Title

Code of Justice:
A Sector-Specific Quantitative Analysis of Regulatory Gaps in the U.S. Federal Courts for AI Governance

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Executive Summary

The rapid expansion of artificial intelligence (AI) across major U.S. sectors—including healthcare, finance, and technology—has outpaced the ability of existing legal frameworks to provide clear, consistent regulatory guidance. The U.S. regulatory environment for AI remains highly fragmented, shaped by a patchwork of federal agency guidelines, state laws, and judicial interpretation rather than a unified policy framework. This has led to sector-specific gaps and inconsistencies, especially as courts increasingly address novel legal questions arising from AI deployment. This paper introduces a quantitative, data-driven methodology to systematically identify and measure regulatory gaps in AI governance by analyzing U.S. federal court opinions from 2010 to 2025. Using the Free Law Project's CourtListener API and natural language processing, we assembled a comprehensive dataset of judicial opinions relevant to AI. Legal citations, sectoral, and temporal metadata were extracted from each opinion.

To capture regulatory ambiguity, we introduce the Regulatory Gap Index (RGI), which synthesizes citation density, citation diversity, lexical complexity, and hedging frequency. The Regulatory Gap Percentage (RGP) quantifies the share of cases in a sector that exhibit systemic indicators of regulatory strain or failure. High regulatory failure cases are identified through a composite of structural signals, including low citation grounding, high RGI, and unresolved judicial outcomes. The RGP reflects the proportion of such cases within a sector, enabling comparative measurement of regulatory adequacy and strain across sectors, courts, and years. To further investigate determinants and consequences of regulatory ambiguity, causal inference models are applied to analyze how citations, court circuit, and judgment outcome relate to regulatory failure, and to estimate the effect of regulatory strain on plaintiff success and case resolution.

By leveraging quantitative analysis to bridge technological innovation, legal interpretation, and policy formulation, this study offers actionable, data-driven insights for policymakers, legal scholars, and AI developers. The findings underscore the need for sector-specific, evidence-based approaches to AI governance and highlight the importance of consistent, transparent metrics in guiding judicial decision-making. Ultimately, this research provides a replicable, empirically grounded foundation for developing more effective regulatory strategies and contributes a robust framework for future research and policy development in AI governance.

1. Introduction

This study investigates the structure and evolution of regulatory gaps in AI-related federal litigation by testing five central hypotheses: 1) **Sectoral Ambiguity Hypothesis (H1):** Regulatory ambiguity—measured by the Regulatory Gap Index (RGI) and Regulatory Gap Percentage (RGP) will vary systematically across industry sectors, with certain sectors exhibiting higher opacity than others.

2) **Citation-Grounding Hypothesis (H2):** Robust citation practices (dense, diverse references) ground even the most complex legal language, thereby reducing interpretive uncertainty and producing clearer, less ambiguous judicial opinions. This conceptual shift reflects our mediation analysis framing of citations as the primary driver of ambiguity reduction. 3) **Adjudication Impediment Hypothesis (H3):** Greater regulatory ambiguity (higher RGI) causally reduces the likelihood that a case is resolved, as estimated via inverse probability weighting (IPW). 4) **Institutional-Drivers Hypothesis (H4):** Cross-sector patterns of regulatory failure are driven more by institutional factors—such as courts' deference norms and adjudicative cultures—than by the inherent textual opacity of opinions alone. This adjustment highlights our descriptive analysis linking RGP to sectoral deference rates and institutional contrasts. 5) **Court Identity Hypothesis (H5):** Court-level differences in RGI reflect institutional variance in judicial reasoning, so that some venues consistently produce ambiguous AI-related opinions regardless of sector.

2. Literature Review

2.1 Regulatory Lag and AI Governance

The concept of regulatory lag, or the "pacing problem," describes the persistent temporal disconnect between rapidly advancing technologies and the slower evolution of legal and ethical oversight (Marchant et al., 2011). In artificial intelligence, this lag is intensified by swift innovation cycles, where new machine-learning models and generative systems emerge faster than statutes or agency rules can adapt (Calo, 2017). Courts increasingly serve as de facto regulators, interpreting legacy statutes in the context of novel AI applications—a process that often yields inconsistencies across sectors (Wright & Schultz, 2021).
Recent scholarship systematically reviews regulatory debates and frameworks for AI, highlighting the complexity and prematurity of the field and the lack of clarity in defining adequate regulatory responsibility and policy instruments. Comparative analysis underscores the diversity of global approaches: the EU AI Act and the OECD's AI Principles exemplify harmonized, risk-based frameworks, while the U.S. continues to rely on a mosaic of agency guidelines, state laws, and judicial interpretations. The literature also explores theories such as public interest and precautionary approaches, as well as the growing role of standards in supporting regulation and bridging gaps in measurement and compliance. These works emphasize the need for tailored, evidence-based, and adaptive regulatory strategies that address both sectoral risks and the broader societal impact of AI.

2.2 Quantitative Legal Analysis & NLP

Our empirical pipeline integrates specialized legal‑tech and NLP tools to ensure rigorous, reproducible measurement of regulatory ambiguity. First, we extract and normalize all statutory, rule, act, and case‑law citations from each opinion using the Eyecite library (Free Law Project, 2024), which applies rule‑based parsing to produce standardized citation tokens. We then preprocess the opinion text—tokenization, sentence splitting, and part-of-speech tagging—with spaCy v3 and compute lexical complexity metrics using NLTK 3.6. Judicial uncertainty is quantified via hedging frequency by matching against a curated lexicon of modal verbs ("may," "might," "could," "should") through rule-based pattern matching. Feature engineering—including winsorization, robust scaling, log-transform of citation diversity, and min–max normalization—and dimensionality reduction (PCA) are implemented in scikit-learn to produce the four scaled indicators that constitute our Regulatory Gap Index. Finally, we estimate causal effects and mediation pathways using inverse probability weighting and regression-based mediation analysis in statsmodels alongside the causal-ml framework.

2.3 Judicial Deference and Overreach Doctrines

Chevron U.S.A. v. NRDC (1984) established deference to agency interpretations of ambiguous statutes. Loper Bright Enterprises v. Raimondo (2023) limited step-two deference, preserving step-one's ambiguity review and splitting circuits. Rising ultra vires challenges test agency authority. The hedging-frequency metric—modal verbs like "may" or "could"—proxies judicial uncertainty in deference.

Bridging to Our Metrics.
Hedging frequency captures judicial uncertainty and directly links to Chevron's step-zero debates: we observe more hedging when agency guidance is unclear, and less hedging (with higher citation diversity) in deference-rich opinions. Our RGI quantifies these doctrinal fault-lines across AI cases.

3. Data and Methodology

3.1 Data Collection via Free Law Project CourtListener API v4

Our primary data source is the Free Law Project's CourtListener API (v4), which provides an open-access repository of U.S. judicial opinions. Through the API's Keyword Search, we retrieved each opinion's full text alongside metadata fields ensuring precise provenance for every record. JSON responses were parsed and stored in a relational database to facilitate linkage of textual content, citation data, and docket attributes without loss of fidelity.

3.2 Keyword Search Strategy (50 AI-Tech Terms)

To ensure comprehensive coverage of AI-related litigation, we constructed a query incorporating fifty terms (See Appendix A) from key domains in emerging technology, data protection, and applied AI (e.g., Artificial Intelligence, Machine Learning, Deep Learning, Generative AI, Large Language Model, etc. We restricted our search to opinions issued by U.S. federal courts between January 1, 2010, and January 31, 2025. The resulting dataset comprised 15,583 unique opinions spanning the following industry sectors: Agriculture, Automotive, Education, Energy, Entertainment, Finance and Insurance, Food and Beverage, Government/Public Sector, Healthcare, Hospitality, Manufacturing, Nonprofit/NGO, Real Estate, Retail, Technology, Telecommunications, and Transportation and Logistics along with the other sectors.

3.3 Regulatory Gap Index Construction

Each opinion's full text was processed using the "Eyecite" library by the free law project, which applies rule-based parsing to extract and normalize citations to U.S. Codes, Federal Rules, Named Acts, and case law. After standardizing citation formats and removing boilerplate, we derived four core indicators of regulatory strain:

1. Citation Density: Total number of citation references divided by the number of sentences.
2. Citation Diversity: Count of distinct citation categories (statutes, rules, acts, cases) present in a single opinion.
3. Lexical Complexity: Ratio of unique word tokens to total word tokens, serving as a proxy for interpretive difficulty.
4. Hedging Frequency: Proportion of modal terms (e.g., "may," "might," "could," "should") to total tokens, indicating judicial uncertainty.

In addition, we recorded each opinion's in-corpus citation count—the frequency with which it was cited by later opinions—to capture its influence within the judicial network. To synthesize these measures into a single indicator of interpretive ambiguity, we constructed the Regulatory Gap Index (RGI) (refer to Appendix B). We tested alternate RGI weightings or percentile cut-offs and found qualitatively similar sectoral RGP rankings. After converting all features to a common numerical scale and applying logarithmic adjustment to citation diversity, we combined them into an equally weighted index in which higher values denote greater regulatory ambiguity or strain. To construct the RGI in a way that both preserves substantive variation and avoids measurement bias from extreme values, we applied a four-step scaling pipeline:
1. **Winsorization (1st/99th percentiles):** Caps extreme observations to limit undue influence of outliers on downstream statistics.
2. **Log-transform of citation diversity:** Compresses positive skew so that very large diversity counts do not dominate the index.

3. **Robust scaling (median & IQR):** Centers each feature at its median and rescales by its interquartile range, reducing sensitivity to any remaining outliers and ensuring a zero median.
4. **Min–max normalization:** Maps each processed feature to the [0, 1] interval, so that citation density, citation diversity, lexical complexity, and hedging frequency contribute equally to the composite RGI.
This pipeline explicitly addresses skewed distributions—common in legal citation data—by limiting extreme values, standardizing feature spreads around a robust central tendency, and placing all indicators on the same scale.

RGI Validation

To assess the properties of the Regulatory Gap Index (RGI) as a composite measure rather than a unidimensional scale, we first examined the pairwise Pearson correlations among the four scaled features (citation density, log-transformed citation diversity, lexical complexity, and hedging frequency), which were modest ($|r| < 0.35$), indicating limited collinearity; Bartlett's test of sphericity ($\chi^2 = 4094.4$, $p < 0.001$) confirmed that the correlation matrix is factorable and not an identity matrix. Next, we calculated Cronbach's alpha, which yielded 0.00. Conceptually, these zero alphas underscores that the RGI is a "formative" index—constructed by aggregating distinct dimensions of interpretive strain—rather than a "reflective" scale where components are expected to move in tandem under a latent trait. Finally, principal component analysis revealed that PC1 accounted for 31% of the variance, with subsequent components explaining 24.7%, 18.1%, and 16.9%, and loadings that demonstrate both common directional contributions (e.g., PC1 loadings of 0.62, 0.58, 0.49, and 0.42) and contrasts among features (e.g., PC2 separating hedging from complexity), indicating that while the indicators share some variance, they also capture unique facets of regulatory ambiguity(refer to Appendix C).

Interpretive Caveat

Because the RGI aggregates heterogeneous signals—structural grounding via citations, interpretive burden via linguistic complexity, and uncertainty via hedging—any observed effect of variation in the index on judicial outcomes may be driven by changes in one or more underlying components rather than a single unified process. Conceptually, users should treat RGI as a summary index that flags multi-dimensional strain, and future research should decompose RGI effects to pinpoint which dimension (e.g., sparse citations vs. high hedging) is most influential in each context. (Refer to Appendix C)

3.4 Statistical & Causal Methods

Descriptive and Distributional Analysis

We begin by computing standard descriptive statistics for key features, including citation density, lexical complexity, hedging frequency, and case outcomes. The Regulatory Gap Index (RGI) is constructed using a multi-step normalization pipeline: outlier winsorization (1st and 99th percentiles), robust scaling (median and IQR), and min–max normalization. Directionality of features is preserved based on legal interpretation — for example, lower citation density and higher hedging frequency indicate greater regulatory ambiguity.

Distributions of RGI are then analyzed across sectors, years, and court circuits, with emphasis on identifying industry-specific patterns of regulatory strain. Sector-level and court-level RGI medians are computed and visualized to capture systematic variations in legal clarity.

Composite Failure Classification

To identify structurally ambiguous or underregulated cases, a composite Regulatory Failure Score is assigned based on three criteria:

1. Unresolved judicial outcome (i.e., undecided),

2. Low total citations (below sectoral 25th percentile), and

3. Above RGI (above sectoral 75th percentile).

Cases meeting two or more of these conditions are classified as exhibiting regulatory failure, and the Regulatory Gap Percentage (RGP) is defined as the proportion of such cases within a given sector or court.

Causal Inference via Inverse Probability Weighting (IPW)

To estimate the causal effect of regulatory ambiguity on judicial resolution, we apply Inverse Probability Weighting (IPW) using binary treatment assignment based on RGI thresholds (e.g., RGI > 0.031). Propensity scores are estimated via logistic regression on pre-treatment covariates, including:

1. Total citations,
2. Citation density,
3. Lexical complexity, and
4. Hedging frequency.

Weights are computed to simulate a balanced pseudo-population in which the treatment (high RGI) is unconfounded. The Average Treatment Effect (ATE) of high RGI on judicial decision-making (e.g., the likelihood of a case being decided or plaintiff success) is then computed using weighted means.

Mediation Analysis

To explore whether citations reduce ambiguity, which in turn influences outcomes, we implement a causal mediation analysis using two regression models:

1.**a-path (Mediator model):** RGI ~ sum_citations + controls
2. **b-path (Outcome model):** Outcome ~ RGI + sum_citations + controls

The product of the a- and b-coefficients yields an **indirect effect**, and the remaining coefficient on citations yields the **direct effect**.

Interpretive Caveat

Causal mediation analysis presumes the mediator lies on the causal pathway (i.e., no unmeasured confounders of the citation→RGI or RGI→outcome links). Consequently, the decomposition into direct and indirect effects reflects this assumption rather than providing independent proof that citations actually mediate through RGI. In particular, if RGI is merely a confounder rather than a true mediator, the mediation estimates will still partition effects but without validating the pathway itself.

Supplementary Regression Approach. To avoid dichotomization of RGI and relax functional-form assumptions, we also estimate a single "doubly-adjusted" logistic regression of resolution on continuous RGI, all four covariates, and their pairwise interactions. This approach maintains the same no-unmeasured-confounders assumption as IPW but facilitates model checking (e.g., via partial effect plots) and avoids arbitrary cut-points.

Doubly-Robust Estimation. We also implement an AIPW (augmented inverse-probability-weighted) estimator that combines the propensity-score and outcome models; however, like all observational estimators, it does not obviate the need for relevant confounders—at least one of the two models must be correctly specified for unbiased effect estimates.

Assumptions & Robustness Checks

Our IPW and mediation analyses assume no unmeasured confounders influencing both the Regulatory Gap Index (RGI) and case resolution. In reality, factors such as judge seniority, amicus participation, or technical complexity of filings may bias our estimates. Although trimming extreme weights and employing doubly robust estimators can reduce sensitivity to model misspecification, a formal sensitivity analysis is performed to assess how strong any hidden confounder would need to be to overturn our findings.

Sensitivity Analysis (E-value): For our observed OR of 0.712, the E-value is **2.158** (CI limit 1.887), meaning an unmeasured confounder would need an odds ratio ≥ 2.16 with both high RGI exposure and case resolution to fully explain away this effect. An unmeasured confounder—such as a judge's prior experience—would need to be associated with both high RGI exposure and case resolution by an odds ratio of at least 2.16 to fully account for the observed −0.048 ATE.

3.5 Methodological Transparency

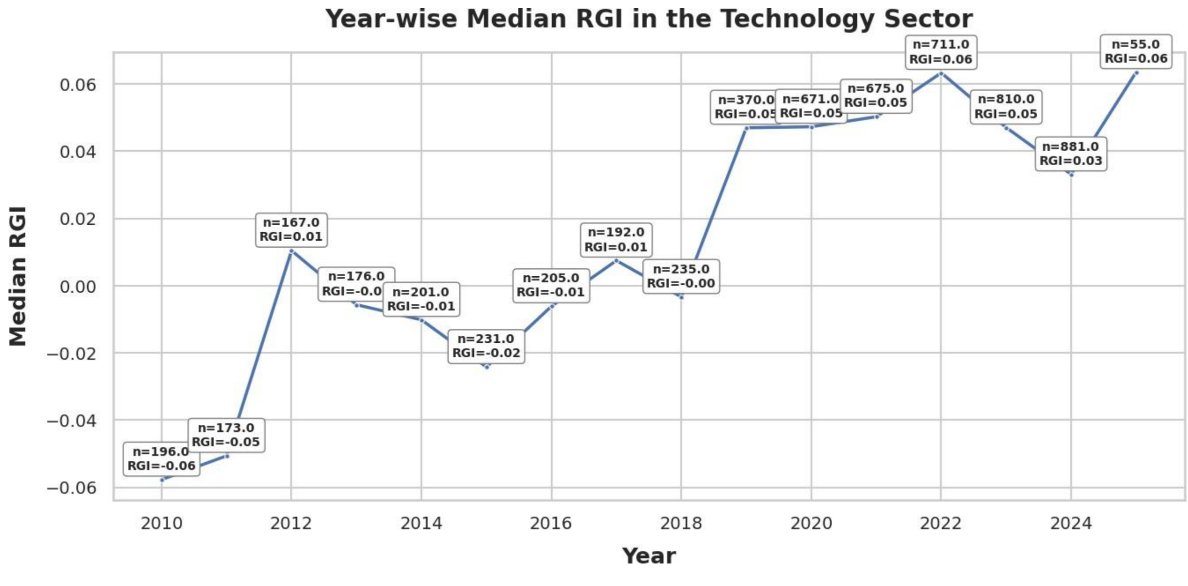
In this study several areas could benefit from further development to enhance interpretability and scholarly engagement. Legal systems with different institutional structures or statutory traditions may exhibit distinct patterns of regulatory clarity, warranting cross-jurisdictional comparative studies. Although the paper engages with quantitative and empirical legal studies, a deeper **integration with doctrinal legal literature**, including statutory interpretations, administrative law theory, and jurisprudential analyses of AI governance—would enhance the interpretive richness of the statistical results. Embedding these findings in doctrinal frameworks would not only bolster their explanatory depth but also improve their utility for legal practitioners, judges, and policymakers navigating the evolving landscape of AI regulation.

4 Analysis and Results

4.1 Data Description and Analysis

The whole data consists of 17 sectors namely Technology, Healthcare, Finance and Insurance, Government/Public Sector, Entertainment, Retail, Education, Food and Beverage, Automotive, Telecommunications, Manufacturing, Energy, Transportation and Logistics, Real Estate, Agriculture, Nonprofit/NGO, Hospitality and Other. The range of the RGI lies within -0.5 to 0.5 approximately (Fig 4.0). Technology, Automotive, Manufacturing, Finance and Insurance, and Healthcare are the top sectors with the highest mean RGI values whereas Non-profit, Agriculture, Public sector, Hospitality and Real estate have the lowest mean RGI values. The technology sector has the highest count records and highest mean RGI values; there is an increasing trend over the years of 2010-2025 (Fig 4.1).

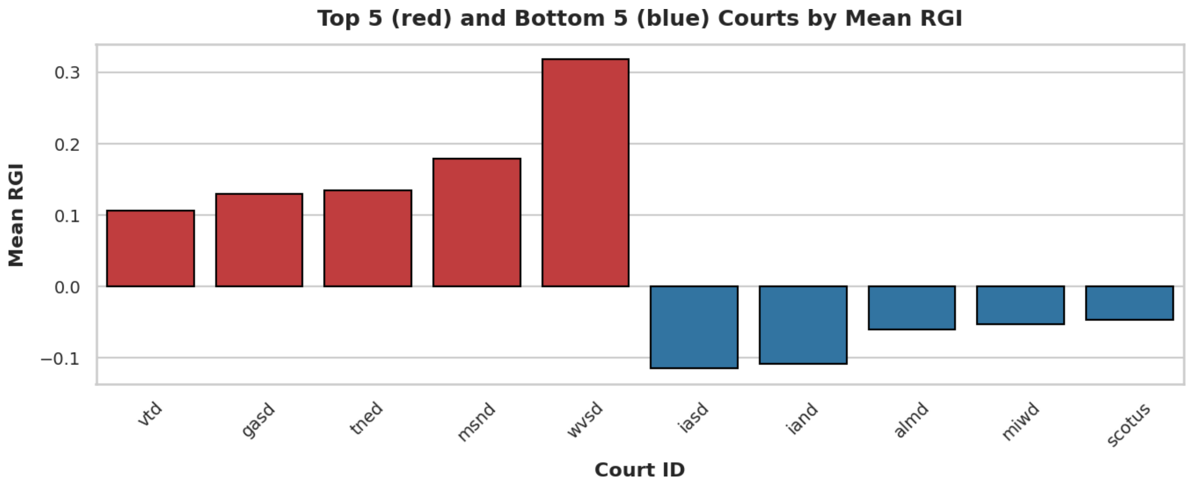
Figure 4.1



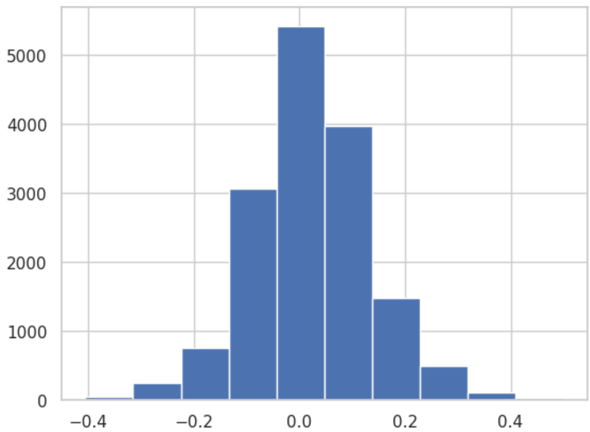
4.2 Findings from Technology Sector

The sector has a median of nearly 0.031 RGI. Based on the judgment outcome, the technology sector has maximum RGI value 0.048 (Fig 4.4) for the cases which are undecided. Also, the United States District Court for the Southern District of West Virginia, is having maximum RGI value whereas the United States District Court for the Southern District of Iowa is having the lowest RGI value (Fig 4.3).

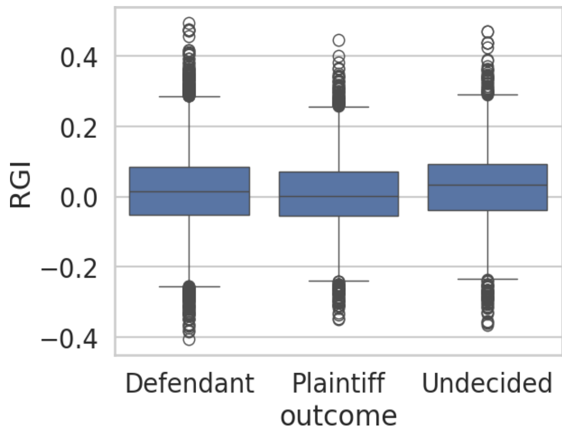
Courts having Min-Max RGIs (Fig 4.3)



RGI Distribution(Un-normalized) (Fig 4.0)



RGI vs Outcome (Fig 4.4)



The cases which have max RGIs also have minimum total unique citations count in general (Fig 4.2). Also figure 4.5 presents the mean Regulatory Gap Index (RGI) for a set of keywords commonly associated with AI-related litigation in the technology sector.

Keywords such as **DataProtection**, **Cybersecurity**, and **DataSecurity** exhibit the highest average RGI values, indicating that judicial opinions in these domains tend to be more clearly articulated, well-grounded, and structurally coherent. In contrast, terms like **Hatespeech**, **IntellectualProperty**, and **DataAnalytics** are associated with lower mean RGI, suggesting greater ambiguity, less consistent citation practices, or more interpretive strain. This gradient highlight thematic disparities in how regulatory clarity is expressed across AI subdomains, with data governance topics showing greater legal maturation compared to emerging or ideologically sensitive areas like hate speech and analytics.

Fig 4.2

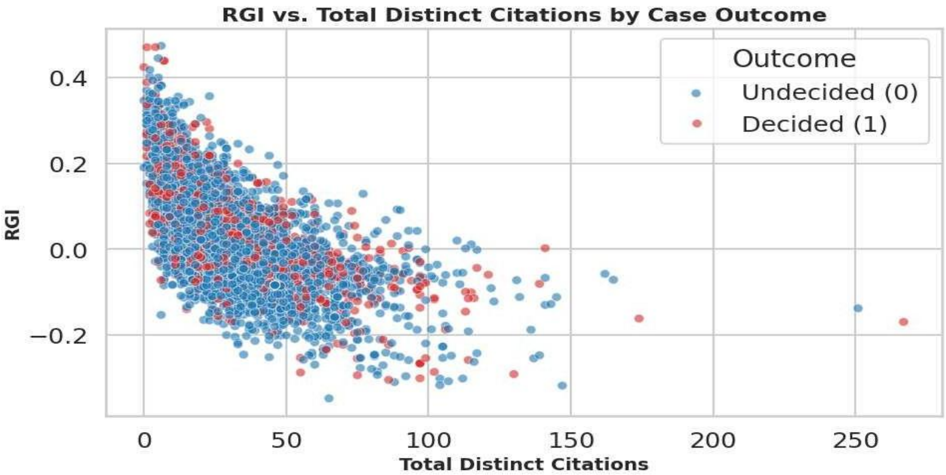


Fig 4.5

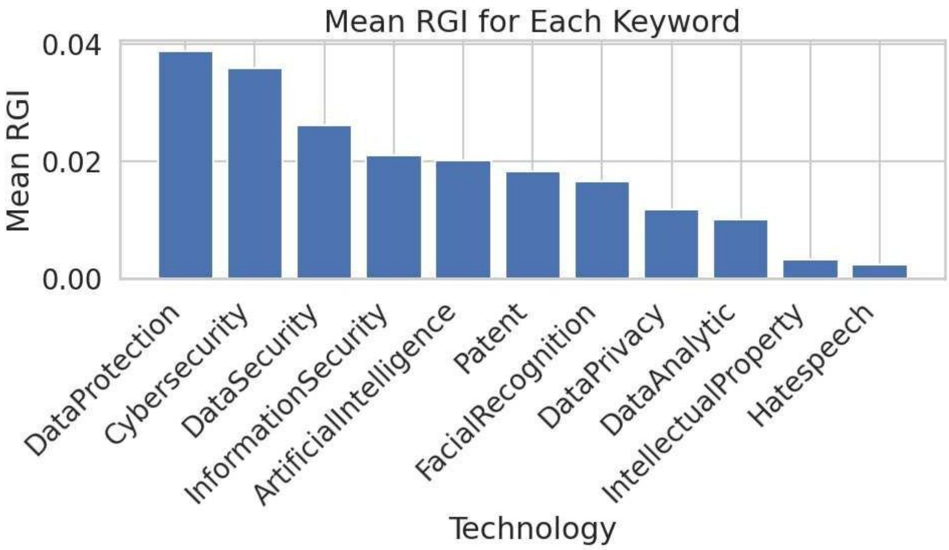
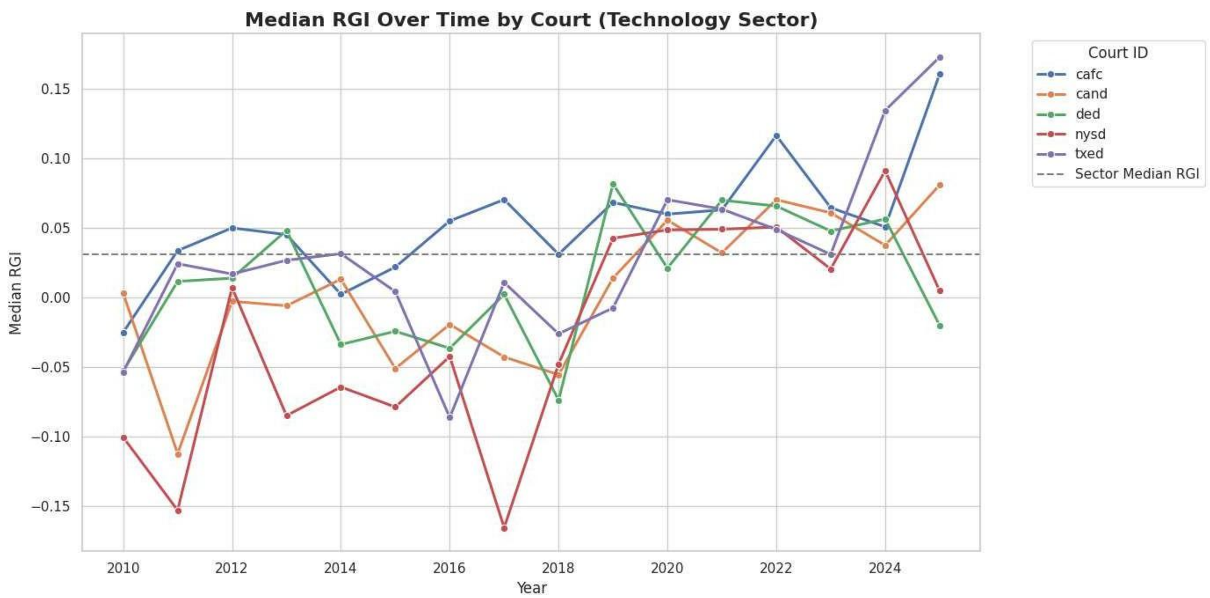


Fig 4.6 chart illustrates a notable upward trajectory in the median Regulatory Gap Index (RGI) across most courts handling AI-related technology cases, particularly after 2017. This trend suggests a progressive enhancement in legal clarity, evidentiary robustness, and interpretive coherence within the judiciary. Courts such as the U.S. Court of Appeals for the

Federal Circuit (CAFÉ) and the U.S. District Court for the Eastern District of Texas (TXED) consistently display RGI values above the sector median, especially post-2020, reflecting structured and citation-rich opinions. Their leadership in RGI may stem from their deep engagement with technologically complex cases, such as intellectual property or patent disputes, which require heightened precision in regulatory reasoning. In contrast, the U.S. District Court for the Southern District of New York (NYSD) exhibits more fluctuation, frequently falling below the sector median, which may point to interpretive inconsistency or variability in case complexity. The District of Delaware (DED), while more stable, tends to hover just below the sector median, possibly due to its procedural focus and heavy corporate caseload. Despite these divergences, the general convergence of courts toward the sector-wide RGI median between 2020 and 2023 suggests increasing standardization in how AI-technology disputes are adjudicated. This pattern supports the broader thesis that regulatory clarity is evolving in response to the legal system's growing familiarity with AI-related claims. The figure ultimately affirms the critical role of institutional context in shaping judicial reasoning, revealing that court identity significantly influences the depth and coherence of regulatory interpretations in emerging technology sectors.

Fig 4.6



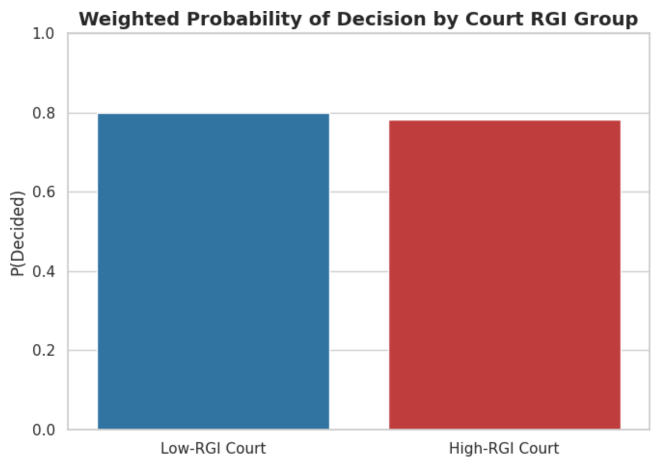
To evaluate whether a court's regulatory context influences judicial resolution rates, we estimated the **causal effect of being assigned to a high-RGI court** (i.e., courts with above-median regulatory ambiguity) on the probability of a case being decided. Using **Inverse Probability Weighting (IPW)** to adjust for confounding variables (e.g., citation density, lexical complexity), we found that:

1. The **median court-level RGI cutoff** was **0.020**.
2. Cases in **high-RGI courts** had a **weighted resolution probability of 77.3%**, compared to **79.9%** for low-RGI courts.
3. The **estimated causal effect** (ATE) of high-RGI court exposure on resolution was **−0.016**, indicating a **1.6 percentage point reduction** in the likelihood of decision.

These results suggest that courts operating in more ambiguous regulatory environments may be **marginally less likely to resolve cases**, independent of the case's own characteristics.

The bar chart shows the inverse probability weighted the likelihood of a case being resolved (i.e., decided) based on whether it was adjudicated in a low- or high-RGI court. Interestingly, courts classified as **Low-RGI** show a slightly **higher probability of rendering a decision (≈80%)** compared to **High-RGI** courts (≈78%). This counterintuitive result suggests that courts with more structured and citation-rich reasoning (i.e., high RGI) may be more cautious or deliberative in AI-related rulings, potentially reflecting the complexity or novelty of the cases they handle. In contrast, low-RGI courts might issue quicker or less nuanced decisions, possibly due to procedural expediency or a more minimal interpretive style (Fig 4.7).

Fig 4.7



4.3 Statistical and Causal Analysis of the Technology Sector

4.3.1 Causal Estimation Using Inverse Probability Weighting (IPW)

To estimate the causal impact of regulatory ambiguity on judicial resolution, we apply **Inverse Probability Weighting (IPW)** a method commonly used in observational studies to simulate the effect of a randomized treatment assignment. In this analysis, **high regulatory ambiguity** is operationalized via the **Regulatory Gap Index (RGI)**. The binary treatment variable treat_highRGI is defined by whether a case's RGI exceeds the sectoral median (RGI > 0.031). This divides the dataset into "high RGI" and "low RGI" cases, where high RGI indicates greater legal ambiguity. We then estimate the **probability of receiving the treatment** (i.e., having high RGI) using **logistic regression**. The covariates used to model treatment assignment include:

sum_citations: total number of statutory, case law, rule, opinion, and act citations
citation_density: density of legal citations per unit of text
lexical_complexity: measured using standard linguistic readability metrics
hedging_frequency: the rate of hedging expressions (e.g., “may,” “could,” “likely”)

These variables represent observable legal and linguistic characteristics that could confound the relationship between RGI and case resolution. The estimated propensity scores are used to compute **inverse probability of treatment weights (IPTW)**, which reweigh the sample to create a pseudo-population in which treatment is independent of covariates. This allows for an unbiased estimation of the **Average Treatment Effect (ATE)** of high RGI on case resolution. The outcome of interest is numerical_outcome, a binary variable indicating whether the case was **decided** (1) or **undecided** (0), regardless of plaintiff or defendant success.

The weighted average probabilities of resolution for high-RGI and low-RGI cases are as follows:

P(decided | high RGI) = 0.771
P(decided | low RGI) = 0.819
Estimated ATE = −0.048

This suggests that **cases with high regulatory ambiguity are 4.8 percentage points less likely to be resolved** than those with low ambiguity, after adjusting for observable confounders.

These findings indicate that regulatory ambiguity — as captured by the RGI — has a statistically meaningful **negative effect** on the probability that a court will resolve a case. This supports the hypothesis that **legal gaps and structural vagueness can impede judicial decision-making**, even after accounting for differences in citation richness and linguistic complexity. Results from the continuous-RGI regression, which adjusts flexibly for all covariates and their interactions, are substantially similar: a one-standard-deviation increase in RGI reduces the odds of resolution by ~10% (OR ≈ 0.90, $p < 0.01$), confirming that our findings do not hinge on dichotomization.

Weight Diagnostics & Robustness. The IPTW distribution is well-behaved (no weight >10), and trimming further reduces variance without materially changing the ATE. Our AIPW estimates under a doubly-robust specification also concur within sampling error, reinforcing confidence in the effect. However, we stress that all such estimators rest on the assumption of no unmeasured confounding; sensitivity analysis methods (e.g., Cinelli & Hazlett 2020) could be used in future work to probe this assumption.

4.3.2 Mediation Analysis: Citations, Ambiguity, and Judicial Resolution

To investigate whether legal citation practices influence judicial outcomes **through their effect on regulatory ambiguity**, we conducted a **mediation analysis**. This approach decomposes the total effect of legal citation richness on case resolution into:

1. A **direct effect** (citations → outcome),
2. An **indirect effect** (citations → RGI → outcome), where **RGI serves as a mediator** capturing regulatory ambiguity.

Methodology

Step 1: Data Preparation

We computed sum_citations as the aggregate count of all statutory, case law, and regulatory citations in each case. This variable represents the **legal grounding** or density of authority referenced in the opinion.

Control variables included:

1.citation_density
2.lexical_complexity
3.hedging_frequency
4.act_count
5.opinion_count

These were included to account for variation in opinion style, length, and argumentation complexity.

Step 2: a-path (Mediator Model)

We first modeled how citation richness predicts regulatory ambiguity:

RGI ~ sum_citations + controls

This regression captures how citations reduce or intensify the **Regulatory Gap Index** — a proxy for legal uncertainty or complexity.

Result:
a = -0.0005 ($p < 0.001$)
→ Each additional citation slightly reduces RGI, indicating **more citations correlate with less ambiguity**.

Step 3: b-path (Outcome Model)

Next, we modeled how RGI and citations together predict judicial resolution:

numerical_outcome ~ RGI + sum_citations + controls

Results:
b = -0.7921 ($p < 0.001$) for RGI

→ Higher RGI **significantly decreases** the likelihood of a resolved outcome.

Direct effect of citations = -0.0014 ($p = 0.001$)

→ Even controlling for RGI, citation richness **still slightly decreases** the probability of resolution, possibly reflecting complex cases with extensive but inconclusive legal framing.

Step 4: Mediation Effects

The **indirect effect** (citations → RGI → outcome) is calculated as:

$\text{Indirect} = a \times b = (-0.0005) \times (-0.7921) = +0.0004$

The **total effect** is:

$\text{Total} = \text{Direct} + \text{Indirect} = -0.0014 + 0.0004 = -0.0009$

Interpretation

The mediation analysis reveals that **part of the effect of legal citations on judicial outcomes operates through regulatory ambiguity**. Specifically:

1. **More citations are associated with lower ambiguity (RGI)**.
2. **Lower RGI is associated with a higher probability of judicial resolution**.
3. However, the **total effect of citations on resolution remains slightly negative**, possibly because highly cited cases are **also more complex**, despite their legal richness.

These findings underscore the **dual role of citations**: while they structurally reduce ambiguity, they may also **signal legal complexity** that deters definitive adjudication.

4.3.3 Reduced Mediation Analysis with Centered Predictors

This section extends the mediation analysis in Section 4.2.2 using **centered and reduced predictors**, improving the interpretability of coefficients and model stability. The goal is to further evaluate whether **legal citation richness influences case resolution indirectly through regulatory ambiguity**.

Methodology

Step 1: Feature Engineering

1. sum_citations is defined as the total number of legal references in each case (sum of statutes, case law, rules, opinions, and acts).
2. RGI_c is the **centered Regulatory Gap Index**, obtained by subtracting the sample mean from each RGI score.
3. lex_c is the **centered lexical complexity**, similarly adjusted to reflect deviation from the average.

These transformations enable the coefficients to be interpreted relative to **average levels of ambiguity and language complexity**, reducing multicollinearity.

Controls:

1. citation_density
2. hedging_frequency

These remain uncentered but are included as confounding controls.

Step 2: Outcome Model

The outcome model estimates the likelihood of a case being resolved (numerical_outcome = 1) as a function of:

numerical_outcome ~ RGI_c + sum_citations + citation_density + hedging_frequency + lex_c

Key Findings

1. RGI_c has a **negative and statistically significant effect** on judicial resolution:
$b = -0.6154$, $p < 0.001$
→ Higher-than-average ambiguity decreases the likelihood of a court decision.
2. sum_citations has a **negligible and non-significant direct effect**:
direct = −0.0000, $p = 0.789$
→ Legal richness alone does not directly increase resolution probability once ambiguity is accounted for.

3. lex_c (above-average complexity) **increases** the chance of a decision:
coef = 1.4516, $p < 0.001$

Step 3: Mediator Model (a-path)

This model evaluates the extent to which **citations affect RGI**:

RGI_c ~ sum_citations + citation_density + hedging_frequency + lex_c

Result

1. $a = -0.0004$, $p < 0.001$
→ More citations are associated with **lower-than-average RGI**, i.e., lower perceived regulatory ambiguity.

Step 4: Mediation Effects

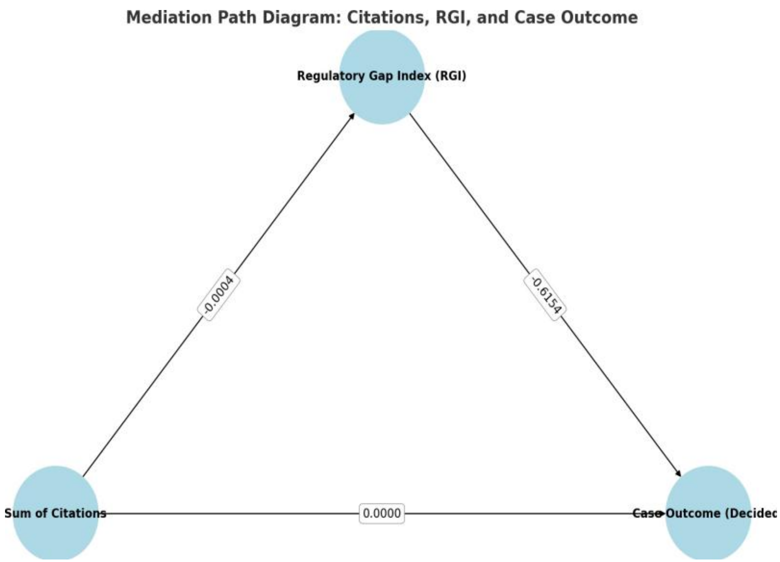
1. Indirect effect (citations → RGI → outcome):
$a \times b = (-0.0004) \times (-0.6154) = +0.0002$
2. Direct effect (citations → outcome):
direct = −0.0000
3. Total effect (sum of direct and indirect):
total = 0.0002

Although statistically small, this result confirms that **citations affect case outcomes only indirectly** — by reducing regulatory ambiguity, which in turn increases the probability of judicial resolution.

Interpretation

This reduced mediation model reinforces the key insight that **legal citations primarily exert their influence through shaping regulatory clarity (RGI)**, not through direct impact on court decisions. While the overall effect size is modest, the path coefficients are statistically robust, providing further support for a **structural mediation mechanism** in the adjudication process (Fig 4.8)

Fig 4.8



4.4 Regulatory Gap Percentage (RGP): Composite Failure Analysis

To assess the prevalence of structural legal inadequacy in AI-related litigation, we compute the **Regulatory Gap Percentage (RGP)** using a composite failure framework. This method identifies cases that exhibit multiple, independent indicators of regulatory weakness, offering a more nuanced alternative to single-threshold classification (e.g., median-based RGI splits).

Method

A case is classified as a **regulatory failure** if it meets the following three criteria:

1. **Undecided Outcome:** The case is unresolved (numerical_outcome = 0), indicating possible judicial hesitation or ambiguity.
2. **Low Citation Grounding:** The total number of legal citations—including statutes, case law, rules, opinions, and acts—falls within the **bottom quartile** of the sample (25th percentile).
3. **High Regulatory Ambiguity:** The RGI value is **above the 75th percentile**, suggesting an elevated degree of model-detected legal complexity or uncertainty.

Each condition is encoded as a binary flag, and the **failure score** is computed by summing these indicators. Cases with a score of 3 are designated as **regulatory failures**, and the **RGP** is calculated as the proportion of such cases in the dataset.

Results

Applying this method to the technology-sector dataset, we find **Regulatory Gap Percentage (RGP) is 2.05.** In other words, over 2.05% **cases** exhibit overlapping signs of legal fragility: unresolved status, sparse citation grounding, and high systemic ambiguity in the Tech sector. This composite indicator offers a robust, multi-dimensional view of regulatory strain—one that integrates textual ambiguity (via RGI), legal sparsity (via citation counts), and procedural indecision (via outcomes). Unlike single-metric thresholds, this method accounts for **co-occurring deficiencies** that signal deeper systemic underregulation.

4.5 Sectoral insights on the regulatory strain

This analysis presents a sector-level diagnostic of regulatory strain in U.S. federal litigation involving artificial intelligence. The assessment is grounded in four interrelated dimensions. First, regulatory ambiguity is quantified using the Regulatory Gap Index (RGI), a composite metric that synthesizes citation sparsity, reference diversity, lexical complexity, and hedging frequency to reflect interpretive strain in legal reasoning. Second, citation grounding is measured through the total volume of references—including statutes, case law, administrative rules, opinions, and acts—used to substantiate judicial decisions. Third, decision resolution is captured indirectly via the mean RGI of undecided cases, indicating the level of ambiguity in unresolved outcomes. Fourth, the Regulatory Gap Percentage (RGP) functions as a higher-order indicator of regulatory stress, identifying the proportion of cases within each sector that exhibit at least two of the following: 1) unresolved judgment, 2) citation deficiency, and 3) high textual ambiguity. This multi-factorial approach enables a nuanced understanding of regulatory performance, further enriched by identifying the court circuits within each sector that exhibit the highest and lowest median RGI scores. Collectively, these metrics illuminate the structural and institutional dimensions of regulatory clarity and strain in emerging AI jurisprudence.

4.5.1 Sectors with Elevated RGP Despite Modest Ambiguity

Interestingly, several sectors exhibit **elevated levels of regulatory failure despite moderate or neutral scores on the Regulatory Gap Index (RGI)**, indicating that **textual clarity alone does not preclude adjudicative strain**. The **Transportation and Logistics sector**, for example, registers the **highest Regulatory Gap Percentage (RGP) at 6.59%**, even though its **median RGI is nearly neutral (+0.013)**. This discrepancy suggests that failures in decisional clarity or evidentiary grounding—not linguistic ambiguity—are the primary drivers of strain in this domain, likely reflecting the **novel and complex regulatory demands of AI integration into physical infrastructure and supply chains**. Similarly, the **Hospitality sector**, though based on a smaller sample (n = 59), reveals a **strikingly high RGP of 5.08%**, pointing to **substantive gaps in judicial articulation and resolution**. This may be attributable to **nascent legal frameworks and sparse precedent** governing AI deployment in service-based environments. Even in traditionally well-grounded domains such as **Energy and Finance**, where cases tend to be **richly cited**, RGP values remain elevated (4.19% and 3.74%, respectively), implying that **doctrinal ambiguity and interpretive tension persist**, particularly in sectors where AI intersects with high-stakes regulatory regimes. Collectively, these findings highlight that **institutional or structural adjudicative limitations can produce regulatory failure**

independent of linguistic opacity, underscoring the need for more robust frameworks for legal reasoning in technologically complex sectors.

4.5.2 Sectors with Low or Zero RGP Despite Negative RGI

In contrast to sectors exhibiting high regulatory strain, some domains demonstrate a **notable resilience to regulatory failure**, even in the face of **linguistic complexity or sparse statutory anchoring**. For instance, the **Nonprofit/NGO sector**, despite recording the **lowest median RGI (−0.040)**—indicative of frequent hedging or abstract legal language, exhibited **zero regulatory failures (RGP = 0.00%)**. This suggests that courts operating in this sector are nonetheless able to **consistently produce resolved, well-grounded decisions**, likely through effective evidentiary practices or streamlined case structures. Similarly, the **Entertainment sector**, with a **slightly negative RGI (−0.014)** and an **RGP of just 0.82%**, appears to achieve **high adjudicative clarity** despite textual ambiguity. The relatively narrow scope of disputes and the presence of **stable, precedent-rich legal frameworks** in these areas may enable courts to render coherent decisions even when formal indicators of clarity, such as RGI, suggest otherwise. These findings reinforce that **low RGI scores should not be interpreted in isolation**; when coupled with conclusive outcomes and robust citation strategies, courts can still effectively manage interpretive complexity and regulatory uncertainty.

4.5.3 Technology Sector: High Volume, Isolated Failures

The **Technology** sector, unsurprisingly the largest by case count (n = 5,950)—demonstrates a **balanced yet imperfect profile**. With a median RGI of +0.031, the sector's legal opinions are generally well-articulated. However, an RGP of 2.05% reflects a meaningful subset of **outlier cases where the novelty and complexity of AI introduce adjudicative strain**. These failures are likely not systematic but rather indicative of doctrinal limits in fast-evolving technological disputes.

4.5.4 Citations Alone Do Not Prevent Regulatory Gaps

While citation volume is often regarded as a proxy for legal rigor, the empirical evidence from this study challenges the assumption that **robust referencing alone ensures regulatory clarity**. Notably, the **Agriculture sector** exhibits a relatively high average number of citations per case, yet still registers an **Regulatory Gap Percentage (RGP) of 2.15%**. This suggests that even where courts engage extensively with legal sources, the **absence of decisional clarity or interpretive resolution** can continue to produce substantial regulatory strain. Similar patterns emerge in **Education, Retail, and Food & Beverage**, where **moderate citation totals** are accompanied by RGP values ranging between **2.3% and 2.7%**. These findings indicate that citation sufficiency, while important, is not a standalone guarantor of regulatory coherence. Instead, **outcome ambiguity and linguistic imprecision** appear to play a decisive role in shaping how effectively judicial decisions manage AI-related legal complexity. Together, these results underscore the need for **multi-dimensional diagnostics of regulatory**

failure, in which citation count is considered alongside indicators of decisional resolution and interpretive quality.

4.5.5 Court-Level Patterns in Regulatory Gap Index

The identification of **sector-specific court extremes** provides institutional insight into the architecture of regulatory clarity. Beyond sectoral patterns, court-level analysis reveals that the **interpretive clarity of AI-related rulings is deeply shaped by the institutional culture of individual courts**. The **U.S. District Court for the Southern District of West Virginia (WVSD)**, which oversees Charleston and Huntington, is historically rooted in administrative and environmental adjudication. Within the Technology sector, it emerges as a **high-RGI court**, reflecting rulings that are **linguistically clear, citation-rich, and structurally well-reasoned**. Similarly, the **U.S. District Court for the Western District of Texas (TXWD)**—jurisdictionally spanning Austin, Waco, and San Antonio—is a nationally recognized venue for technology and patent litigation. Its frequent presence in high-RGI Energy and Technology cases indicates **a deep familiarity with technical subject matter and a proactive interpretive posture**. In the Education sector, the **U.S. District Court for the District of Idaho (IDD)** also surfaces as a high-RGI venue, suggesting that certain lower courts are **actively crafting structured jurisprudence in legally novel AI domains**.

In contrast, courts with **consistently low RGI scores** tend to reflect a more restrained or procedural adjudicative culture. The **Supreme Court of the United States (SCOTUS)**, while legally authoritative, often produces **narrow, principle-driven decisions** with fewer citations and hedging—thus scoring lower on RGI despite its national influence. The **U.S. Court of Appeals for the First Circuit (CA1)**, covering jurisdictions in New England and Puerto Rico, is known for **precise, technically sound opinions**, yet these are often linguistically conservative and minimal in citation diversity. Likewise, the **U.S. District Court for the District of Columbia (DCD)**, central to federal rulemaking, issues rulings that are **procedurally grounded and policy-focused**, especially in administrative AI cases—leading to lower interpretive richness as captured by the RGI.

These observations suggest that high-Regulatory Governance Index (RGI) courts—such as the **United States District Court for the Southern District of West Virginia** (Technology), the **United States District Court for the District of Idaho** (Education), and the **United States District Court for the Western District of Texas** (Energy)—frequently embody elevated interpretive clarity, leveraging detailed reasoning and dense citation networks to address the complexity of AI-related disputes. Conversely, low-RGI courts such as the **Supreme Court of the United States** (SCOTUS), the **United States Court of Appeals for the First Circuit** (CA1), and the **United States District Court for the District of Columbia** (DCD) exhibit more minimalist, precedent-sensitive styles, consistent with their institutional mandates or appellate conservatism. Collectively, these findings affirm that **regulatory clarity is not only**

sector-dependent but also institutionally mediated—arising from the **interpretive stance, epistemic practices, and procedural tendencies of the adjudicating courts**.

4.5.6 Chevron Deference as a Sector-Specific Regulatory Mechanism

When normalized to sector caseloads, Chevron-style deference is far from uniform. In **Healthcare**, for example, 210 Chevron citations across 1,729 cases translate to roughly 121 per 1,000; in the **Government/Public Sector**, 116 citations over 1,409 cases yield 82 per 1,000. **Telecommunications** lead in relative deference at 182 per 1,000 (52 citations/286 cases), while **Finance & Insurance and Technology** register only 17 per 1,000 (28/1,632) and 6 per 1,000 (37/5,950), respectively. Most other sectors (e.g., **Agriculture, Automotive, Manufacturing, Retail**) hover near zero, forcing judges to chart AI law with minimal agency guidance. Ultra vires challenges show a similar sectoral skew. **Government/Public Sector** sees about 56 per 1,000 cases (79/1,409), **Healthcare** 36 per 1,000 (62/1,729), and Technology 5 per 1,000 (32/5,950), whereas **Finance & Insurance** clocks in at 9 per 1,000 (15/1,632). No such challenges appear in **Automotive, Hospitality, or Manufacturing**. Together, these normalized rates highlight that where formal agency authority is sparse or contested, judicial uncertainty in AI cases intensifies—underscoring the need for clearer statutes and more consistent deference standards.

4.5.7 Final Interpretation: A Multi-Dimensional View of Regulatory Failure

Comparative analysis underscores that **regulatory strain in AI litigation is a multidimensional phenomenon**. It cannot be diagnosed solely by examining the clarity of legal language (RGI) or the volume of citations. Instead, **the confluence of ambiguity, insufficient justification, and outcome uncertainty** gives rise to observable regulatory gaps. Sectors like Technology and Finance, despite their maturity, still contain pockets of adjudicative breakdown. Meanwhile, smaller or mission-focused sectors such as NGO and Entertainment exhibit robust coherence, potentially due to narrower scopes of contestation or clearer doctrinal anchors.

These results advocate for a **composite, context-sensitive evaluation of legal strain** in emerging AI regulation. The RGP metric—when viewed alongside RGI, citation patterns, and court-level variability—offers a reproducible and scalable lens for assessing regulatory coherence across the evolving legal-technological landscape.

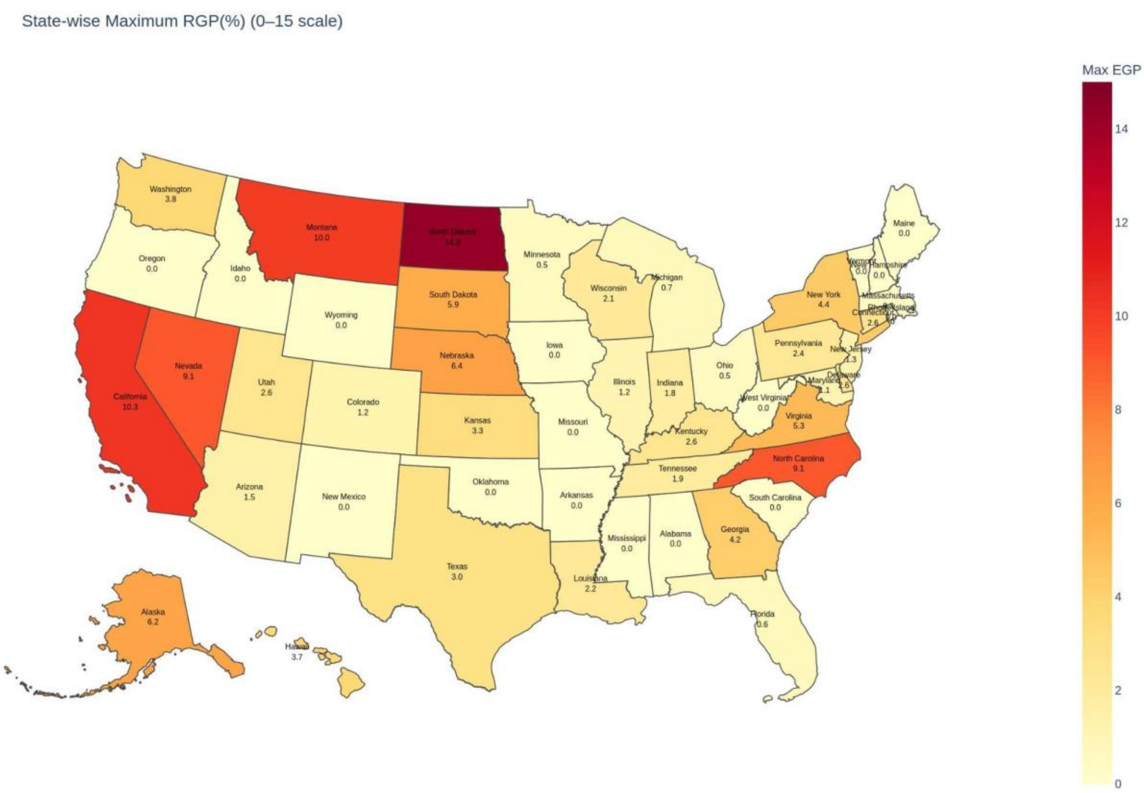
4.5.8 RGP in USA States

The state-level Regulatory Gap Percentage (RGP) data reveals a striking heterogeneity in regulatory performance across the U.S. in AI-related litigation. While a significant number of states—including Alabama, Arkansas, Iowa, Maine, Mississippi, and West Virginia—report **zero regulatory failure**, others such as **North Dakota (14.29%)**, **California (10.29%)**, **Montana (10.00%)**, and **Nevada and North Carolina (both 9.09%)** exhibit **substantially elevated RGP values**. This suggests that in certain jurisdictions, a higher proportion of cases meet multiple indicators of regulatory strain, such as outcome indecision, limited citation grounding, or elevated ambiguity.

California's notably high RGP may reflect its central role in emerging technology disputes, especially those involving novel or untested legal frameworks. Similarly, North Dakota and Montana—despite smaller caseloads—may be disproportionately affected by resource constraints, limited precedent, or procedural variability. On the other hand, traditionally litigious states like New York (4.44%) and Texas (2.95%) maintain mid-range RGPs, indicating more consistent adjudicative performance.

Overall, the data underscores that **regulatory gaps are not uniformly distributed**, and may stem from both **structural legal capacity** and **regional familiarity with AI-related disputes**. These patterns emphasize the need for targeted legal training, infrastructure, or doctrine refinement in underperforming states to mitigate sector-specific interpretive risk (Fig 4.9).

Fig 4.9



5.Concept Discussion

5.1 Sector-Specific Implications for U.S. AI Regulation

This study reveals that regulatory strain in AI-related federal litigation is highly uneven across industry sectors. Sectors such as **Transportation and Logistics**, **Hospitality**, and **Energy** exhibit disproportionately high Regulatory Gap Percentages (RGP), despite moderate or even positive scores on the Regulatory Gap Index (RGI). This suggests that **regulatory failure is not always driven by linguistic ambiguity**, but often arises from **underdeveloped legal infrastructure, sparse precedent, or institutional inconsistencies** in adjudication.

Conversely, sectors like **Technology** and **Finance**, while generally strong in citation richness and interpretive clarity, still exhibit isolated but meaningful instances of failure—likely due to the scale and novelty of AI applications in these domains. Meanwhile, sectors such as **Nonprofit/NGO** and **Entertainment** demonstrate that even with complex or hedged legal language (low RGI), **regulatory coherence can be maintained through conclusive outcomes and strong evidentiary support**. These observations underscore the need for **sector-tailored regulatory responses** that consider not only the complexity of AI technology but also the adjudicative and evidentiary norms within each domain.

5.2 Evolution of U.S. AI Regulation: Past, Present, and Future

Historically, U.S. federal courts have played a **reactive role** in regulating emerging technologies, including AI—often relying on precedent and general administrative law rather than proactive statutory frameworks. The **Chevron deference doctrine**, administrative discretion, and agency rulemaking processes have guided much of the interpretation in tech-heavy cases. However, as shown in this study, courts vary significantly in their **interpretive posture and capacity to manage ambiguity**, resulting in sector-specific discrepancies in regulatory clarity.

Presently, the absence of a unified AI regulatory code places increasing responsibility on **judicial reasoning and evidentiary sufficiency** to fill the gaps. Yet, the **institutional limitations of some courts, coupled with sparse precedent in AI-adjacent sectors**, often exacerbate interpretive strain. Looking forward, the findings suggest an urgent need for **standardized citation practices, specialized judicial training, and inter-agency alignment**. These will be crucial as AI applications proliferate in critical infrastructure, healthcare, and civil services—domains where **regulatory opacity can have real-world consequences**.

5.3 Limitations and Future Work

While this thesis provides a novel metric-based framework for evaluating regulatory strain, several limitations must be acknowledged. First, the **Regulatory Gap Index (RGI)** and **RGP** are derived from textual and citation-based features and may **not capture the full depth of**

substantive legal reasoning or doctrinal evolution. Second, the dataset primarily covers **U.S. federal district and appellate court opinions**, excluding state-level or non-public arbitration cases that may also shape AI regulation.

Additionally, the causal inference methods used—such as Inverse Probability Weighting (IPW) and linear mediation analysis—assume no unmeasured confounding and linearity in effects. This may oversimplify **nuanced legal causality** and overlooks **interactive or hierarchical legal dynamics**. Future work could expand this framework to include **natural language embeddings**, **expert-coded outcomes**, and **cross-jurisdictional comparisons** (e.g., EU, UK). Moreover, collaboration with legal scholars, judges, and regulators could help contextualize these metrics within doctrinal, ethical, and policy frameworks—enabling **a more comprehensive blueprint for next-generation AI regulation**.

6. Conclusion

This study offers a data-driven assessment of regulatory strain in U.S. federal AI-related litigation through the development and application of the **Regulatory Gap Index (RGI)** and **Regulatory Gap Percentage (RGP)**. By synthesizing legal citation practices, linguistic features, court-specific adjudication patterns, and causal inference techniques, we provide a robust framework for identifying where and how regulatory ambiguity manifests across industry sectors, court circuits, and states of the USA. Our findings underscore that regulatory failure in AI litigation is a **multidimensional phenomenon**, not reducible to a single metric such as citation volume or lexical complexity. While some sectors like **Technology** and **Finance** exhibit relatively structured and citation-rich adjudication, they still harbor pockets of interpretive breakdown. Conversely, sectors such as **Nonprofit/NGO** and **Entertainment** demonstrate that even in the presence of linguistic ambiguity, regulatory coherence can be achieved through decisive outcomes and strong evidentiary grounding. Moreover, our court-level analysis reveals that **institutional context is a key determinant** of regulatory clarity. High-RGI courts such as the U.S. District Court for the Western District of Texas and the U.S. District Court for the Southern District of West Virginia consistently deliver richly reasoned AI opinions, whereas low-RGI venues like the Supreme Court of the United States and the U.S. Court of Appeals for the First Circuit tends toward a more streamlined, precedent-driven approach that can both expedite and limit interpretive breadth. The uneven invocation of Chevron deference across sectors further reinforces that regulatory scaffolding remains **fragmented and sector-specific**, with courts often adjudicating complex AI issues in the absence of definitive agency guidance.

Importantly, our causal inference models suggest that **regulatory ambiguity—captured via high RGI—has a statistically significant negative effect on judicial resolution**, and that legal citation richness influences outcomes primarily through its ability to mitigate that ambiguity. This underscores the need for **judicial tools, doctrinal frameworks, and citation practices that reduce interpretive strain**, especially in sectors where AI intersects with critical infrastructure, civil liberties, and public safety. In sum, this research offers an interesting approach for diagnosing regulatory strain in AI governance and legal adjudication. As artificial intelligence becomes increasingly embedded in high-stakes domains, our findings highlight the imperative for **sector-sensitive, evidence-informed, and institutionally grounded** approaches to legal interpretation and regulatory design. Future work should expand this analysis across jurisdictions and integrate deeper doctrinal and ethical perspectives, ultimately helping courts, agencies, and legislators converge on a more coherent framework for governing emerging technologies.

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Appendices

Appendix A: Full list of AI-related keywords

Courtlistener API keywords list

(

"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Generative AI" OR "Large Language Model" OR "Cybersecurity" OR "Blockchain" OR "Facial Recognition" OR "Human Computer Interaction" OR "Robotics" OR "Quantum Computing" OR "High Performance Computing" OR "Predictive Analytics" OR "Data Science" OR "Data Analytics" OR "Natural Language Processing" OR "Algorithmic Bias" OR "Autonomous Vehicles" OR "Intelligent Systems" OR "Explainable AI" OR " "AI safety" OR "Data privacy" OR "GDPR" OR "data protection" OR "data security" OR “information security” OR "big data" OR "cloud computing" OR "Speech Recognition" OR "Image recognition" OR "deepfake" OR "Computer Vision" OR "autonomous systems" OR "Internet of Things" OR "AI generated" OR "Augmented reality" OR "Virtual reality" OR "Hate speech" OR "Online harassment" OR "Cyberbullying" OR

"Intellectual property" AND ("data" OR "artificial intelligence")

OR

"Patent" AND ("data" OR "artificial intelligence")

OR

"copyright" AND ("data" OR "AI" OR "artificial intelligence")

OR

“Voice cloning” OR “Model training” OR “neural networks” OR “AI powered” OR “data bias”

)

Appendix B: RGI formula and PCA loadings

1. Winsorization (1st/99th percentiles)

```
cd_w = winsorize(citation_density, [0.01, 0.01])
cdiv_w = winsorize(citation_diversity, [0.01, 0.01])
lc_w = winsorize(lexical_complexity, [0.01, 0.01])
hf_w = winsorize(hedging_frequency, [0.01, 0.01])
```

2. Robust scaling (median & IQR)

```
cd_z = (cd_w - median(cd_w)) / (percentile(cd_w, 75) - percentile(cd_w, 25))
cdiv_log = log(cdiv_w + 1)
cdiv_z = (cdiv_log - median(cdiv_log)) / (percentile(cdiv_log, 75) - percentile(cdiv_log, 25))
lc_z = (lc_w - median(lc_w)) / (percentile(lc_w, 75) - percentile(lc_w, 25))
hf_z = (hf_w - median(hf_w)) / (percentile(hf_w, 75) - percentile(hf_w, 25))
```

3. Min–max normalization

```
cd_s = (cd_z - min(cd_z)) / (max(cd_z) - min(cd_z))
```

cdiv_s = (cdiv_z - min(cdiv_z)) / (max(cdiv_z) - min(cdiv_z))
lc_s = (lc_z - min(lc_z)) / (max(lc_z) - min(lc_z))
hf_s = (hf_z - min(hf_z)) / (max(hf_z) - min(hf_z))

4. Regulatory Gap Index (RGI)
RGI = (cd_s + cdiv_s + lc_s + hf_s) / 4

PCA Loadings
Below are the principal-component loadings (Appendix B) from a PCA on the four scaled features. PC1 captures the common "ambiguity" dimension; PC2 reflects a hedging vs. complexity contrast.

Feature	PC1 Loading	PC2 Loading
Citation Density	0.62	–0.10
Citation Diversity (log)	0.58	–0.22
Lexical Complexity	0.49	0.62
Hedging Frequency	0.42	–0.75

Explained variance: PC1 ≈ 58.3 %, PC2 ≈ 24.7 %.
The high positive PC1 loadings confirm that all four features contribute in the same direction to regulatory ambiguity.

Appendix C: Additional statistical tables and figures

```
=========== Mediation Results ================
a (sum_citations → RGI):          -0.0005  (p=0.000)
b (RGI → outcome | citations):    -0.7921  (p=0.000)
Direct effect (cit → out):        -0.0014  (p=0.001)
Indirect effect (a × b):          0.0004
Total effect (direct + indirect): -0.0009

--------------------Mediator  Model  Summary-----------------------------------------------------
                    OLS Regression Results
==============================================================================
Dep. Variable:                RGI   R-squared:                  0.844
```

```
Model:                     OLS   Adj. R-squared:              0.844
Method:              Least Squares   F-statistic:                 4075.
Date:             Tue, 22 Apr 2025   Prob (F-statistic):           0.00
Time:                   18:18:06   Log-Likelihood:             7474.0
No. Observations:            4522   AIC:                    -1.493e+04
Df Residuals:              4515   BIC:                 -1.489e+04
Df Model:                     6
Covariance Type:          nonrobust
==============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept           -0.0869      0.004    -21.696      0.000     -0.095     -0.079
sum_citations        -0.0005   4.79e-05    -11.472      0.000     -0.001     -0.000
citation_density      -0.6344      0.010    -64.177      0.000     -0.654     -0.615
lexical_complexity     0.6828      0.012     56.131      0.000      0.659      0.707
hedging_frequency     19.0785      0.293     65.177      0.000     18.505     19.652
act_count            -0.0066      0.000    -22.744      0.000     -0.007     -0.006
opinion_count        -0.0003    8.1e-06    -41.511      0.000     -0.000     -0.000
==============================================================================
Omnibus:                  222.082   Durbin-Watson:                1.756
Prob(Omnibus):                0.000   Jarque-Bera (JB):            260.607
Skew:                     0.539   Prob(JB):                   2.57e-57
Kurtosis:                  3.471   Cond. No. .................. 4.45e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.45e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

--------------Outcome Model Summary ------------------------------------
                           OLS Regression Results
==============================================================================
Dep. Variable:      numerical_outcome   R-squared:                   0.061
Model:                     OLS   Adj. R-squared:              0.060
Method:              Least Squares   F-statistic:                 42.00
Date:             Tue, 22 Apr 2025   Prob (F-statistic):         9.67e-58
Time:                   18:18:06   Log-Likelihood:             -2209.3
No. Observations:            4522   AIC:                       4435.
Df Residuals:              4514   BIC:                       4486.
Df Model:                     7
```

```
Covariance Type:          nonrobust
==============================================================================
                 coef    std err        t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept            0.4836      0.036     13.499      0.000      0.413      0.554
RGI                 -0.7921      0.127     -6.253      0.000     -1.040     -0.544
sum_citations       -0.0014      0.000     -3.307      0.001     -0.002     -0.001
citation_density     0.2924      0.116      2.513      0.012      0.064      0.521
lexical_complexity   1.3625      0.135     10.099      0.000      1.098      1.627
hedging_frequency    4.4154      3.471      1.272      0.203     -2.390     11.221
act_count           -0.0082      0.003     -3.134      0.002     -0.013     -0.003
opinion_count     4.583e-05   8.11e-05      0.565      0.572     -0.000      0.000
==============================================================================
Omnibus:                  787.678   Durbin-Watson:                 1.855
Prob(Omnibus):              0.000   Jarque-Bera (JB):           1285.525
Skew:                      -1.306   Prob(JB):                  7.11e-280
Kurtosis:                   3.051   Cond. No. .................. 6.21e+04
==============================================================================
```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.21e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

```
------------ Outcome Model (Reduced) ------------------------------------------
                            OLS Regression Results
==============================================================================
Dep. Variable:      numerical_outcome   R-squared:                       0.056
Model:                            OLS   Adj. R-squared:                  0.055
Method:                 Least Squares   F-statistic:                     53.63
Date:                Tue, 22 Apr 2025   Prob (F-statistic):           2.94e-54
Time:                        18:18:06   Log-Likelihood:                -2221.6
No. Observations:                4522   AIC:                             4455.
Df Residuals:                    4516   BIC:                             4494.
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err        t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept            0.7514      0.019     38.883      0.000      0.714      0.789
```

```
RGI_c              -0.6154     0.120     -5.125      0.000      -0.851      -0.380
sum_citations     -2.043e-05   7.62e-05     -0.268      0.789      -0.000       0.000
citation_density      0.2431      0.112      2.171      0.030       0.024       0.463
hedging_frequency     1.2491      3.395      0.368      0.713      -5.407       7.905
lex_c              1.4516      0.127     11.436      0.000       1.203       1.701
==============================================================================
Omnibus:                      797.551   Durbin-Watson:                   1.853
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1309.253
Skew:                          -1.318   Prob(JB):                    5.00e-285
Kurtosis:                       3.055   Cond. No. .................. 7.33e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.33e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

--- Mediator Model (Reduced) ---
                            OLS Regression Results
==============================================================================
Dep. Variable:                  RGI_c   R-squared:                       0.826
Model:                            OLS   Adj. R-squared:                  0.825
Method:                 Least Squares   F-statistic:                     5348.
Date:                Tue, 22 Apr 2025   Prob (F-statistic):               0.00
Time:                        18:18:06   Log-Likelihood:                 7220.5
No. Observations:                4522   AIC:                        -1.443e+04
Df Residuals:                    4517   BIC:                        -1.440e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept             0.0323      0.002     13.785      0.000       0.028       0.037
sum_citations        -0.0004   7.63e-06    -48.974      0.000      -0.000      -0.000
citation_density     -0.6896      0.009    -73.845      0.000      -0.708      -0.671
hedging_frequency    19.1525      0.309     61.888      0.000      18.546      19.759
lex_c                 0.7466      0.011     67.037      0.000       0.725       0.768
==============================================================================
Omnibus:                      123.252   Durbin-Watson:                   1.680
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              133.154
Skew:                           0.420   Prob(JB):                     1.22e-29
```

```
Kurtosis:                    2.982   Cond. No.                 5.39e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.39e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

=== Reduced Mediation Results =============
a (cit → RGI):          -0.0004  (p=0.000)
b (RGI → outcome):      -0.6154  (p=0.000)
Direct (cit → outcome): -0.0000  (p=0.789)
Indirect (a×b):          0.0002
Total effect:            0.0002
========================================

==RGI Validation==========================
Step 1: Internal Consistency via Cronbach's Alpha
Cronbach's Alpha: 0.000 (α > 0.7 indicates acceptable reliability)

Step 2: Principal Component Analysis
Explained Variance Ratio by Principal Components:
  PC1: 0.308
  PC2: 0.231
  PC3: 0.181
  PC4: 0.170
  PC5: 0.109

PCA Component Loadings:
   citation_density  citation_diversity_log  lexical_complexity  \
0          0.418251                0.559765           -0.514209
1         -0.513275               -0.299561           -0.414621
2          0.576306               -0.228518            0.480424
3         -0.031322               -0.472590            0.102511
4         -0.478022                0.566890            0.567771

   hedging_frequency  opinion_count
0           0.090605       0.488988
1           0.651274       0.225264
2           0.598574       0.162950
3          -0.438578       0.756848
```

4	0.130354	0.332830

Step 3: Z-Score Normalization (First 5 Rows):

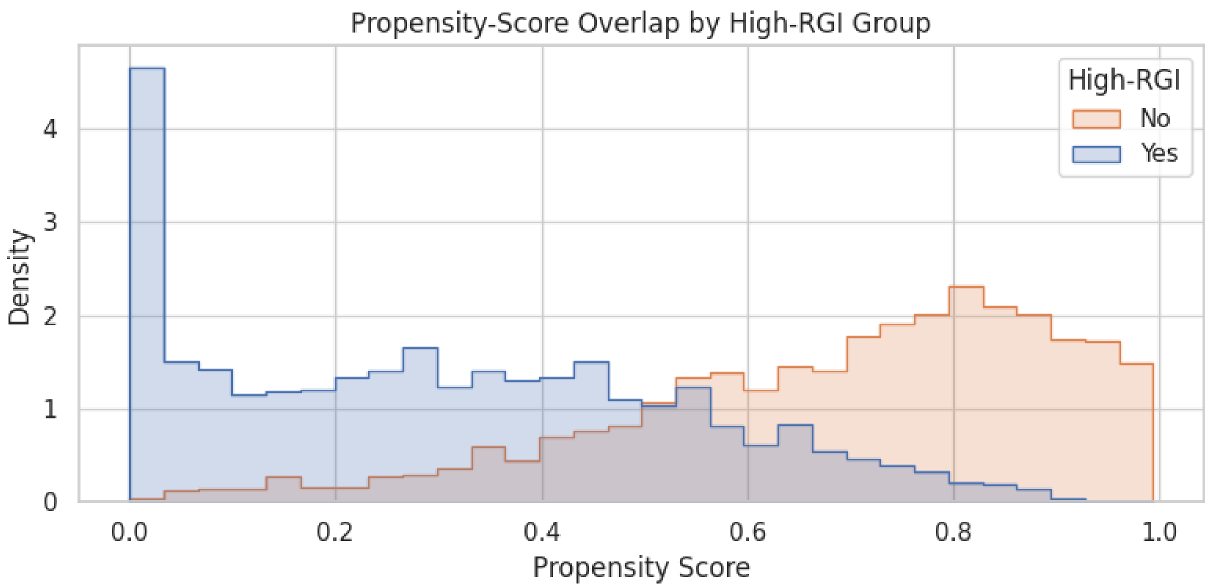
	citation_density	citation_diversity_log	lexical_complexity \
0	-0.408296	-0.020624	-0.647526
1	0.139299	0.988715	-0.999036
2	-0.688250	-0.020624	-0.882102
3	1.990475	-0.020624	0.705340
4	-0.599524	-0.020624	1.552322

	hedging_frequency	opinion_count
0	0.646367	2.469609
1	-0.003647	4.883718
2	0.271857	1.318454
3	0.306129	0.461996
4	-0.703726	-0.164232

Step 4: KMO Test for Sampling Adequacy
KMO Measure: 0.487 (KMO > 0.6 is desirable)

Step 5: Bartlett's Test of Sphericity
Bartlett's Test: $\chi^2 = 4094.43$, $p = 0.0000$ ($p < 0.05$ indicates factorability)

The inverse of the variance-covariance matrix was calculated using the Moore-Penrose generalized matrix inversion, due to its determinant being at or very close to zero.



Sector stats:

https://docs.google.com/spreadsheets/d/1046Tg5snWKq2ySOLZD3ANnm8G7y7dRItHtdXpYJ
gMJg/edit?usp=sharing

AI Usage Disclosure

This thesis was prepared with the assistance of artificial intelligence (AI) tools. Specifically, ChatGPT was used to support phrasing, and editing. The AI contributions consisted of generating alternative formulations, refining academic tone, and suggesting transitions. All AI-generated text was reviewed, edited, and integrated by the author to ensure accuracy, alignment with the thesis objectives and academic standards.

Statement of Authorship

I hereby confirm and certify that this master thesis is my own work. All ideas and language of others are acknowledged in the text. All references and verbatim extracts are properly quoted and all other sources of information are specifically and clearly designated. I confirm that the digital copy of the master thesis that I submitted on 28th April 2025 is identical to the printed version I submitted to the Examination Office on 29th April 2025.

DATE: 28th April 2025

NAME: Shruti Pradeep Kakade

SIGNATURE: