

Generative AI Governance and Media Sentiment: Comparative Evidence from Five Global Regulatory Regimes

DR. SHRIDUL GUPTA

shridulgupta.faculty@mains.ac.in

Maharaja Agrasen Institute of Management Studies

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Generative AI Governance and Media Sentiment: Comparative Evidence from Five Global Regulatory Regimes

Dr. Shridul Gupta

Associate Professor

Maharaja Agrasen Institute of Management Studies, Delhi (India)

Abstract

Generative AI governance differs a great deal across jurisdictions. Strict regulatory frameworks are often expected to draw more critical media coverage. However, the extent to which media discourse reflects this expectation remains underexplored. This study looks at media tone and coverage across five selected Generative AI governance types. These are the US (Market-First), EU (Rights-Focused), UK (Sector-Led Hybrid), China (State-Sovereign), and Singapore (Pragmatic Sandbox). Media coverage from January 2024 to December 2025 was gathered using GDELT DOC 2.0. This produced 105,051 articles across 3,031 active jurisdiction-day observations. No-coverage days were treated as missing for tone and retained as zero for volume on returned dates. 17 dates missing from all seven source-country streams were treated as missing. A one-way ANOVA, with Tukey's HSD test for follow up comparisons, was used to assess differences in media tone across jurisdictions. This analysis was backed up further by the Kruskal–Wallis test, the Alexander–Govern test for differences in variance, weekly aggregation of data, and a Germany-only EU sensitivity check. Event-window models compared coverage spikes following one technological and one regulatory event. Media tone did differed across jurisdictions, $F(4, 3026) = 159.7, p < .001, \eta^2 = .174$. But the findings contradicted the expectation based on regulatory strictness, showing the following pattern, EU (+3.23) > China (+2.09) $\approx$ Singapore (+2.09) > UK (+1.26) $\approx$ US (+1.09). Coverage density did not explain this pattern. Audience orientation was consistent with the reversed tone ordering but could not be pinned down as a cause. Outlet composition was not tested. Regulatory-event spikes exceeded technological-event spikes in the EU (+509% against +264%) and Singapore (+458% against +282%). The reverse happened in the U.K. and U.S. China showed almost equal increases for both events. None of the ten country-event series followed an exponential decrease. Five rows had small positive λ values, all below .019, with R^2 values no higher than .08. The other five rows had no estimate and were marked as not applicable. The study also corrects bias caused by combining zero-coverage days and identifies uneven audience representation in a dataset limited to English. Cross-national sentiment scores

should be viewed as indicators of news coverage that remain open to review, not as direct expressions of citizens' views.

Keywords: media tone; generative AI rules; comparison across countries; bias in indicators; study of major events; ethics in language-processing AI

1. Introduction

1.1 The Macroeconomic and Societal Disruption of Generative AI

Generative Artificial Intelligence extends automation past systems that follow fixed rules or perform one specific task. Large language models, transformer architectures, and systems that process several input formats perform complex generative tasks. They are able to write code and produce text, images, and other content. Automation now applies to work that depends heavily on knowledge and communication (Vaswani et al., 2017; Kaplan & Haenlein, 2019).

More and more, these systems are used in hospitals, schools, courts, police work, and government offices. They can make it easier to handle and store information. They can also help fit services to each person and share resources more fairly. But as they are used more, people also start to worry. They worry about who is responsible, keeping information safe, and being treated unfairly. People also ask if it is right for machines to make important decisions (Dwivedi et al., 2021; Eubanks, 2018).

Governing these systems becomes hard for two reasons. First, digital systems spread fast across many countries. Second, laws usually only work inside one country's borders. This mismatch causes problems. Big technology systems work all over the world, but the rules that govern them stay local. Different countries have different laws, different abilities to enforce them, and different ideas about how much risk is okay (Bradford, 2020; Smuha, 2021).

The money effects go beyond just making markets run well. They also affect how much people produce and how many people have jobs. They show how companies stay in control and how money and value get shared out. Often, the risk gets pushed onto workers, buyers, and public services instead of staying with big companies (Frey & Osborne, 2017; Acemoglu & Restrepo, 2019; Brynjolfsson & McAfee, 2014).

When big decisions depend on systems that are hard to understand or owned by private companies, it becomes harder to hold anyone responsible. People's trust in these systems may also go down (Giddens, 1990; Zuboff, 2019). Against this backdrop, this study compares

English-language media tone and attention across five jurisdictional blocks. However, it does not treat media tone as an exact measure of citizen opinion. Figure 1 shows the conceptual basis behind for this analysis.

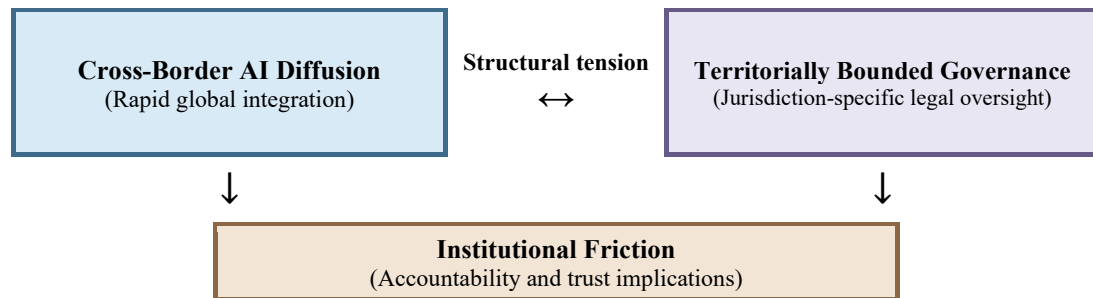


Figure 1. Conceptual framework linking cross-border AI diffusion and territorially bounded governance to institutional friction

1.2 The Convergence of Social Intelligence and Autonomy

Socially responsive AI covers areas such as affective computing, social-signal processing, and context-aware interaction (Picard, 1997). These systems use text, audio, images, or a mix of these inputs. From this input, they try to identify emotions, intent, and the context of a conversation. In this way, they can make interactions between people and machines feel more responsive and persuasive. Even so, their outputs are based on probability, not certainty. The results also depend on the training data, the system design, and the settings in which it is used. These systems are now increasingly used as intermediaries, recommenders, and decision-support tools in sensitive social and technical settings (Rahwan et al., 2019).

Simulated empathy and social understanding can also bring ethical risks. Users may think these systems truly understand them, the way a person would. They may also give these systems more authority than they deserve. But these systems generate responses using statistics, not real moral or social understanding. Because of this, biases in training data and system design can show up in personalised interactions. These unfair patterns can make old inequalities worse. This is especially true when such systems deal with people who are more at risk or affect important decisions about their lives (Bender et al., 2021).

Situation-sensitive and generative AI also make legal duty harder to assign. System creators, operating bodies, organisations that put the technology into use, and affected people might each carry part of this duty. Since results depend on circumstances and probability, it is difficult to explain a specific outcome or assign legal liability. When harm occurs, legal duty is often

spread across several actors instead of one person (Mittelstadt et al., 2016). Figure 2 compares logic-driven AI with socially attuned AI.

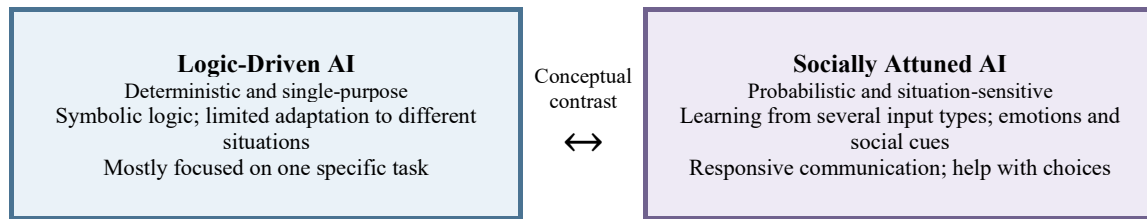


Figure 2. A theory-based view of logic-driven and socially attuned artificial intelligence

1.3 The Global Governance Crisis of Fairness, Bias, and Surveillance

Generative AI rules focus on three key concerns: fairness in automated systems, unclear information, and surveillance. Machine-learning systems trained on past data might repeat unfair treatment from the past or make it worse. This is more likely in criminal justice, lending, employment, and public services (Barocas & Selbst, 2016; O’Neil, 2016).

Low transparency makes supervision more difficult. Complex neural systems often do not clearly show how specific inputs lead to a particular result. This makes it harder for affected people, reviewers, and government agencies to examine or challenge these systems (Burrell, 2016; Pasquale, 2015). Figure 3 shows how unfair patterns in training data, and models that are hard to understand, can cause unfair results and unclear responsibility.

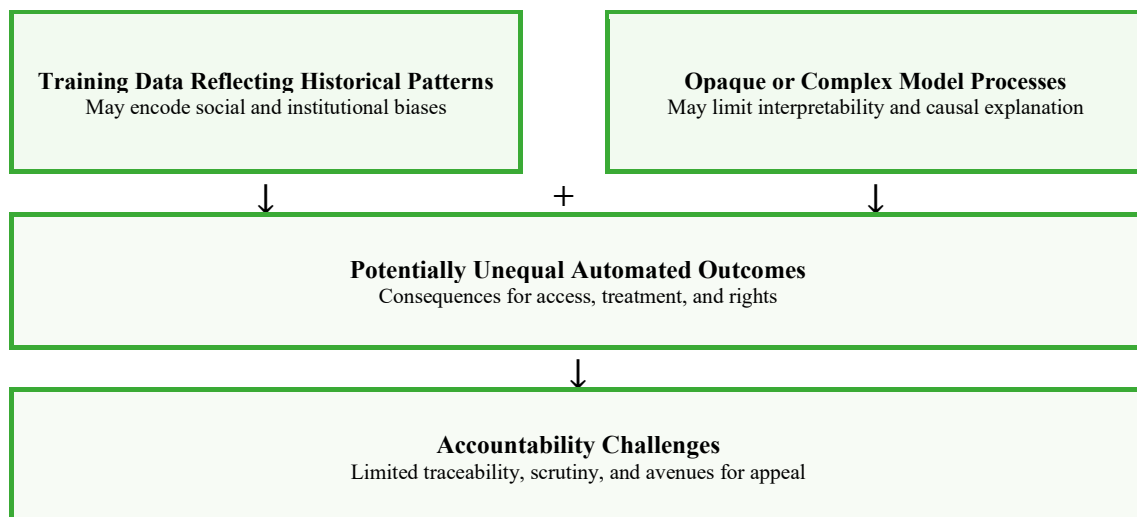


Figure 3. Conceptual pathways linking training-data bias and model opacity to unequal outcomes and accountability challenges

Privacy and surveillance risks differ depending on the system and its context. Socially responsive applications may collect large amounts of behavioural, biometric, conversational, and contextual data. Problems arise when this data is collected without real choice, without

transparency, or without a fair limit on how much is gathered. In such cases, privacy and informed consent may become meaningless (Eubanks, 2018; Zuboff, 2019).

Jurisdictions govern these concerns differently. This is because their laws, political institutions, economic priorities, and cultural views of risk differ (Jobin et al., 2019; Smuha, 2021). This difference raises a question as to whether governance systems are linked to consistent differences in the tone and attention of English-language media reporting?

1.4 Interdisciplinary Positioning of the Study

Explaining these differences needs ideas from several subjects put together. These include data science, digital ethics, the study of institutions and money, media studies, and how different countries make rules (Floridi et al., 2018; Hagendorff, 2020). Looking at the media connects these subjects by showing how trust, risk, and responsibility are talked about. This study sees rules and media discussion as connected to each other. Even so, it does not assume that the tone of the news directly shows how much people trust something, or how well the rules are working (Cath, 2018; Taeihagh, 2021).

The study looks at daily tone scores and article numbers from GDELT DOC 2.0. This data compares chosen English-language news sources with each other. It does not look at each jurisdiction's complete domestic media discussion. This limit is treated as a measurement concern which cannot be overlooked. The study uses statistical tests, event-window analysis, and measurement auditing to assess variation across jurisdictions. Together these methods, keep media indicators separate from broader claims about public opinion (Grimmer & Stewart, 2013; Lazer et al., 2014). Figure 4 shows the analytical framework used in the study.

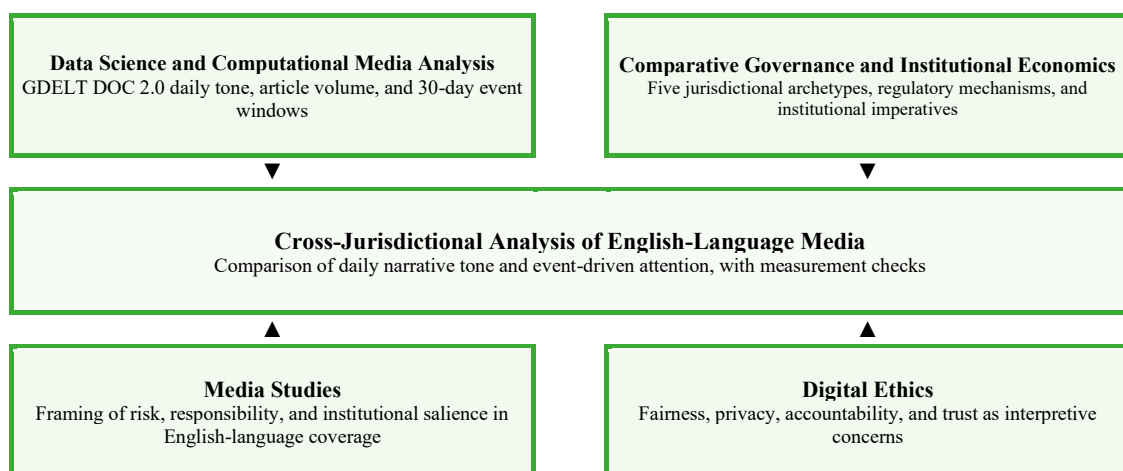


Figure 4. Interdisciplinary analytical framework of the study

1.5 Research Questions and Objectives

This study looks at whether English-language media tone, and the attention given to events related to generative AI, differ across five jurisdictional blocks. It does not determine the causal effect of regulatory systems. It also does not directly measure national public opinion. Two research questions guide the analysis.

RQ1. How much does daily English-language media tone about generative AI differ across the United States, the European Union, the United Kingdom, China, and Singapore?

RQ2. How do a major technological and regulatory milestone relate to the size and post-event patterns of English-language media attention across these jurisdictional blocks?

The study pursues four empirical objectives.

- a. To pull daily tone and article-volume data from GDELT DOC 2.0 covering the period from January 2024 to December 2025. On dates with no coverage, tone is treated as missing while volume is treated as zero. Treat both tone and volume as missing for 17 dates missing from every stream.
- b. Compare five data streams, each representing a different jurisdiction. These are the Market-First United States, Rights-Focused European Union, Sector-Led Hybrid United Kingdom, State-Sovereign China, and Pragmatic Sandbox Singapore.
- c. Measure differences in narrative tone through one-way ANOVA and Tukey HSD comparisons. These are supported by non-parametric tests, unequal-variance tests, weekly aggregation, and Germany-only sensitivity analyses. Media attention is then assessed using 30-day event-window models.
- d. Examine how differences in media coverage affect the measurements. Also examine how coding days with no articles and using a single-language dataset may affect the findings.

The study makes three contributions. The first is about methods, where the study measures and corrects a problem called the empty-day aggregation artefact that pushes sparse data series toward neutrality. It also identifies differences caused by relying on only one language in the corpus. The study also offers a workflow that is transparent and low in cost. The second contribution is theoretical, using institutional trust and technology diffusion as two perspectives to look at differences in media tone and event attention. The third contribution is substantive,

recording a starting point of observed differences across the five selected jurisdictional streams. These findings also support the recommendations on interoperability made in Section 6.

2. Literature Review and Hypothesis Development

2.1 Institutional Trust and Technological Diffusion

This study explains differences across jurisdictions in English-language media responses to generative AI. It does this using two theories. The first is the theory of Institutional Trust (North, 1990; Zucker, 1986). The second is the theory of Technological Diffusion under Regulatory Uncertainty (Rogers, 2003; Hall & Khan, 2003).

Institutional Trust and the Socio-Technical Contract

Institutional confidence refers to the expectation that regulatory bodies and public organizations will enforce rules, protect rights, and manage market hazards (Mayer et al., 1995; North, 1990). Zucker (1986) describes three ways confidence develops. One grows from earlier interactions and reputation. Another develops from shared group identity, ethnic background, or cultural ties. A third develops from established arrangements, protection of rights, and professional qualifications.

Generative AI might reduce confidence in established bodies when deep-learning systems begin handling medical diagnosis, credit approval, or social-benefit administration. This may weaken accountability mechanisms that are already in place (Eubanks, 2018; Mittelstadt et al., 2016).

"Black-box" deep-learning systems are hard to see into. This creates information asymmetry and limits oversight (Burrell, 2016). The way transformer-based systems reach their outputs is often hard to trace. This makes it hard to check whether they meet fairness and non-discrimination standards. Media tone is not treated as public sentiment. Instead, news coverage is looked at as a setting in which risk, responsibility, and institutional legitimacy are framed and given attention (Entman, 1993; McCombs & Shaw, 1972). Figure 5 shows this conceptual pathway.

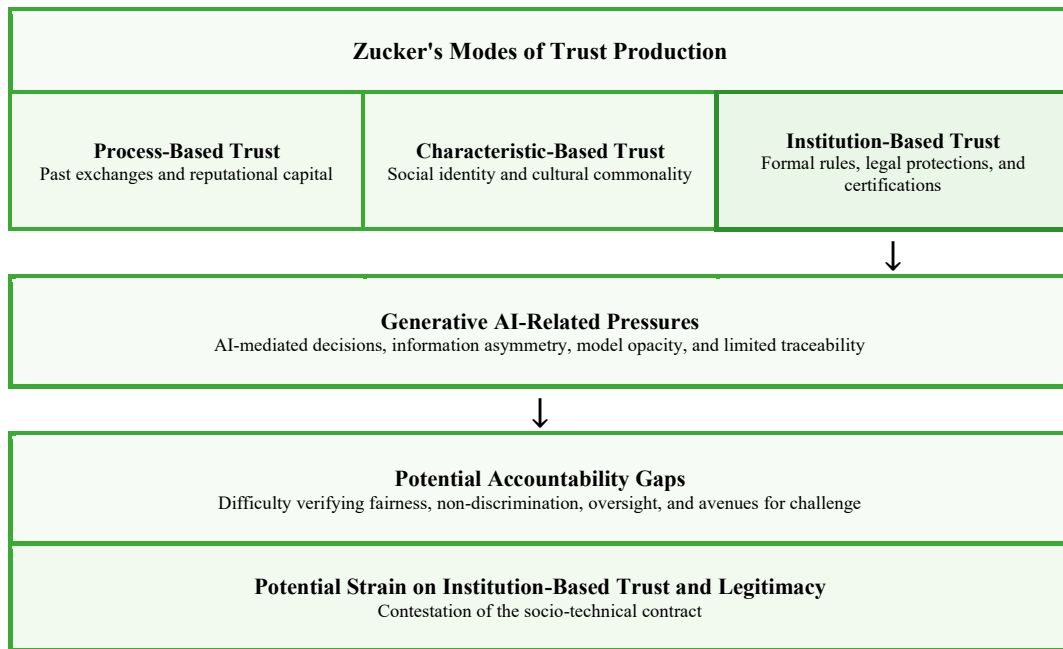


Figure 5. Conceptual pathway linking generative AI to potential strain on institution-based trust

Technological Diffusion under Regulatory Uncertainty

Adoption of a new technology depends partly on the rules that govern it. Rogers (2003) links diffusion of a technology to five factors. These are relative advantage, compatibility, complexity, trialability, and observability. AI can create side effects such as job losses, automated bias, or biometric surveillance. When this happens, adoption may also depend on expected legal duties and the costs of meeting them (Hall & Khan, 2003).

Hall and Khan (2003) show that firms may delay adopting new technology when they are unsure about its costs, its benefits, or how conditions may change in future. Firms may also delay if the rules they expect could ban certain uses or bring high costs for following them.

Very limited regulation can also slow the spread of new technology if weak protections reduce confidence or increase the chance of damage to reputation (Mayer et al., 1995; NIST, 2023). The five chosen countries use different kinds of rules, and their institutions care about different things. Figure 6 and Table 1 show the different types of government control used in the study.

2.2 Five Selected AI Governance Archetypes

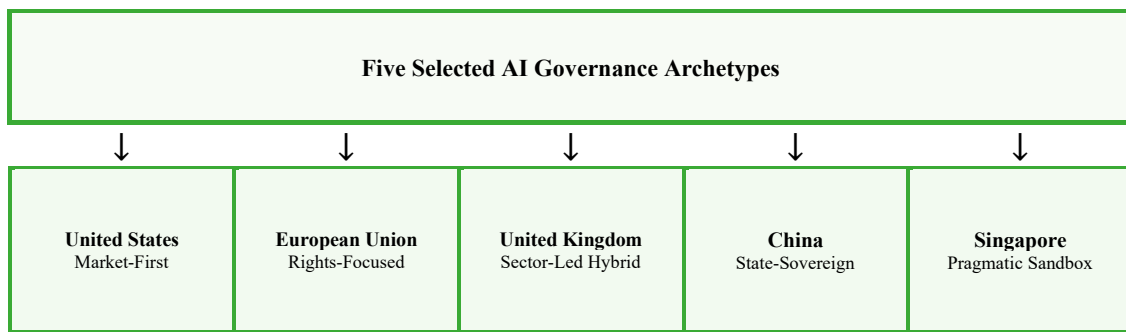


Figure 6. Five selected AI governance archetypes used in the study

The study looks at five governance models. Each one shows a different mix of economic interests, political structures, and ways of defining risk.

1. United States (Market-First)

The US model relies on market liberalism and corporate self-regulation. It rests on sector-specific rules rather than one broad AI law. Digital governance stays divided across fields such as healthcare and finance (Taeihagh, 2021).

The Executive Order on Safe, Secure, and Trustworthy AI set federal rules. It did this through existing executive authority. Meanwhile, the standards developed by NIST remain largely voluntary (NIST, 2023; The White House, 2023).

2. European Union (Rights-Focused)

The European Union uses one broad, rights-based law to govern AI. The EU AI Act sorts AI applications by their level of risk (European Parliament & Council of the European Union, 2024).

- a. Unacceptable risk covers uses that are banned outright, such as social scoring and certain types of biometric classification.
- b. High risk includes uses in critical infrastructure, employment, and law enforcement. These uses need prior assessment, data governance, and human oversight before they are used.
- c. GPAI (General-Purpose AI) includes large language models. These systems must follow rules about being open and clear, called transparency rules.

The EU wants to set a standard for digital safety that spreads to other countries too. It does this through something called the "Brussels Effect." Under this approach, companies follow strict

European rules to keep access to the EU market (Bradford, 2020). The EU model focuses on rights and assesses AI before it is put into use. This approach was expected to lead to more skeptical news coverage in English, with greater focus on possible harm (Veale & Zuiderveen Borgesius, 2021).

3. United Kingdom (Sector-Led Hybrid)

The UK approach lies between the US and EU approaches. It supports innovation and does not depend on one central AI law (DSIT, 2023). It is also less focused on the market than the US. Regulators such as the Competition and Markets Authority and the Financial Conduct Authority apply shared principles within their own sectors.

The UK government describes this approach as suited to different circumstances, flexible, and friendly to innovation. It also cites the Bletchley Park AI Safety Summit as evidence of the UK's coordinating role in international AI-safety discussions (DSIT, 2023; UK Government, 2023).

4. China (State-Sovereign)

China uses a system where the government controls how AI is ruled. This system puts national security, keeping society stable, and following the government's views ahead of letting technology grow freely without limits. Instead of one big law, China makes specific rules for different AI jobs (CAC, 2023; Roberts et al., 2021). These rules include the 2022 Provisions on Administrative Management of Recommendation Algorithms, the 2023 Deep Synthesis Provisions, and the 2023 Interim Measures for the Management of Generative AI Services.

People who build these systems must register their programs with the Cyberspace Administration of China. In some cases, they must also pass a safety check and hand in certain records before the product is released to the public. AI systems that create content must follow government rules too. These rules are about following the government's core values, protecting national security, and keeping society stable (CAC, 2023; Creemers, 2017).

5. Singapore (Pragmatic Sandbox)

Singapore uses a governance model led by experts, not by strict laws. This model relies on rules that companies choose to follow on their own. It aims to help businesses grow through trying new things and working together. At the center of this is the Model AI Governance Framework for Generative AI. It is backed by AI Verify and other tools that test and check AI

systems (AI Verify Foundation & IMDA, 2024). Across all five models studied, DOC 2.0 only measures two things. It looks at the overall tone of the news, and how many articles were published. It does not look at which topics come up most, who owns the news sources, how much the government controls them, or what the public actually thinks.

Table 1. Comparative Governance Matrix of the Five Selected Regulatory Archetypes

Jurisdiction	Core Regulatory Mechanism	Institutional Imperative
United States	Sectoral Fragmentation	Market Dominance & Growth
European Union	Omnibus Risk Tiers (EU AI Act)	Fundamental Human Rights
United Kingdom	Decentralized Sector-Led	Institutional Flexibility
China	Targeted Algorithm Registry	National Security & Harmony
Singapore	Voluntary Sandbox Testing	Enterprise Scalability

2.3 Empirical Gaps in Macro-Comparative AI Literature

Comparative studies usually rely on qualitative analysis. They interpret statutes, white papers, and policy declarations, but this approach has a limit. It cannot measure how strong or how varied regulatory narratives are over time (Jobin et al., 2019).

The five-jurisdictional-block design widens the comparative scope. Most studies stop at comparing the US and the EU, or the US and China. This design goes further and adds the post-Brexit United Kingdom and Singapore. Together, these five blocks cover the Market-First, Rights-Focused, Sector-Led Hybrid, State-Sovereign, and Pragmatic Sandbox models.

2.4 Hypothesis Development

H1. Media tone toward generative AI, based on daily English-language coverage, differs across the five jurisdictions. The European Union is expected to have a lower average tone than the United States and Singapore.

Rationale. Zucker's theory of institution-based trust offers an explanation. The EU's rights-based, ex-ante model is likely to draw more critical, filtered coverage in English-language media. US market incentives and Singapore's pragmatic deployment approach, by contrast, are likely to draw a more positive, opportunity-oriented tone. This expectation rests on the institutional and policy designs set out in the EU and Singapore frameworks. (AI Verify Foundation & IMDA, 2024; European Parliament & Council of the European Union, 2024; Zucker, 1986).

H2. Certain technology and regulatory milestones are followed by a spike in media attention across the five jurisdictional blocks. After each spike, how fast that attention fades depends on the type of governance model in place.

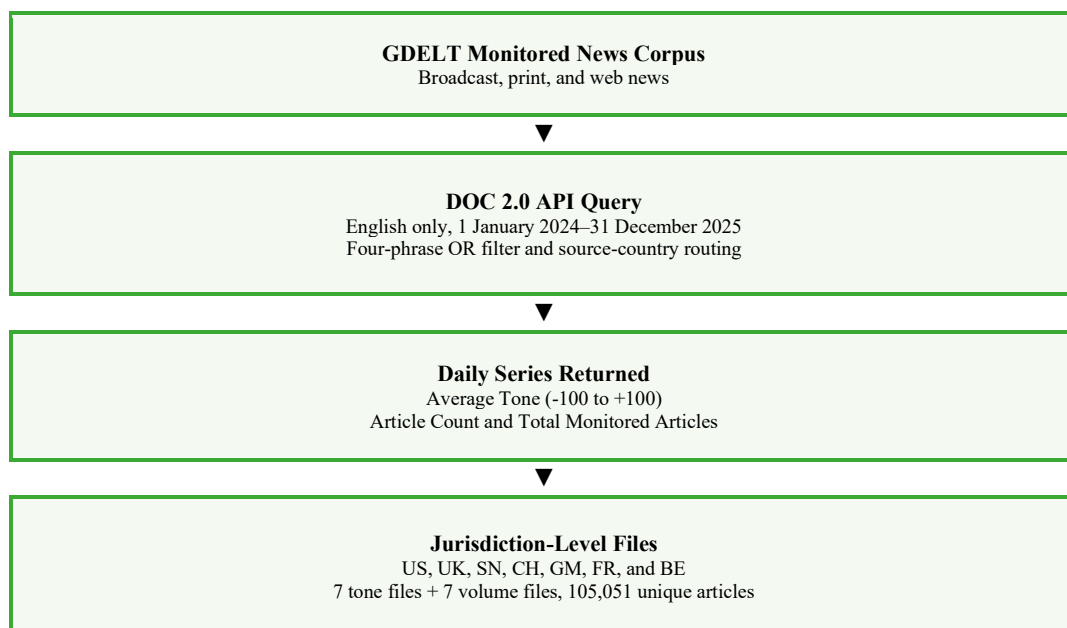
Rationale. Rogers' diffusion model connects media attention to regulatory uncertainty over new rules. Two events are expected to trigger spikes in attention. The first is Google's announcement of Gemini 1.5 Flash and related Gemini 1.5 updates on 14 May 2024. The second is the EU AI Act coming into force on 1 August 2024 (European Commission, 2024; Google, 2024). Jurisdictions driven by market forces should return to their normal attention level faster. More regulated jurisdictions should keep that attention high for longer, as debate over compliance continues. This pattern of a spike followed by a slow fade matches the issue-attention cycle described by Downs (1972). The differences in how fast attention fades across countries come down to how their media systems are built (Hallin & Mancini, 2004).

3. Methods and GDELT Data Architecture

3.1 Data Source Selection and the GDELT Project Ecosystem

This study uses the Global Database of Events, Language, and Tone (GDELT), to build a clear index for comparing media across countries. GDELT tracks broadcast, print, and web news, and pulls structured data from each (GDELT Project, 2017; Leetaru & Schrod, 2013). This study used Route A, which draws on the DOC 2.0 interface, to collect daily tone and article-count data. Figure 7 shows how this Route A collection process worked.

Article-level thematic fields were left out of this study. Two measures, governance-tag co-occurrence and capability-trust, need Route B V2Themes data instead, so they are set aside for later work. This study treats filtered English-language news as an automated data stream (Vargo et al., 2018). That approach fits with other computer-based text research on policy uncertainty, market sentiment, and institutional change (Baker et al., 2016; Hassan et al., 2019).



The codebook maps DOC 2.0 outputs to GKG 2.1 field definitions where applicable. Route A used DOC 2.0 daily-series output; article-level V2Themes were not extracted and remain deferred to Route B.

Figure 7. Executed Route A GDELT DOC 2.0 extraction pipeline

Although GDELT covers news in many languages, this study's search was limited to English (GDELT Project, 2017). This works well for the United States, United Kingdom, and Singapore, where it captures everyday English-language news and discussion within the country. For China and the EU, it may instead capture more of the communication those countries direct outward, toward English-speaking audiences. The data used here is combined at a high level, meaning it involves no direct human-participant data. The recorded search settings allow others to check and repeat the daily-series extraction. They do not allow a re-check of duplicate removal at the level of individual articles.

3.2 Operationalization of Variables

1. *Dependent Variable (Narrative Tone)*

Narrative tone is a score GDELT works out in for each article, based on how many positive and negative words it contains. The score runs from -100 to $+100$, with 0 meaning neutral. Most news falls in a much narrower band than that, usually between -10 and $+10$ (GDELT Project, 2015, 2017).

For H1, this study uses the daily Average Tone score that GDELT already works out for each jurisdiction-day with activity. This produces an unbalanced panel which is then used to compare English-language media tone across the different jurisdictions (GDELT Project, 2017; Leetaru & Schrodtt, 2013).

2. Independent Variable (Source Geography)

The independent variable is the operational base of the publishing outlet. GDELT records this through source-country routing codes (GDELT Project, 2017). Using these codes, records are sorted into five jurisdictional streams. These are the United States (US), the United Kingdom (UK), Singapore (SN), China (CH) and the European Union (EU) which combines Germany (GM), France (FR), and Belgium (BE).

3. Contextual Variable (Media Attention Volume)

Media attention volume means the number of different articles each day that match certain chosen words, called keyword filters, in each country. This number stands in for how much attention an issue is getting, not for what the public thinks or how urgent it feels. In H2, one part of the study, this number is used to track sudden jumps in attention around big events, and how that attention changes afterward. (McCombs & Shaw, 1972; Rogers, 2003).

4. Index Variable (Date)

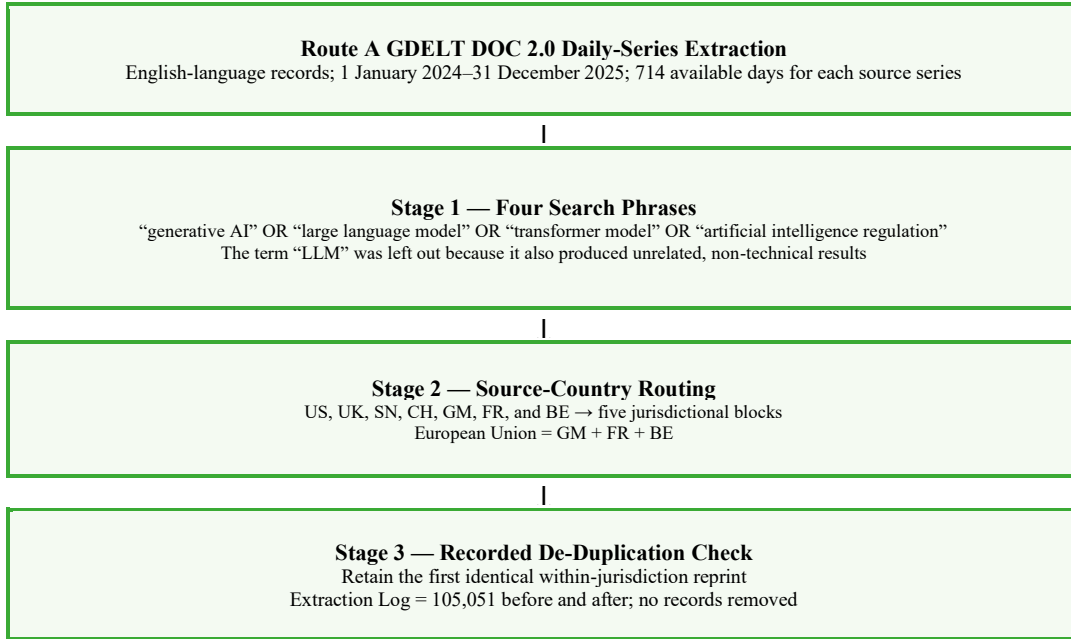
Date comes from a part of GDELT called the DATE field, shortened to show just the day. The study covers 1 January 2024 through 31 December 2025.

5. Constructed Variable (Event Window)

The event period covers 30 days after each event, starting on day 0. Section 3.4 uses this period in the model that tracks counts after each event.

3.3 Sampling Design and Data Filtration

H2 includes two events identified before the analysis began: Google's announcement of Gemini 1.5 Flash and related Gemini 1.5 updates on 14 May 2024, and the EU AI Act taking effect on 1 August 2024 (European Commission, 2024; Google, 2024). Figure 8 shows the screening steps.



The retained daily-series CSVs contain 714 returned dates per source stream. The same 17 calendar dates from 15 June to 1 July 2025 are absent across all seven streams. Article-level text and duplicate flags are not retained, so the recorded de-duplication step cannot be independently re-audited from these aggregate files.

Figure 8. Executed Route A data filtration protocol

Thematic extraction. The exact English-language search filter used the terms generative AI, large language model, transformer model, and artificial intelligence governance, joined by the word OR. The plain acronym LLM was left out on its own, since it pulled in unrelated results that had nothing to do with the topic. Stating the filter this way lets others check and repeat how the set of articles was chosen (boyd & Crawford, 2012; Grimmer & Stewart, 2013).

Geographic routing. Records were sorted by source-country codes into the five jurisdictional streams.

De-duplication. When a wire report appeared in more than one outlet within a setting, only the earliest copy was used, following common duplicate-removal practice (Grimmer & Stewart, 2013). The collection record contained 105,051 records at both stages, so nothing was removed. Since record-level text and duplicate markers were not saved, this step cannot be repeated separately using only the day-level series files.

3.4 Statistical Model Specification

Analysis of Variance (ANOVA)

A one-way ANOVA tests H1 by comparing the average tone across the five settings.

$$Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$$

where

Y_{ij} represents the average narrative tone on day j in setting i when news coverage is present

μ represents the overall average across all setting-days with news coverage

α_i represents the effect linked to setting i , where i refers to the US, EU, UK, China, or Singapore

ε_{ij} represents the unexplained part. Standard ANOVA assumes these values follow a normal distribution and have equal spread across groups

Each group contains 470 to 713 days with news coverage, which is enough for approximate normality. Standard ANOVA is not ideal here because the groups have different variances and nearby days are related over time (Field, 2018). Tukey HSD compares two groups while controlling the overall chance of Type I error (Tukey, 1949). Section 3.5 also uses the Alexander-Govern test, Kruskal-Wallis test, weekly aggregation, and a Germany-only EU analysis.

Event-Window Model

The event study compares news coverage near Events A and B. Each relative spike is calculated from the reported pre-event baseline and the highest article count in the 30 days after it. The saved analysis files do not specify the baseline window or preserve the unrounded baseline numbers behind the reported percentages. So, the spike values are treated as reported descriptive results, rather than independently reconstructed estimates.

A 30-day post-event exponential form is reported as $V_t = V_0 e^{(-\lambda t)}$. Here V_t is volume at fitted day t , V_0 is the reported peak event-window volume, and λ is the decay constant. Ten jurisdiction-event series cover the five jurisdictional blocks across two events. Model adequacy is checked using λ and R^2 . The saved files do not record whether $t = 0$ was the chosen event date or the actually observed peak date. Some returned dates show zero-volume, because they are observed dates with no matching articles. Seventeen dates are missing from all source-country streams, and are treated as missing, not as zero.

3.5 Reliability, Validity, and Sensitivity Checks

The DOC 2.0 output uses a standardized Average Tone measure, built on the GDELT tone framework (GDELT Project, 2015, 2017; Leetaru & Schrod, 2013). Automated tone measures

are common in media and economic research. Their interpretation depends on corpus selection and measurement design (Gentzkow et al., 2019; Tetlock, 2007). The analysis uses the daily series returned by the stated search, not a census of all media. So, coverage and filtration bias remains and is documented in the replication protocol (Lazer et al., 2014). The extraction process includes removing identical syndicated reprints, subject to the aggregate-file limitation noted in Section 3.3.

No-coverage days are treated differently by variable. DOC 2.0 records tone as 0 when no article matches, even though tone is undefined (GDELT Project, 2017). H1 treats these days as missing (Little & Rubin, 2019), since including them shifts sparse jurisdiction means toward zero. Singapore's average score would drop from +2.09 to +1.38. Germany's average score would drop from +3.43 to +2.24. For volume and H2, zero is valid and retained on returned dates. The 17 dates absent from every raw stream stay missing.

Unequal variances across groups are checked using the Alexander–Govern test (Alexander & Govern, 1994) and the Kruskal–Wallis test (Kruskal & Wallis, 1952). Weekly aggregation addresses daily serial dependence meaning values close together in time tend to be related. Lag-one autocorrelation reaches .29 in the U.S. daily but falls below .05 in four of five jurisdictions weekly. EU composition is tested by replacing the three-country block with Germany alone. Interpretation favors effect sizes and confidence intervals over p values alone (Cohen, 1988; Field, 2018).

4. Empirical Results

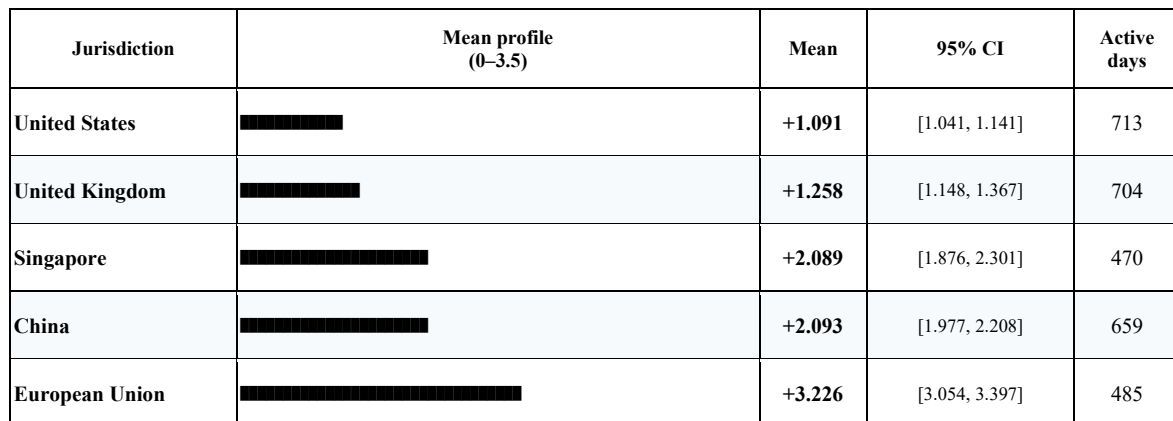
4.1 Narrative Tone Across Jurisdictions (Testing H1)

The 24-month extraction produced 714 returned dates per source-country stream and 105,051 unique English-language articles. The same 17 calendar dates from 15 June to 1 July 2025 are absent across all seven raw streams. Because tone is undefined on no-coverage days, H1 uses 3,031 active jurisdiction-days instead. This gives an unequal number of records for each country, called an unbalanced panel. There are 713 records for the U.S., 704 for the U.K., 659 for China, 485 for the EU, and 470 for Singapore. DOC 2.0 shows tone as zero when no article matches, but these zeros mean there was no coverage, not that the reporting was neutral. For H1, one part of the study, days with no coverage are treated as missing data. Table 2 shows the basic statistics. Figure 9 shows the order of average tone scores, along with a range showing how sure we can be about them.

Table 2. *Descriptive Statistics for Daily Narrative Tone by Jurisdiction (Active Jurisdiction-Days)*

Jurisdiction	Active Days (<i>N</i>)	Mean Tone (μ)	Standard Deviation (σ)	95% Confidence Interval
United States (US)	713	+1.091	0.678	[+1.041, +1.141]
European Union (EU)	485	+3.226	1.927	[+3.054, +3.397]
United Kingdom (UK)	704	+1.258	1.482	[+1.148, +1.367]
China (CH)	659	+2.093	1.514	[+1.977, +2.208]
Singapore (SN)	470	+2.089	2.351	[+1.876, +2.301]

The one-way ANOVA showed clear differences in day-level narrative tone across settings, $F(4, 3,026) = 159.7$, $p < .001$, $\eta^2 = 0.174$. Differences between settings accounted for about 17% of the variance, which is considered substantial under standard thresholds (Cohen, 1988). The Kruskal-Wallis test returned $H(4) = 659.6$, $p < .001$, and the Alexander-Govern test for unequal variance returned $A = 612.5$, $p < .001$. Weekly means reduced lag-one autocorrelation below .05 in four settings and produced $F(4, 510) = 119.1$, $p < .001$, $\eta^2 = 0.483$. A Germany-only EU model preserved the ordering, $F(4, 3,008) = 186.2$, $p < .001$, $\eta^2 = 0.198$.

**Figure 9.** *Average Narrative Tone by Setting, with 95% Confidence Intervals and Number of Coverage Days*

Tukey HSD gave an order different from H1's expectation. The EU had the most positive mean tone ($\mu = +3.23$) and differed from all other settings ($p < .001$). China and Singapore were in the middle, with no clear statistical difference between them (both $\mu = +2.09$; $p = 1.00$). Both had more positive tone than the U.K. and U.S. (all $p < .001$). The U.K. ($\mu = +1.26$) and U.S. ($\mu = +1.09$) also showed no clear statistical difference ($p = .29$). The EU and China had more positive mean tones, while the U.K. and U.S., which had the largest English-language news sets, had less positive tones. H1 was supported for differences across settings, but its expected order was not supported.

4.2 Media Attention Around Selected Events (Testing H2)

To assess H2, news coverage was tracked near two events identified before the analysis began. Figure 10 shows the complete time series and marks both event days.

Technology milestone A: Google announced Gemini 1.5 Flash and associated Gemini 1.5 updates on 14-05-2024 (Google, 2024).

Event B (a Rule-Related Event): the EU AI Act became law on 1 August 2024 (European Commission, 2024).

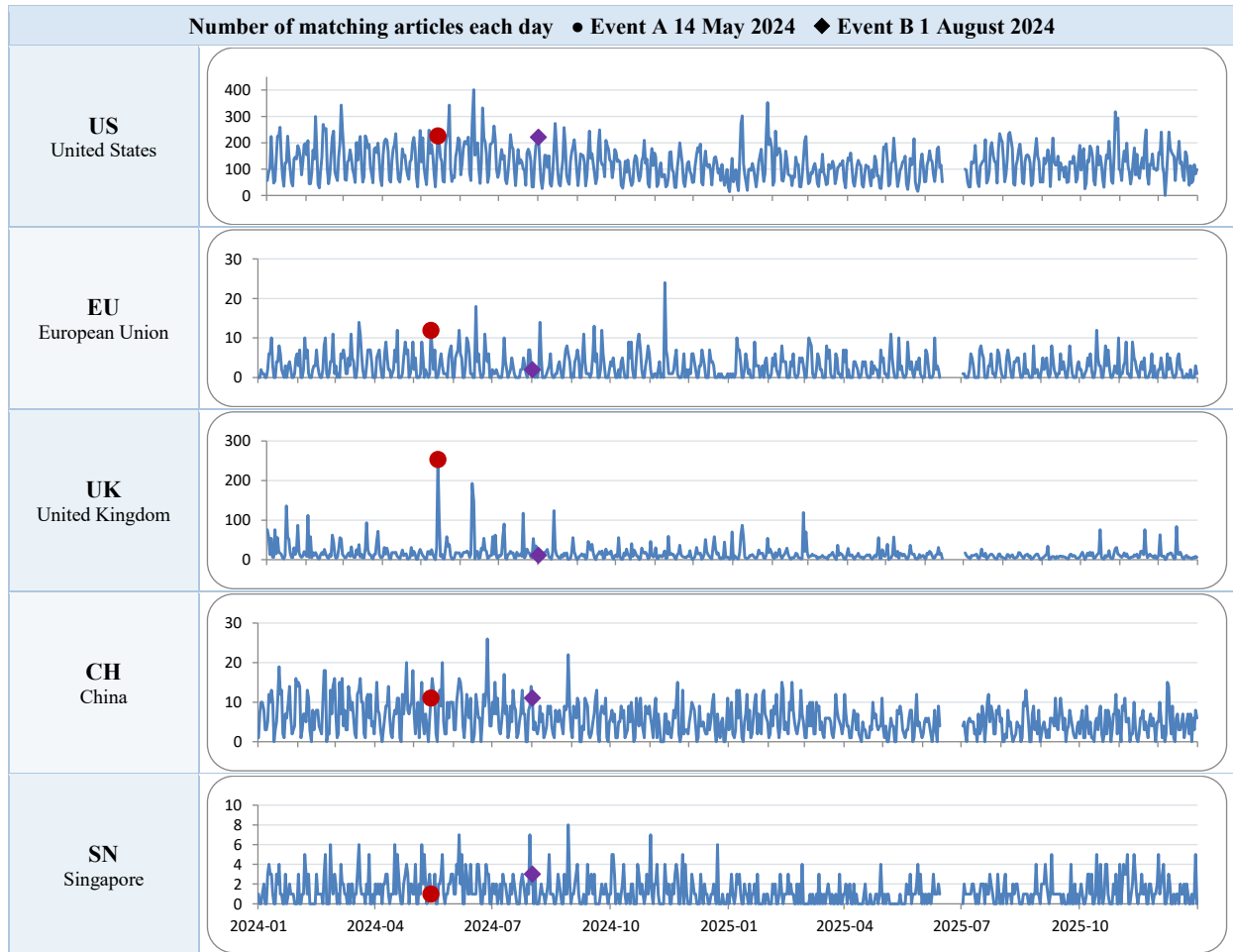


Figure 10. Number of matching articles each day by country, 1 January 2024–31 December 2025

The biggest jump around Event A happened in the U.K. The number of articles rose from a normal average of 12.0 per day to 253 on the day of the event, an increase of +2,014%. It then dropped back down to 8 within 48 hours. The saved analysis reports this using a 30-day exponential form, matching the expected rise-and-decay attention cycle around an event (Downs, 1972).

$$V_t = V_0 \cdot e^{-\lambda t}$$

where

- V_t is the volume at fitted day t .
- V_0 is the reported peak event-window volume.
- λ represents the decay constant.

None of the ten jurisdiction-event series showed exponential decay. Five rows reported small positive λ estimates from .001 to .019 with R^2 from .00 to .08. The other five rows had no recorded value at all. the verdict was the same, no real decay was found.

How much attention each event drew varied by jurisdiction. The regulatory-event spike exceeded the technological-event spike in the EU (+509% versus +264%) and Singapore (+458% versus +282%). The technological-event spike was larger in the U.K. (+2,014% versus +454%) and U.S. (+207% versus +102%). China showed similar spikes for both (+159% versus +168%). H2 is only partially supported only as a descriptive pattern of relative salience. The predictions of exponential decay and differential decay are both rejected.

4.3 Possible Explanations for the Inversion

Table 2 contradicts a simple prediction based on regulatory stringency alone. Three mechanisms based on how national media pick and frame are examined (Galtung & Ruge, 1965; Hallin & Mancini, 2004). The design permits only partial tests.

Coverage density. Mean tone was inversely related to log of article volume across jurisdictions (Pearson $r = -.75$). But with only five cases, it did not reach statistical significance ($p = .15$). If sparse coverage caused more positive tone, then within each jurisdiction, daily volume and tone should move in opposite directions too. Spearman correlations were -0.01 for the EU, $+0.01$ for the U.K., $+0.06$ for the U.S., $+0.08$ for Singapore, and $+0.12$ for China. The EU showed a small negative relationship, while the other settings did not follow the expected relation. Differences in the amount of coverage do not account for this ordering.

Audience orientation. Media from places where English is not the main language might rely more on international outlets and official sources. Media from English-speaking places might better reflect domestic discussion. The EU and China had a more positive average tone ($\mu = +2.57$) than the U.S., U.K., and Singapore ($\mu = +1.40$), Welch $t = -18.20$, $p < .001$, Cohen $d = 0.69$ (Welch, 1947). Singapore is different because English is widely used there, yet its mean tone ($\mu = +2.09$) is closer to China's than to the U.S. and U.K. Media framing might also be

linked to this result (Entman, 1993), but the data do not separate its influence from audience orientation.

Outlet composition. The share of English-language news from wire services, trade publications, and state-linked outlets might differ across settings. Studying this requires outlet-level information, which is not available in the saved DOC 2.0 files. A fuller assessment would require record-level extraction described in the replication procedure.

Coverage density is rejected as an explanation. Audience orientation remains plausible, but it cannot be isolated from other factors. Outlet composition remains untested altogether. Across five jurisdictions, regulatory regime, language, audience, and the size of the source data remain tangled together.

5. Discussion of the Five Governance Archetypes

5.1 Interpreting Empirical Divergence through Institutional Economics

This study draws on institutional economics and technology diffusion (North, 1990; Hall & Khan, 2003). It uses 24-months GDELT data to compare English-language media tone and attention across five governance types. It covers 3,031 active jurisdiction-days from 105,051 unique articles. Jurisdiction accounts for 17.4% of daily tone variance, $F(4, 3,026) = 159.7$, $p < .001$, $\eta^2 = .174$. But this is an association, not a cause.

The result reverses the predicted stringency order. Mean tone was higher in the EU ($\mu = +3.23$) and China ($\mu = +2.09$) than in the U.K. ($\mu = +1.26$) and U.S. ($\mu = +1.09$). Zucker's (1986) work on how trust is built suggests that corpus function may matter more than stringency alone. Hard-law and state-run systems may present governance projects favourably to international audiences (Bradford, 2020; Creemers, 2017). While outward-facing communication can serve a country's wider influence (Nye, 2004). The English-only corpus may under-sample local-language EU AI Act debate. Even so the design cannot separate audience, outlet type, or other factors. Germany supplies 1,815 of the 1,964 articles in the EU block, though the Germany-only test kept the same ordering.

Cross-national English-language media indices do not uniformly measure national public sentiment. They are more likely to capture domestic discussion in English-speaking jurisdictions and outward-facing communication elsewhere. The Welch test result fits this

pattern. But Singapore, along with the overlap between language, source size, and regulatory regime rules out causal attribution.

The U.S. and U.K. provide the two largest news-item sets, at 86,837 and 11,211, with no statistically detectable difference in mean tone ($p = .29$). Debate in these countries might include investor enthusiasm and labour anxiety (Tetlock, 2007; Acemoglu & Restrepo, 2019), although those topics were not separately coded. Different regulatory models are associated with similar aggregate tone in these two settings, but the analysis does not reveal how institutional confidence forms. The Tukey mean difference between the EU and U.S. was +2.134 (adjusted $p < .001$). Figure 11 compares their regulatory approaches and English-language media results.

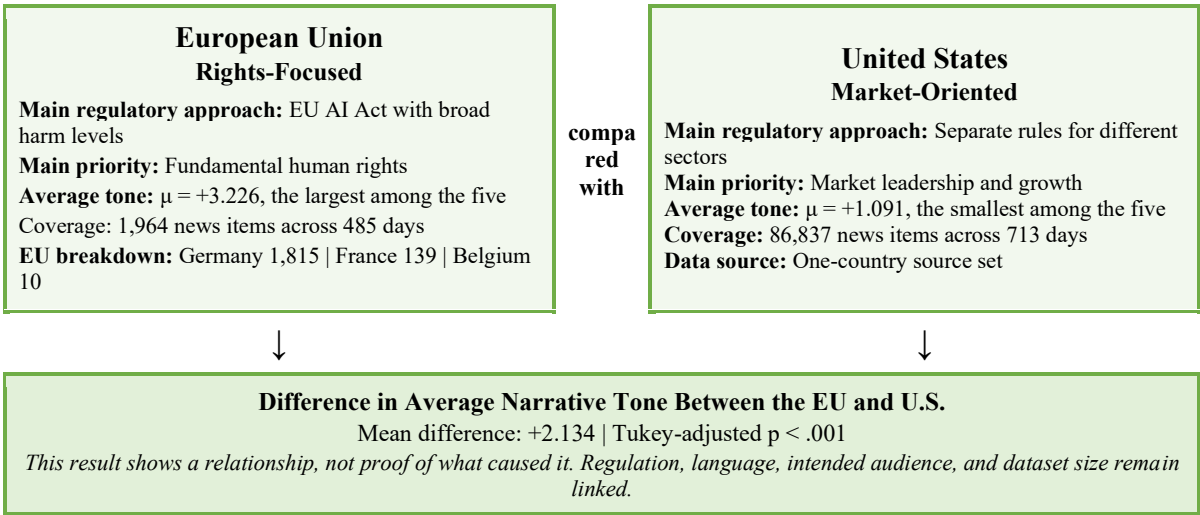


Figure 11. EU and U.S. AI Rules and English-Language Media Results

5.2 The Empirical Profile of the Pragmatic Sandbox Model

Singapore has the fewest English-language news items, with 927 items across 470 days of coverage. Its average tone is very close to China's ($\mu = +2.09$; $p = 1.00$), with no clear statistical difference. The regulation-related event led to a +458% rise in news items, compared with +282% for the technology-related event. Singapore and the EU were the only two settings where the regulation-related event produced the larger rise. Since English is widely used within Singapore, audience orientation alone does not fully account for this outcome. These figures refer only to the amount of attention and do not show tone during the event period or prove that one factor caused another.

Singapore's Pragmatic Sandbox model relies on tools that companies choose to use for testing, like AI Verify, along with controlled trying out of new ideas, instead of one strict law (AI

Verify Foundation & IMDA, 2024; Taeihagh, 2021). This setup may be connected to how Singapore reacted to events and its positive average tone. But this study did not test that connection as a cause, or prove that this way works better, works well, or would work the same in other places.

5.3 The English-Language Profile of the State-Sovereign Model

China's stream of English-language news in this study has 4,112 articles, with an average tone of +2.09 ($\sigma = 1.51$, a measure of how spread out the scores are). Its jumps in attention for both the technology event and the rule-related event, at +159% and +168%, were the closest match in the whole study. This shows both events got similarly high attention, not that the coverage was carefully controlled. The news stream may include messages aimed at people in other countries, but since this study only looked at English, it cannot tell exactly who the audience was meant to be.

China's system requires companies to register their AI programs and follow government rules and core values (CAC, 2023; Creemers, 2017; Roberts et al., 2021). This State-Sovereign model links tech rules closely to government power and the country's key systems. But this study does not show that these rules actually caused the tone, the way people reacted to events, or the differences seen. Any ideas about how they communicate, limits on new ideas, or how people feel remain guesses, not proven facts.

5.4 The Sector-Led Hybrid Profile in the United Kingdom

The U.K. ($\mu = +1.26$; $\sigma = 1.48$) lies between the EU's all-in-one framework and the U.S.' scattered, sector-by-sector approach. After leaving the EU, the U.K. decided not to make one big law for AI. Instead, it uses the regulators that already look after different areas, like the CMA and FCA (DSIT, 2023).

The U.K. has the second-largest set of articles, at 11,211. It had the biggest jump in attention around the tech event, at +2,014%, compared with +454% around the rule event. This shows how much attention depends on certain events, not on how well the rules actually work. Its average tone is almost the same as the U.S. ($p = .29$), even though the two countries have different rule systems. So, the overall tone does not directly match a country's laws. The Bletchley Park AI Safety Summit gives some background on the U.K.'s role in bringing countries together (UK Government, 2023). But this data does not check its effect on costs or public trust.

5.5 Theoretical Synthesis

Some parts of the theory the study was based on were supported by the findings, but other parts were not. H1 confirms that media tone does vary by jurisdiction, which fits North's (1990) account of institutional variation. But it rejects the predicted ordering. The positive tone seen in the EU and China may reflect external self-presentation, audience orientation, outlet composition, or other unmeasured factors. The descriptive H2 spike pattern is only partly consistent with Rogers' (2003) diffusion logic. The regulatory-event spike was larger in the EU and Singapore. The technological-event spike was larger in the U.K. and U.S. China showed roughly similar spikes for both. None of the ten jurisdiction-event series supported exponential decay pattern the model predicted. Zucker's (1986) institution-based trust framework still holds value, but media tone does not directly measure trust or any deliberate signalling of trust. The conclusions drawn remain interpretive rather than causal.

6. Conclusion, Policy Implications & Limitations

6.1 Key Empirical Contributions

This study analyses 3,031 active jurisdiction-day observations, drawn from 105,051 unique English-language articles published between January 2024 and December 2025. It uses pre-calculated daily tone and volume series calculated by GDELT DOC 2.0, with codebook links to GKG 2.1 where applicable. It provides a transparent comparative workflow for daily-series extraction and H1 analysis. It also shows how building of corpus, and handling of empty days can bias cross-national media indices (GDELT Project, 2015, 2017; Lazer et al., 2014; boyd & Crawford, 2012). The H2 baseline and decay-time settings remain only partly documented in the saved analysis files.

The study compares five selected governance types. These are the U.S. (Market-First), EU (Rights-Focused), U.K. (Sector-Led Hybrid), China (State-Sovereign), and Singapore (Pragmatic Sandbox).

Daily tone differed across jurisdictions, $F(4, 3,026) = 159.7$, $p < .001$, $\eta^2 = .174$. But the order this produced ran opposite to what regulatory strictness alone would predict. From highest to lowest average tone, EU (+3.23) > China (+2.09) $\approx$ Singapore (+2.09) > U.K. (+1.26) $\approx$ U.S. (+1.09). For attention spikes, the regulatory event drew a bigger response than the technological event in the EU and Singapore. While it was the other way round for U.K. and U.S., China showed roughly similar spikes for both events. None of the ten jurisdiction-event

series matched the exponential decay. Coverage density did not explain the tone ordering across jurisdictions. Audience orientation fit the pattern, but it could not be isolated, and outlet composition remained untested. Two things stand out from this. Empty days cannot be treated as neutral tone, and single-language corpora may represent different audiences across jurisdictions. Ignoring either feature can distort comparisons. Figure 12 presents the institutional priorities assigned in Table 1 to the five selected archetypes.

United States — Market-First	→	Market dominance & growth
European Union — Rights-Focused	→	Fundamental human rights
United Kingdom — Sector-Led Hybrid	→	Institutional flexibility
China — State-Sovereign	→	National security & harmony
Singapore — Pragmatic Sandbox	→	Enterprise scalability

Figure 12. Institutional imperatives across the five selected governance archetypes

Note. These are analytical classifications from Table 1, not outcomes measured by the GDELT analysis. The European Union block uses Germany, France, and Belgium source-country streams.

6.2 Actionable Policy Frameworks for International Governance

The findings do not show that one governance model is better than the others. They also do not show that a single set of rules for the whole world would fail to work. Any comparison between countries needs to think about their laws, language, how their media works, and how the study measured things. Working well together across countries, clear ways to check results, and testing across borders may help countries work together. But this does not mean conditions are the same in every country.

Equivalency mechanisms. Agreements between countries could let proof from Singapore's AI Verify or the US NIST framework count toward specific EU AI Act checks. A tool that already matches up NIST and AI Verify shows that connecting different countries' rules is possible. But treating them as exactly the same under the law would need extra checking to prove it works (NIST AI Resource Center, 2023; Smuha, 2021).

Common technical audit metrics. Shared definitions and criteria for algorithmic fairness, privacy protection, and explainable AI (XAI) could support comparisons across legal systems.

This recommendation follows from the study's measurement findings but was not tested (Floridi et al., 2018; Mittelstadt et al., 2016).

6.3 Measurement and Design Limitations and Future Research Directions

Language constraint. The English-only DOC 2.0 search may not fully represent domestic-language discussion in China and EU member states. This fits with the idea of an imbalance in audience orientation, but the design cannot separate language, audience, framing, and outlet composition from one another. English-language coverage from non-English-speaking jurisdictions may lean more toward audiences abroad.

Macro-level aggregation. GDELT's daily tone and volume figures describe aggregated English-language media coverage. They do not describe citizen opinion, institutional trust, or the differences between outlet types within a country.

Event-window specification and attribution. Each relative spike uses the highest article count found within 30 days after each milestone. The retained analysis files do not specify the pre-event baseline window, preserve the unrounded baselines used for the reported percentages, or document whether the exponential fit was measured from the event date or re-indexed from the observed peak. Peaks may also reflect other news within that window. So the spike comparisons are descriptive only and cannot be attributed causally to the selected events.

Temporal completeness. Each retained source stream contains 714 of the 731 calendar dates within the study period. The same 17 dates, from 15 June to 1 July 2025, are missing from every stream and are treated as missing rather than zero. This common gap does not overlap the two 2024 event windows. But it means we cannot say for sure that every single day was fully covered.

Uneven collection and grouping of articles. The number of articles varies a lot, from 86,837 in the United States to just 927 in Singapore. The EU group itself combines Germany, France, and Belgium unevenly. Germany provides 1,815 of the 1,964 articles, collected over 467 active days. France provides 139 articles over 104 days, and Belgium provides 10 articles over 10 days. So the EU's result mostly reflects English-language coverage from Germany. Replacing the block with Germany alone retains the ANOVA result and ordering, $F(4, 3,008) = 186.2$, $p < .001$, $\eta^2 = .198$. But this does not broaden representativeness. The EU finding remains the least generalisable result pending a wider panel of member states.

Future research should combine daily GDELT indices with article-level analysis across multiple languages, along with broader coverage of EU. Ireland could help separate the effect of language from regulatory regime. Adding more member states would reduce dependence on German output. Article-level data could further test outlet composition, and the Route B propositions on governance-tag co-occurrence and the link between capability and trust using GKG V2Themes data (GDELT Project, 2015). Qualitative coding and cross-national surveys could look into what drives these media patterns. Also, whether media tone actually relates to citizen-level trust.

Five constraints bound the findings. First, the raw daily series leave out the same 17 dates across all source streams. Second, the event-window baseline and the starting time for decay time are not fully documented, and a 30-day peak may reflect other news. Third, the EU figure is largely German. The sensitivity analysis confirms the ordering of results but not representativeness. Fourth, the tone-inversion mechanism cannot be identified, since regulatory regime, publication language, audience orientation, and corpus size remain partly tangled together. Fifth, the exponential-decay part of H2 is disproven across all ten jurisdiction-event series, although relative attention still shows a pattern. Attention to the regulation-related event was greater in the EU and Singapore, while attention to the technology-related event was greater in the U.K. and U.S. China showed very similar increases for both events. These limitations identify areas that later research should examine.

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