "The Logic of 'Offstage' Signaling: Domestic Politics, Regime Type, and Major Power-Protégé Relations." *International Organization* 71 (4): 701–33. https://doi.org/10.1017/S0020818317000297.

Miller, Steven V. 2022. "{Peacesciencer}: An R Package for Quantitative Peace Science Research." *Conflict Management and Peace Science* 39 (6): 755–79. https://doi.org/10.1177/07388942221077926.

Min, Eric. 2025. *Words of War: Negotiation as a Tool of Conflict*. Cornell University Press.

Ministry of Defence of Ukraine. 2013. "White Book 2013 The Armed Forces of Ukraine."

———. 2015. "White Book 2015 The Armed Forces of Ukraine."

Miyajiwala, Aamir, Arnav Ladkat, Samiksha Jagadale, and Raviraj Joshi. 2022. "On Sensitivity of Deep Learning Based Text Classification Algorithms to Practical Input Perturbations." arXiv. https://doi.org/10.48550/arXiv.2201.00318.

Mohammad, Saif M., Svetlana Kiritchenko, Parinaz Sobhani, Xiaodan Zhu, and Colin Cherry. 2016. "SemEval-2016 Task 6: Detecting Stance in Tweets." In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, edited by Steven Bethard, Marine Carpuat, Daniel Cer, David Jurgens, Preslav Nakov, and Torsten Zesch, 31–41. San Diego, California: Association for Computational Linguistics. https://doi.org/10.18653/

v1/S16-1003.

Mohr, John W., Robin Wagner-Pacifici, Ronald L. Breiger, and Petko Bogdanov. 2013. "Graphing the Grammar of Motives in National Security Strategies: Cultural Interpretation, Automated Text Analysis and the Drama of Global Politics." *Poetics* 41 (6): 670–700. https://doi.org/10/gd23f6.

Montani, Ines, Matthew Honnibal, Adriane Boyd, Sofie Van Landeghem, and Henning Peters. 2023. "Explosion/spaCy: V3.7.2: Fixes for APIs and Requirements." Zenodo. https://doi.org/10.5281/ZENODO.1212303.

Montgomery, Jacob M., Brendan Nyhan, and Michelle Torres. 2018. "How Conditioning on Posttreatment Variables Can Ruin Your Experiment and What to Do about It." *American Journal of Political Science* 62 (3): 760–75. https://www.jstor.org/stable/26598780.

Morgenthau, Hans. 1948. *Politics Among Nations*. 7th edition. Boston: McGraw-Hill Education.

Morrow, James D. 1986. "A Spatial Model of International Conflict." *American Political Science Review* 80 (4): 1131–50. https://doi.org/10/c9wkxq.

Moyer, Jonathan D, Collin J Meisel, Adam Szymanski-Burgos, Andrew C Scott, Matteo C M Casiraghi, Alexandra Kurkul, Marianne Hughes, Whitney Kettlun, Kylie X McKee, and Austin S Matthews. 2025. "When Heads of Government and State (HOGS) Fly: Introducing the Country and Organizational Leader Travel (COLT) Dataset Measuring Foreign Travel by HOGS." *International Studies Quarterly* 69 (2): sqaf013. https://doi.org/10.1093/isq/sqaf013.

"National Security Strategy of the United States." 1991. The White House.

———. 2022. The White House.

Neal, Andrew W., and Roy B. Gardner. 2024. "National Security and Defence Documents Dataset (1987-2024)." University of Edinburgh. School of Social and Political Science. Politics and International Relations. https://doi.org/10.7488/ds/7797.

Onuf, Nicholas G. 1989. *World of Our Making: Rules and Rule in Social Theory and International Relations*. Columbia, SC: University of South Carolina Press.

Ornstein, Joseph T., Elise N. Blasingame, and Jake S. Truscott. 2025. "How to Train Your Stochastic Parrot: Large Language Models for Political Texts." *Political Science Research and Methods* 13 (2): 264–81. https://doi.org/10.1017/psrm.2024.64.

Overbeck, Maximilian, Christian Baden, Tali Aharoni, Eedan Amit-Danhi, and Keren Tenenboim-Weinblatt. 2025. "Beyond Sentiment: An Algorithmic Strategy for Identifying Evaluations Within Large Text Corpora." *Communication Methods and Measures* 19 (1): 24–45. https://doi.org/10.1080/19312458.2023.2285783.

Palmer, Glenn, Roseanne W McManus, Vito D'Orazio, Michael R Kenwick, Mikaela Karstens, Chase Bloch, Nick Dietrich, Kayla Kahn, Kellan Ritter, and Michael J Soules. 2021. "The MID5 Dataset, 2011– 2014: Procedures, Coding Rules, and Description." *Conflict Management and Peace Science*, February, 0738894221995743. https://doi.org/10.1177/0738894221995743.

Palomino, Marco A., Aditya Padmanabhan Varma, Gowriprasad Kuruba Bedala, and Aidan Connelly. 2017. "Investigating the Lack of Consensus Among Sentiment Analysis Tools." In *Human Language Technology. Challenges for Computer Science and Linguistics: 8th Language and Technology Conference, LTC 2017, Poznań, Poland, November 17–19, 2017, Revised Selected Papers*, 58–72. Berlin, Heidelberg: Springer-Verlag. https://doi.org/10.1007/978-3-030-66527-2_5.

Paruchuri, Vik. 2024. "VikParuchuri/Marker."

Pemstein, Daniel, Stephen A. Meserve, and James Melton. 2017. "Democratic Compromise: A Latent Variable Analysis of Ten Measures of Regime Type." *Political Analysis* 18 (4): 426–49. https://doi.org/10/bq365m.

Pevehouse, Jon CW, Timothy Nordstrom, Roseanne W McManus, and Anne Spencer Jamison. 2020. "Tracking Organizations in the World: The Correlates of War IGO Version

3.0 Datasets." *Journal of Peace Research* 57 (3): 492–503. https://doi.org/10.1177/0022343319881175.

Ponza, Marco, Paolo Ferragina, and Francesco Piccinno. 2019. "Swat: A System for Detecting Salient Wikipedia Entities in Texts." *Computational Intelligence* 35 (4): 858–90. https://doi.org/10.1111/coin.12216.

Post, Abigail S. 2023. "Words Matter: The Effect of Moral Language on International Bargaining." *International Security* 48 (1): 125–65. https://doi.org/10.1162/isec_a_00466.

Qi, Weihong. 2023. "Beyond Sentiment: Leveraging Topic Metrics for Political Stance Classification." arXiv. https://doi.org/10.48550/arXiv.2310.15429.

Quackenbush, Stephen L. 2006. "Identifying Opportunity for Conflict: Politically Active Dyads." *Conflict Management and Peace Science* 23 (1): 37–51. https://doi.org/10.1080/07388940500503804.

———. 2024. "Politically Active Dyads Revisited: An Update Through 2014." *Conflict Management and Peace Science*, October, 07388942241286311. https://doi.org/10/g73v38.

Ramsay, Kristopher W. 2011. "Cheap Talk Diplomacy, Voluntary Negotiations, and Variable Bargaining Power." *International Studies Quarterly* 55 (4): 1003–23. https://doi.org/10.1111/j.1468-2478.2011.00687.x.

Rauh, Christian. 2018. "Validating a Sentiment Dictionary for German Political Language—a Workbench Note." *Journal of Information Technology & Politics* 15 (4): 319–43. https://doi.org/10.1080/19331681.2018.1485608.

Razeto, Sebastián Briones, and Nicole Jenne. 2021. "Security and Defence Policy Documents: A New Dataset." *Defense & Security Analysis* 37 (3): 346–63. https://doi.org/10.1080/14751798.2021.1959730.

Schelling, Thomas. 1960. *The Strategy of Conflict*. Harvard University Press.

———. 1966. *Arms and Influence*. New Haven; London: Yale University Press.

Signorino, Curtis S., and Jeffrey M. Ritter. 1999. "Tau-b or Not Tau-b: Measuring the

Similarity of Foreign Policy Positions." *International Studies Quarterly* 43 (1): 115–44. https://www.jstor.org/stable/2600967.

Singer, J. David. 1988. "Reconstructing the Correlates of War Dataset on Material Capabilities of States, 1816–1985." *International Interactions* 14 (2): 115–32. https://doi.org/10.1080/03050628808434695.

Smith, Julian. 2023. "PyMuPDF: A High Performance Python Library for Data Extraction, Analysis, Conversion & Manipulation of PDF (and Other) Documents."

Snider, Don M. 1995. "The National Security Strategy: Documenting Strategic Vision Second Edition." *Monographs, Collaborative Studies, & IRPs*, March.

Snider, Don M., and John Nagl. 2001. "The National Security Strategy: Documenting Strategic Vision." In *U.S. Army War College Guide to Strategy*, edited by Joseph R. Cerami and James F. Holcomb, 127–42. Fort Belvoir, VA: Defense Technical Information Center. https://doi.org/10.21236/ADA392553.

Song, Kaitao, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2020. "MPNet: Masked and Permuted Pre-training for Language Understanding." In *Advances in Neural Information Processing Systems*, 33:16857–67. Curran Associates, Inc.

Stolberg, Alan. 2012. "How Nation-States Craft National Security Strategy Documents."

Sukin, Lauren, and Alexander Lanoszka. 2024. "Credibility in Crises: How Patrons Reassure Their Allies." *International Studies Quarterly* 68 (2): sqae062. https://doi.org/10.1093/isq/sqae062.

Takei, Makito. 2024. "Audience Costs and the Credibility of Public Versus Private Threats in International Crises." *International Studies Quarterly* 68 (3): sqae091. https://doi.org/10.1093/isq/sqae091.

Tama, Jordan. 2015. "Does Strategic Planning Matter? The Outcomes of U.S. National Security Reviews." *Political Science Quarterly* 130 (4): 735–65. https://doi.org/10/gt9g4d.

———. 2017. "The Politics of Strategy: Why Government Agencies Conduct Major

Strategic Reviews." *Journal of Public Policy* 37 (1): 27–54. https://doi.org/10.1017/S0143814X15000148.

Terechshenko, Zhanna. 2020. "Hot Under the Collar: A Latent Measure of Interstate Hostility." *Journal of Peace Research* 57 (6): 764–76. https://doi.org/10.1177/0022343320962546.

Thapa, Surendrabikram, Shuvam Shiwakoti, Siddhant Bikram Shah, Surabhi Adhikari, Hariram Veeramani, Mehwish Nasim, and Usman Naseem. 2025. "Large Language Models (LLM) in Computational Social Science: Prospects, Current State, and Challenges." *Social Network Analysis and Mining* 15 (1): 4. https://doi.org/10.1007/s13278-025-01428-9.

Thompson, William R. 2001. "Identifying Rivals and Rivalries in World Politics." *International Studies Quarterly* 45 (4): 557–86. https://www.jstor.org/stable/3096060.

Thompson, William R., and David R. Dreyer. 2012. *Handbook of International Rivalries, 1494-2010*. Correlates of War Series. Washington, DC: CQ Press.

Thompson, William R., Kentaro Sakuwa, and Prashant Hosur Suhas. 2021. *Analyzing Strategic Rivalries in World Politics: Types of Rivalry, Regional Variation, and Escalation/De-escalation*. Springer Nature.

Trager, Robert F. 2010. "Diplomatic Calculus in Anarchy: How Communication Matters." *American Political Science Review* 104 (2): 347–68. https://doi.org/10.1017/S0003055410000158.

———. 2011. "Multidimensional Diplomacy." *International Organization* 65 (3): 469–506. https://doi.org/10.1017/S0020818311000178.

———. 2012. "Long-Term Consequences of Aggressive Diplomacy: European Relations After Austrian Crimean War Threats." *Security Studies* 21 (2): 232–65. https://doi.org/10.1080/09636412.2012.679204.

———. 2016. "The Diplomacy of War and Peace." *Annual Review of Political Science* 19: 205–28. https://doi.org/10.1146/annurev-polisci-051214-100534.

Trani, Salvatore, Claudio Lucchese, Raffaele Perego, David E. Losada, Diego Ceccarelli, and Salvatore Orlando. 2018. "SEL: A Unified Algorithm for Salient Entity Linking." *Computational Intelligence* 34 (1): 2–29. https://doi.org/10.1111/coin.12147.

Tritten, James J. 1991. "America Promises to Come Back: The President's New National Security Strategy." *Security Studies* 1 (2): 173–234. https://doi.org/10.1080/09636419109347466.

Tucker, Colin. 2023. "Leader Statements and the Effect of Accommodative and Coercive Language in Interstate Conflict." *Journal of Global Security Studies* 8 (1): 1–18. https://doi.org/10.1093/jogss/ogac036.

van Atteveldt, Wouter, Mariken A. C. G. van der Velden, and Mark Boukes. 2021. "The Validity of Sentiment Analysis: Comparing Manual Annotation, Crowd-Coding, Dictionary Approaches, and Machine Learning Algorithms." *Communication Methods and Measures* 15 (2): 121–40. https://doi.org/10.1080/19312458.2020.1869198.

Vogler, Anselm. 2023. "Barking up the Tree Wrongly? How National Security Strategies Frame Climate and Other Environmental Change as Security Issues." *Political Geography* 105: 1–11. https://doi.org/10/gt9g39.

Walsh, James I. 2005. "Persuasion in International Politics: A Rationalist Account." *Politics & Policy* 33 (4): 642–70. https://doi.org/10.1111/j.1747-1346.2005.tb00217.x.

Wang, Alex, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2020. "SuperGLUE: A Stickier Benchmark for General-Purpose Language Understanding Systems." arXiv. https://doi.org/10.48550/arXiv.1905.00537.

Wang, Yu. 2024. "On Finetuning Large Language Models." *Political Analysis* 32 (3): 379–83. https://doi.org/10/g73vwd.

Weede, Erich. 1976. "Overwhelming Preponderance as a Pacifying Condition Among Contiguous Asian Dyads, 1950-1969." *Journal of Conflict Resolution* 20 (3): 395–411. https:

//www.jstor.org/stable/173286.

Weitsman, Patricia A. 1997. "Intimate Enemies: The Politics of Peacetime Alliances." *Security Studies* 7 (1): 156–93. https://doi.org/10.1080/09636419708429337.

Wendt, Alexander. 1999. *Social Theory of International Politics*. Cambridge University Press.

Wu, Chuan, Evangelos Kanoulas, Maarten de Rijke, and Wei Lu. 2020. "WN-Salience: A Corpus of News Articles with Entity Salience Annotations." In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, edited by Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, et al., 2095–2102. Marseille, France: European Language Resources Association.

Xiang, Jun. 2010. "Relevance as a Latent Variable in Dyadic Analysis of Conflict." *The Journal of Politics* 72 (2): 484–98. https://doi.org/10.1017/S0022381609990909.

Yarhi-Milo, Keren. 2013. "In the Eye of the Beholder: How Leaders and Intelligence Communities Assess the Intentions of Adversaries." *International Security* 38 (1): 7–51. https://doi.org/10.1162/ISEC_a_00128.

Yoder, Brandon K., and William Spaniel. 2022. "Costly Concealment: Secret Foreign Policymaking, Transparency, and Credible Reassurance." *International Organization* 76 (4): 868–900. https://doi.org/10.1017/S0020818322000248.

Yoon, Hohyun. 2025. "Anger Expressions and Coercive Credibility in International Crises." *American Journal of Political Science* 0 (0): 1–17. https://doi.org/10.1111/ajps.12937.