Code for Equity: A Human-AI Process for Reviewing Education Policy Against CARE Frameworks

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Abstract

This article presents a methodology combining AI-powered text mining with culturally responsive, antiracist, and equitable (CARE) principles to analyze educational policy. Using sentiment and word-count analyses, we evaluate policies from four U.S. states (North Carolina, California, Oregon, and Washington) and federal legislation. Findings reveal that procedural, compliance-focused language predominates, limiting transformative potential—patterns mirrored in school and district implementation challenges. California demonstrates stronger culturally responsive integration. We offer a replicable rubric that researchers, educators, and policymakers can use to evaluate policy design and identify implementation barriers. This approach provides an accessible method for equity-centered policy review while addressing ethical considerations inherent in AI-assisted analysis, including transparency about tool limitations and the primacy of researcher judgment over automated outputs. This methodology extends a prior qualitative policy analysis (Ouedraogo-Thomas et al., 2025) into a reproducible computational framework applicable across policy contexts.

Keywords: AI-assisted policy analysis, bias, CARE frameworks, critical policy analysis, text analysis

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Introduction

Society seeks innovative ideas and policies to overcome political deadlocks, address current challenges, and improve community well-being (powell et al., 2019). We argue that AI-assisted text analysis, when grounded in CARE principles and guided by researcher expertise, surfaces equity gaps in policy language that traditional review methods miss and produces frameworks practitioners can use without specialized technical training. This paper introduces an AI-assisted method informed by design symbiosis (Ouedraogo-Thomas, 2026), a conceptual framework founded in critical and engaged pedagogy (Freire, 1970; hooks, 1994). It emphasizes relational human-AI collaboration while centering human agency and conscientização, or critical consciousness (Freire, 1970), over efficiency-driven approaches. This approach respects individual voices and supports the development, improvement, and evaluation of policy through culturally responsive (CR), antiracist (AR), and equitable frameworks (Ouedraogo-Thomas et al., 2025).

Education policies are vital for addressing systemic inequities while advancing broader societal goals. Their success depends on managing the complexities of interpretation and implementation. A policy that is too strict or too vague can cause rigidity or inconsistent application, undermining its effectiveness. School leadership reforms respond to shifts in decentralization, school autonomy, accountability, and outcome emphasis (Pont,

2020), adding implementation complexity. Overly strict or vague policies risk inconsistency and diminished impact.

To implement culturally responsive, antiracist, and equitable (CARE) frameworks, policies must incorporate these principles into their design and objectives. This article demonstrates AI-assisted policy evaluation across four states using CARE principles. It offers recommendations for policy improvements to support diverse schools. Using AI techniques such as text mining and sentiment analysis, this research uncovers both implicit and explicit commitments to equity in state education efforts. A rubric for assessing and improving policies may serve to help educators and policymakers embed equity and justice. The analyses demonstrate how the CARE rubric identifies equity gaps and guides policy development aligned with equity principles.

Drawing on frameworks like Ladson-Billings' (1995) culturally relevant pedagogy and Crenshaw's (1989) intersectionality, Kendi's (2019) antiracism connects theory to practice. The analysis outlines ways to create justice-focused education systems. It encourages policymakers and educators to adopt equity-centered frameworks for evaluating and improving policies in line with CARE. Since contextual factors can influence leadership and policy implementation (Pont, 2020), this review considers both explicit policy language and implicit barriers.

State-level policy language directly shapes implementation at the school and district level. Vague or procedural language in state mandates often leads to inconsistent local practices, resulting in inequitable outcomes for students (Ball, 2015; Coburn, 2004). For example, North Carolina's transcript policy (GRAD-009, revised November 2024) explicitly prohibits Pass grades for non-elective graduation requirements while permitting them for elective courses. This distinction offers no guidance for supporting students undergoing credit recovery, funding program transitions, or addressing GPA impacts on marginalized learners (North Carolina State Board of Education, 2024). Policy analysis scholarship demonstrates how such implementation gaps disproportionately affect under-resourced schools and historically marginalized students (Datnow & Park, 2009; Lipsky, 2010). Critical discourse analysis of equity-oriented district policies further reveals that institutional language often reflects strategic positioning rather than substantive commitment (Green et al., 2026). We address this gap by demonstrating how AI-assisted analysis surfaces equity concerns in policy language and provides practitioners with accessible frameworks for identifying barriers before implementation.

Our experience in education leadership suggests that technology adoption has consistently followed cost pressures, political mandates, and the appearance of modernization rather than pedagogical evidence. AI enters this same pattern with greater speed and less transparency than any tool that preceded it. By 2025, 72% of U.S. school districts had experimented with AI technology, yet only 29% of teachers reported feeling adequately trained to use it (as reviewed in Joshi, 2025). This is a problem of adoption without infrastructure. The consequences of deploying AI without justice-centered frameworks are neither theoretical nor hypothetical. An example of this can be seen in that, within 16 hours of release, Microsoft's Tay posted over 95,000 racist tweets (Olavsrud, 2022). Also, Grok praised Hitler and called for genocide (Hagen, 2025). Yet another example is when multiple teenagers died by suicide following interactions with AI chatbots that validated rather than interrupted suicidal ideation (Chatterjee, 2025). These were not isolated incidents; rather, they reflect what occurs when tools developed without ethical frameworks are deployed among users without sufficient protections. The question for educational AI, then, is not whether to use it since adoption is already underway, but whether practitioners and policymakers have the tools to evaluate AI-adjacent systems through a justice lens before harm becomes the evidence.

The integration of artificial intelligence into educational research has advanced significantly over the past decade. Research indicates that while concerns about equity in AI-enhanced education are widely acknowledged, few standardized methods exist for assessing policies against CARE principles or integrating AI-assisted approaches with critical, justice-oriented frameworks that center human agency. Khalifa et al. (2016) establish that culturally responsive leadership requires policies that actively attend to systemic inequities rather than defaulting to procedural neutrality. Green et al. (2026) further demonstrate how equity-oriented policy language frequently reflects institutional positioning rather than substantive commitment to structural change. Similarly, Diem et al. (2022) argue that antiracist work requires explicit equity commitments across policy and institutional domains, as systemic racism persists through normalized practices that resist substantive change. These gaps motivate the following research questions:

1. How can AI-assisted analysis evaluate education policies against culturally responsive, antiracist, and equitable (CARE) principles?

2. What implicit bias and equity gaps emerge in state policies using this approach?

Literature Review

The following review synthesizes scholarship across three intersecting areas: AI applications in educational policy analysis, computational methods including text mining and sentiment analysis, and ethical considerations around AI bias and equity.

AI Applications in Policy Analysis

Studies agree that AI in education poses risks to equity and biases, requiring technical, governance, and participatory solutions. However, none provide an operational method for evaluating policies within a clear CARE framework. Menon & Chen (2023) used BERT embeddings to measure similarity between federal documents and governance stages, showing AI-assisted mapping but not CARE-specific evaluation. Hoca & Nuredin (2025) highlight biases that appear and recommend diverse data, explainable AI, and inclusive governance. Agarwal & Bhatnagar (2025) review AI interventions that support inclusion, focusing on implementation and ethics, not on policy evaluation. Barnes & Hutson (2024) discuss ethical risks and mitigation strategies, but do not provide validated tools for assessing policies. Overall, the literature identifies key risks and solutions, including technical safeguards, governance, and participatory practices. The absence of an operational, justice-centered evaluation system is a research gap and a structural vulnerability in a field deploying AI at scale, without frameworks for asking who is harmed when the tools get it wrong.

Zhai et al. (2021) conducted a review of AI applications in education from 2010 to 2020, highlighting text analysis and policy evaluation as emerging fields with significant potential. However, AI-supported policy analysis remains underdeveloped, constituting a notable research gap. Critical discourse analysis of equity-oriented district policies further reveals that institutional language often reflects strategic positioning rather than substantive commitment, with districts positioning themselves as opposers, fixers, bystanders, or perpetrators of racism in their equity-oriented policy language (Green et al., 2026). Kuang et al. (2024) further show that AI and text-mining techniques reveal implicit biases and equity issues in policy language that traditional methods may overlook. As educational governance becomes more complex, with responsibilities distributed across multiple levels, conducting context-sensitive analysis is essential. Policy implementation varies at these levels, and leadership impact relies heavily on context (Pont, 2020). This multilevel complexity underscores the need for AI-driven policy analysis that accounts for contextual differences, equity considerations, and implementation methods.

Text Mining and Sentiment Analysis in Policy Research

To address these limitations, researchers have increasingly turned to computational methods such as text mining, including sentiment analysis. Isoaho (2021) describes how topic modeling and computational text analysis complement qualitative approaches, emphasizing the need to balance AI-assisted methods with researcher expertise. Advances in text categorization have improved the ability to interpret complex policy language, allowing analyses that go beyond keyword searches to deeper semantic and contextual insights (Kowsari et al., 2019). Additionally, sentiment analysis has shown promise in identifying implicit orientations and values embedded in policy texts, as demonstrated in service management research (Kumar et al., 2021). These techniques help differentiate procedural language from more transformative equity commitments. Methodological approaches from organizational analytics demonstrate how language patterns reveal institutional priorities, offering tools adaptable to educational policy evaluation (Gupta et al., 2022).

AI Bias and Ethical Considerations

The intersection of AI applications and educational equity presents both opportunities and challenges. NLP methods including topic modeling, sentiment analysis, and discourse analysis offer increasingly sophisticated

tools for detecting gaps between stated equity priorities and actual policy language patterns, though most existing applications focus on English-language texts and lack explicit equity frameworks, limiting generalizability (Besigomwe, 2025). Studies mapping machine learning applications across domains of social advance (Lee & Lim, 2021) identify labor, employment, and policy impacts as areas requiring further attention, suggesting that purely technical efficiency frameworks are insufficient for understanding AI's broader societal effects. These gaps underscore the need for frameworks like design symbiosis that operationalize justice-centered human-AI collaboration.

Gaps in Literature

Although interest in AI-supported policy analysis is increasing, notable gaps remain, particularly around equity frameworks, methodological merging, contextual use, and AI bias. Researchers emphasize efficiency or compliance over justice-oriented outcomes (Kuang et al., 2024), and few studies align AI with critical, equity-focused policy analysis. There is limited guidance on applying AI tools within specific state or regional settings or on addressing biases inherent in AI systems. Educators and policymakers also lack straightforward models for utilizing AI tools without requiring advanced technical expertise.

Attention to human networks is similarly limited, as Davies et al. (2011) point out; policy implementation relies on the people and relationships connecting organizations. This view is especially relevant when examining how mandates influence classroom practice. Our analysis addresses these gaps by integrating AI tools into CARE frameworks to assess equity alignment while acknowledging the possibilities and limitations of AI-driven approaches.

Design Symbiosis

A Framework for Ethical Human-AI Collaboration. Design symbiosis (Ouedraogo-Thomas, 2026) bridges CARE principles and AI-assisted policy analysis. This conceptual framework, developed through a retrospective study of 21 months of human-AI collaboration, grounds ethical AI use in critical and engaged pedagogy (Freire, 1970; hooks, 1994). Its five principles counter efficiency-driven approaches: (1) relational intent opposing extractable data treatment of human knowledge, (2) voice preservation preventing predetermined framework deposits, (3) mutual boundaries prioritizing wellbeing, (4) dialogic co-creation between human and AI capabilities, and (5) human pacing centering critical consciousness over speed.

In this study, design symbiosis positions AI as supporting the researcher's culturally responsive, antiracist interpretive lens. Design symbiosis addresses a literature gap: while studies acknowledge AI bias risks (Barnes & Hutson, 2024; Hoca & Nuredin, 2025), few provide frameworks for the ethical use of AI in equity research. The framework ensures AI analysis remains accountable to justice-oriented outcomes, supporting community voices while rejecting the procedural approaches this analysis critiques. Design symbiosis provides theoretical grounding for the researcher's role, demonstrating how expertise guides AI applications rather than being displaced by them.

Theoretical Framework

The theoretical challenge lies in connecting 'local educational sites' with 'bigger picture educational reforms' through policy analysis (Davies et al., 2011). This means understanding how state-level policy intentions are translated across multiple governance levels to reach students. The multilevel governance structures that characterize contemporary education systems (Pont, 2020) create opportunities and barriers for equity-focused implementation.

Foundational scholarship on culturally relevant pedagogy highlights the need for policies that affirm students' identities while addressing systemic inequities (Ladson-Billings, 1995; Gay, 2010). Antiracist theory calls for policies that actively disrupt racism instead of surface-level equity (Kendi, 2019). Intersectionality highlights how disparities compound across identities (Crenshaw, 1989). Targeted universalism advocates for universal goals supported by targeted strategies that address the specific barriers faced by marginalized groups, ensuring policies are both inclusive and responsive to structural inequity (powell et al., 2019).

Attention to implementation remains essential: frontline educators shape how equity commitments are realized in practice (Lipsky, 2010), emphasizing safety, trust, and relevance for historically marginalized students. Critical perspectives remind us that policies encode dominant societal values, thereby reinforcing inequities unless they are intentionally justice-oriented (Foucault, 1977, 1991). Leadership committed to equity is, therefore, crucial for transformative change (Shields, 2010). Grounded in CARE principles, this framework offers a practical guide for evaluating justice-oriented reform.

Methodology

Policy Selection and AI-Driven Process

This analysis uses AI tools to assess the degree to which policies align with culturally responsive, antiracist, and equitable (CARE) frameworks. Policies were identified through keyword searches and web scraping, using Python tools in Google Colab. Web scraping, the automated collection of data from websites (Mitchell, 2018), enabled access to important documents from official sources. This analysis examined nine policy documents across five jurisdictions: two from North Carolina (§115C-376.5 and SHLT-003), two from California (Senate Bill 224 and Education Code Section 48900), two from Oregon (ORS 339.341 and ORS 418.529), two from Washington (RCW 28A.415.445 and Senate Bill 2861), and federal ESSA. Policies were selected through purposive sampling informed by prior qualitative analysis of North Carolina's trauma-informed education policy landscape (Ouedraogo-Thomas et al., 2025), which identified comparative state benchmarks and recommended federal policy inclusion. Selection criteria required that policies address school-based mental health, student equity, or educator training within a K-12 context and be publicly accessible through official government sources. Policies predating 2015 or addressing non-educational contexts were excluded. Document lengths ranged from single statutory sections to multi-section legislative acts; all were analyzed in their full accessible text form. Temporal scope spanned 2015 through 2024, capturing the post-ESSA policy landscape.

Defining CARE Dimensions and Analytical Methods

This analysis used AI tools to evaluate policies against CARE principles, offering both qualitative and quantitative insights into their alignment. To promote cultural responsiveness, keywords included cultural competence, reciprocity, diversity, and funds of knowledge (Gay, 2010; Ladson-Billings, 1995). CARE dimension keywords were drawn from the coding framework established in a prior qualitative document analysis of North Carolina's SHLT-003 policy (Ouedraogo-Thomas et al., 2025), ensuring theoretical consistency with the seminal literature across dimensions. In antiracism, key terms are antiracist, intersectionality, decolonization, and justice (Kendi, 2019; Crenshaw, 1989). Regarding equity, keywords are disparity reduction, inclusion, marginalized, and barriers (powell et al., 2019; Shields, 2010). Keyword frequencies were categorized as low (0–2 occurrences), moderate (3–4), or high (5+). These thresholds were established through an iterative analytical process: a percentile-based approach was initially explored and subsequently refined to fixed values based on the observed distribution of counts across the policy corpus, reflecting researcher judgment applied to the data rather than automated calculation. Sentiment analysis evaluated policy language for implicit beliefs, tone, and CARE alignment. Visualization methods such as word clouds, counts, and tables provided clear views of themes, sentiment, and alignment.

Sentiment Analysis Procedure Using Google Colab

Sentiment analysis was conducted in Google Colab using a Python script that applied the VADER (Valence Aware Dictionary and sEntiment Reasoner) model from NLTK. VADER was selected for its lexicon-based, rule-driven design, which produces interpretable and reproducible results without requiring domain-specific training data. Its four-score output maps directly onto the dimensions of policy tone this analysis sought to examine, and as a non-black-box tool it supports the transparency prioritized by this work's equity commitments. VADER was originally developed and validated for social media text (Hutto & Gilbert, 2014); while computational text analysis methods have been applied to education policy research more broadly (Besigomwe, 2025; Kuang et al., 2024), its performance on formal legislative language has not been independently validated, a constraint addressed in the limitations section.. VADER produces four scores: positive, negative, neutral, and a compound score

summarizing overall sentiment on a -1 to +1 scale. The full text of each policy was imported into Colab, preprocessed (lowercased and non-text characters removed), and then passed through VADER to generate sentiment scores. The resulting values were graphed using Matplotlib to visualize differences in tone across the policies. ESSA was incorporated through direct text input into the analytical environment, as automated web scraping encountered access restrictions on the primary federal source; the analyzed text was verified against the official Congressional record (ESSA, 2015).

CARE Frameworks Rubric for Policy Evaluation

The rubric was created to evaluate policy language, intent, and implementation readiness. It provides a structured tool for identifying strengths and gaps in CARE alignment. Each criterion is scored on a scale from 0 (Needs Major Support) to 4 (Exemplary), enabling nuanced analysis and actionable feedback. AI-driven insights, including word counts, sentiment analysis, and thematic alignments, informed the application of the rubric in this analysis.

Table 1

Rubric Criteria and Performance Levels

CARE Criteria	Needs Major Support (0)	Emerging (1)	Developing (2)	Proficient (3)	Exemplary (4)
Culturally Responsive (CR)	The policy fails to acknowledge cultural diversity.	Recognizes cultural diversity but lacks straightforward integration into systemic strategies or frameworks.	Some integration of cultural responsiveness is evident, but implementation is inconsistent or incomplete.	Policies incorporate cultural responsiveness with actionable strategies and professional learning opportunities.	Policies fully embed cultural responsiveness into systemic practices, supported by comprehensive training and accountability measures.
Antiracist Practices (AR)	No mention or acknowledgment of systemic racism in policy language or implementation strategies.	Indirectly addresses systemic inequities but lacks explicit antiracist language or strategies.	Antiracist language is present but lacks robust implementation or accountability measures.	Explicit antiracist language is included, with systemic strategies to address inequities.	Fully operationalizes antiracism through clear mandates, systemic reforms, and robust accountability measures.
Equity Frameworks (E)	Policies often fail to address systemic inequities or structural barriers.	Recognizes inequities but lacks systemic approaches to address them.	Some elements of equity frameworks are present, but their comprehensive application is lacking.	Equity frameworks are integrated into policies with targeted reforms and measurable outcomes.	Policies comprehensively operationalize equity frameworks, incorporating clear metrics, effective monitoring mechanisms, and active community involvement.

The rubric assigns a score (0–4) to each CARE criterion based on the policy's alignment with performance levels, supported by evidence from policy texts, sentiment analysis, and word count evaluations. Rubric scoring followed an iterative validation process. Policies were scored independently, then cross-checked using AI-assisted analysis in Google Colab to identify inconsistencies or overlooked patterns. Co-author review provided an additional layer of interpretive accountability. Where scores diverged or policy language was ambiguous, the team reconciled through discussion, revisiting rubric criteria and refining descriptors as needed. This process ensured that final scores reflected principled, collaborative interpretation rather than AI-generated output alone.

The rubric assesses the balance between procedural language and transformative intent, addressing systemic inequities. Scores generate recommendations that address gaps and improve policy alignment with CARE principles. The rubric accommodates various policy contexts and maintains transparency through visualizations, with scoring trends informing broader policy strategies. In this way, the rubric bridges theory and practice, operationalizing CARE principles for both policy evaluation and implementation.

The Role of the Researcher

Although AI tools facilitated technical analysis, the researcher's expertise in education and policy guided the process. Trial-and-error adjustments ensured focused and actionable results. CARE principles, grounded in seminal literature, shaped the design of queries and informed interpretation, mitigating the risk of AI overreach or irrelevant outputs. This iterative approach demonstrates how AI can complement subject-matter expertise by operationalizing the principles of design symbiosis (Ouedraogo-Thomas, 2026) to democratize policy analysis while maintaining the user's interpretive authority.

Translating Technical Analysis for Practitioner Use

The authors' professional experience supporting school and district policy subcommittees revealed persistent gaps between state policy language and school-level implementation needs. This experience informed the development of accessible tools for practitioners without technical expertise. While the AI-assisted methods described above enabled systematic policy evaluation, a parallel goal was to translate these insights into frameworks that school and district leaders could use independently.

Through iterative engagement with policy texts and AI outputs, we distilled patterns from sentiment analysis and word count findings into equity-centered guiding questions. These questions operationalize CARE principles without requiring coding knowledge or specialized software. The framework organizes questions into three domains aligned with critical policy analysis (Table 2). Ongoing refinements through professional learning sessions with practitioners continue to inform the framework's evolution.

Table 2

Equity-Centered Guiding Questions for Policy Analysis

Domain	Sample Questions
Impact & Consequences	Who benefits most? Who might be burdened? What are the possible unintended consequences?
Narratives & Assumptions	What does this policy assume about students and families? What values does it reflect?
Redesign & Action	What could be changed or reimagined? How could students/families be more involved?

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Results

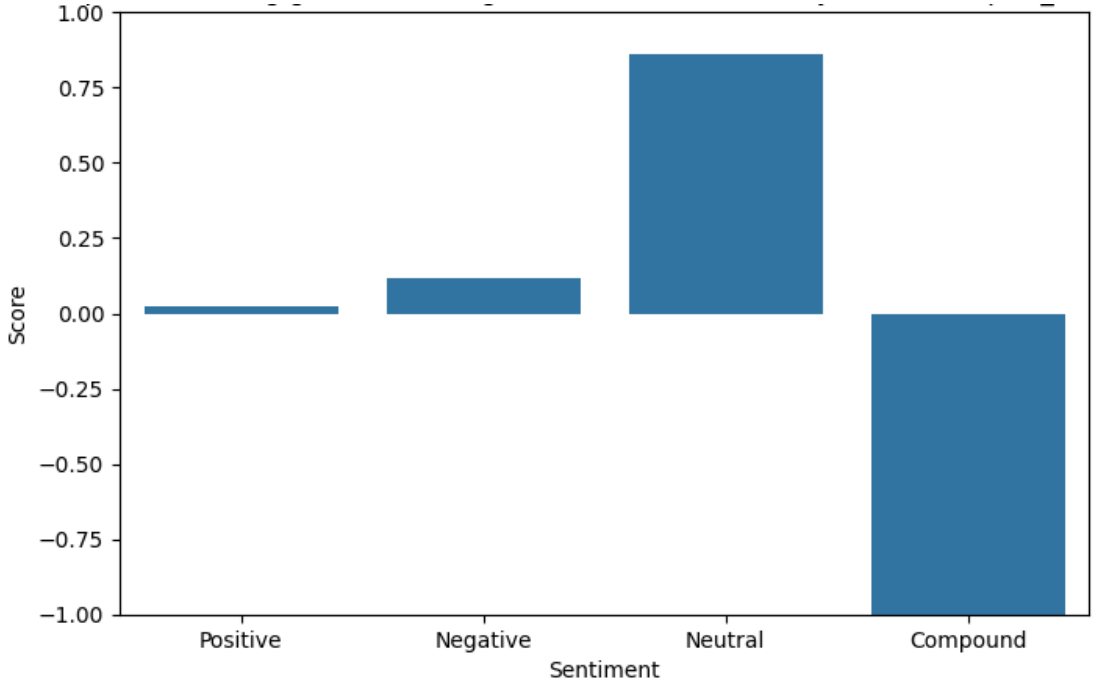
This analysis evaluates select policies and their alignment with culturally responsive, antiracist, and equitable (CARE) frameworks across multiple jurisdictions, including North Carolina, California, Oregon, and Washington. The findings reveal varying levels of integration, highlighting both systemic strengths and gaps in policy design. Analyses were informed by the CARE Framework Rubric, which evaluates policies based on culturally responsiveness (CR), antiracist practices (AR), and equity frameworks (E).

Sentiment Results

Sentiment analysis evaluated the tone and implicit beliefs embedded within policy language, providing insights into systemic orientations and priorities. Key results were analyzed by state, highlighting variations in sentiment trends. As shown in Figure 1, the sentiment analysis of North Carolina's §115C-376.5 (Health Needs of Students) policy predominantly revealed a neutral tone. These results reflect a procedural approach with limited aspirational or equity-driven language.

Figure 1

Sentiment Scores for NC §115C-376.5

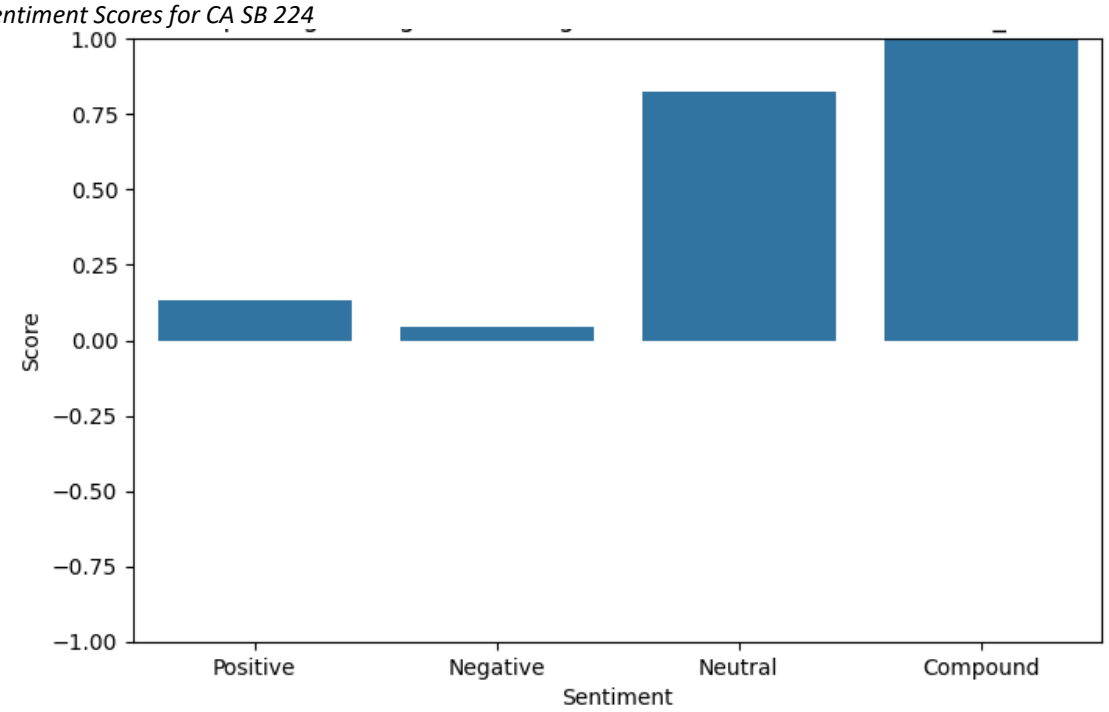


Note. Sentiment visualizations generated using VADER analysis in Google Colab. Statute pulled from www.ncleg.gov.

Sentiment analysis of North Carolina's policy, NC §115C-376.5, indicated a neutral, procedural tone. In contrast, Figure 2 displays Google Colab's sentiment results for California's Senate Bill 224, indicating a more balanced sentiment.

Figure 2

Sentiment Scores for CA SB 224



Note. Sentiment visualizations generated using VADER analysis in Google Colab. Statute pulled from legalinfo.legislature.ca.gov.

California policies, including Senate Bill 224, adopt a more positive tone by explicitly promoting equity and cultural diversity. Google Colab sentiment analysis of Oregon's ORS 418.529 and Washington's RCW 28A.415.445 reveals sentiment differences and alignment with CARE principles across the two states. Sentiment results for policies in Oregon and Washington are mostly neutral, with little use of antiracist or culturally responsive language. ESSA exhibits a neutral sentiment, characterized by low positive and almost no negative sentiment, reflecting a focus on procedural and compliance language typical of national frameworks. Table 3 provides a comprehensive overview of sentiment results across policies.

Table 3

Sentiment Analysis Results Across Policies

Policy Location	Positive	Neutral	Negative	Compound Score
NC	Low	High	Low	Slightly Positive
CA	Moderate	High	Low	Positive
OR	Low	High	Low	Neutral
WA	Low	High	Low	Neutral
Federal	Low	High	Low	Neutral

The sentiment analysis shows varied alignment with CARE principles across states. California's policies, including Senate Bill 224, contain strong aspirational and equity language, demonstrating a commitment to inclusion. Most other states adopt neutral, compliance-focused tones, promoting consistency but limiting transformative change. Oregon and Washington emphasize structured implementation through professional standards but primarily rely on procedural language, with limited explicit equity commitments. Gaps include a lack of focus on antiracism, culturally responsive practices, and broader equity goals. North Carolina's policies tend to be neutral and lack inspiring language.

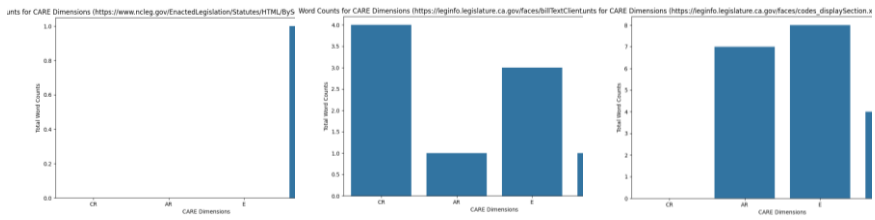
Word Count Results

Figure 3 presents word-count results for three policies. The x-axis in each chart is grouped by the CARE dimensions: Culturally Responsive (CR), Antiracist Practices (AR), Equity Frameworks (E). The y-axis indicates the total count of words aligned with each CARE dimension.

Figure 3

Word Counts for CARE Dimensions in NC and CA Policies

NC §115C-376.5	Senate Bill 224	Ed Code Section 48900



Note. Word count visualizations generated using Python text analysis in Google Colab. Charts display the frequency of CARE-aligned terminology across policy documents.

North Carolina policies exhibit low use of CR- and AR-related terms. Equity (E) language was moderately included. There is an underrepresentation of the Culturally Responsive (CR) and Antiracist Practices (AR) dimensions in the word-count data. In contrast, California policies exhibited high word counts for Culturally Responsive (CR) and Equity (E) dimensions. Although antiracist language was present, it accounted for only a small proportion of the policy frameworks' word count. Across all policies, neutral sentiment predominates, with limited variation in negative sentiment and modest increases in positive sentiment in states with more explicit equity language.

Discussion

The dominance of procedural, compliance-driven language across policies suggests that current approaches to education reform prioritize administrative consistency over transformative, equity-oriented change (Ouedraogo-Thomas et al., 2025). This pattern reflects what design symbiosis identifies as the consequence of efficiency-driven systems that prioritize procedural compliance over relational, justice-oriented engagement. Without frameworks that center human agency and critical consciousness, policy analysis risks reproducing the very inequities it seeks to address. The analysis highlights strengths in procedural language and areas for improvement. Neutral language emphasizes compliance and systematic execution, while positive sentiment aligns with aspirational, community-driven reforms. The lack of explicit equity directives reveals notable gaps in advancing CARE frameworks. The tone is procedural and goal-oriented, addressing trauma but lacking broader cultural or emotional considerations. Overall, the tone underscores broad equity practices but lacks explicit

commitments to cultural, systemic change. While procedural alignment and structured implementation are strengths, there is a need for more explicit commitments to equity, antiracism, and cultural responsiveness.

The word count analysis highlights strengths and gaps in the alignment of state and federal policies with CARE frameworks. As Table 4 indicates, strengths include commitments across states. However, gaps persist, notably in the limited inclusion of culturally responsive (CR) principles and antiracist (AR) practices, particularly in North Carolina and federal policies. CR and AR dimensions are underdeveloped, indicating areas for improvement.

Table 4

Overall Word Count Results

Location	CR Word Count	AR Word Count	E Word Count	Interpretation
NC	Moderate	Low	High	Limited CR and AR integration.
CA	High	Moderate	High	Strong CR integration.
OR	Moderate	Low	High	Limited CR and AR.
WA	Moderate	Low	Moderate	Balanced but weaker CR and AR focus.
Federal	Low	Low	High	Gaps in CR and AR integration.

Analysis of Word Count Results

Neutrality and procedural focus dominate policy language across jurisdictions. While equity-related terms are prevalent in California and Oregon, culturally responsive and antiracist language remains significantly underrepresented across all states (Figure 3). Word cloud analysis of policy texts reinforced these patterns, revealing that procedural terms such as “compliance,” “requirements,” and “standards” dominate, while aspirational equity language remains sparse. California policies uniquely emphasize terms such as “diversity” and “inclusion,” distinguishing them from policies that prioritize compliance over transformative CARE practices. Most policies lack explicit commitments to equity and antiracism, underscoring the need for holistic CARE frameworks in policy design.

Application of the CARE Framework Rubric

The rubric evaluates policies across five performance levels, ranging from 0 (Needs Major Support) to 4 (Exemplary), allowing for nuanced assessments of alignment with CARE principles. Informed by AI analyses, these scores offer a multidimensional perspective on policy language, tone, and thematic emphasis.
The rubric’s application involves four iterative steps:

1. Conduct an initial policy evaluation using the rubric criteria.
2. Integrate AI-generated insights to support evidence-based scoring.
3. Identify areas for growth through gap analysis.
4. Propose recommendations for systemic improvement.

This process empowers policymakers, educators, and activists to use both qualitative and quantitative data to improve policies and close equity gaps. This analysis shows how AI can support educational policy evaluation when it is based on cultural relevance, using the CARE rubric. It addresses AI hallucinations—responses that seem

factual but lack verified context. The CARE framework allows policy evaluation by combining AI techniques with context-aware inquiry, ensuring alignment with culturally responsive, anti-racist, and equity-focused principles. While AI tools improve analysis speed, educators' and communities' expertise remains crucial. This work recognizes the social injustices built into AI development, such as the exploitation of underpaid labor in data processing, and emphasizes the importance of confronting these inequities. By applying AI ethically, this research illustrates how to balance technological benefits with justice and equity, ensuring policies serve all students.

From State Policy Analysis to School-Level Implementation

The equity gaps identified through AI-assisted analysis of state policies manifest as concrete implementation challenges for school and district leaders. When we presented our findings at professional conferences, practitioners recognized that procedural language and the absence of equity directives create barriers they face daily. The following illustrative scenarios represent recurring themes from these engagements.

North Carolina's GRAD-009 policy exemplifies this pattern. Our analysis identified low counts of culturally responsive (CR) and antiracist (AR) words alongside neutral sentiment scores. Practitioners described corresponding implementation challenges: the need for "complete program overhauls" without guidance, concerns that grading credit-recovery courses "could make students feel set up to fail," and a lack of "resources to support necessary adjustments." These perspectives illuminate what our rubric revealed: policies scoring low on the CR and AR dimensions impose implementation burdens that disproportionately affect marginalized students.

Families and students articulated concerns that our technical analysis could not capture directly. Parents are concerned that policy changes will prevent students from "moving forward because their GPA will not recover fast enough." Student advocates noted that ambiguous policies "could discourage students from even trying." These voices underscore what Ball (2015) and Lipsky (2010) predict: vague policy language creates space for local interpretation that can either advance or undermine equity, with street-level bureaucrats filling gaps in ways that may reproduce inequities.

The equity-centered guiding questions framework (Table 2) helped practitioners systematically identify these concerns. When participants applied questions such as "Who might be burdened?" to local policies, they surfaced implementation barriers ranging from resource constraints to unstated assumptions about family capacity. Taken together, these findings demonstrate that without explicit integration of culturally responsive and antiracist principles, education policies risk functioning as procedural instruments rather than transformative tools for equity.

Implications and Recommendations

Statutes such as §115C-376.5 are strict, limiting updates, whereas SBE policies are more adaptable, allowing terms such as "inclusion," "cultural competence," and "equity" to align with CARE principles. Policy improvements should address systemic issues, such as training in CARE principles that foster accountability. Successful policy development relies on input from educators, policymakers, and communities to meet local needs.

The rubric compares how states align policies with CARE principles, highlighting strengths and gaps. California (SB 224) leads with 93% CARE alignment by mandating mental health education and culturally responsive practices, but could better embed antiracist frameworks. Use of Oregon (ORS 418.529) in education and antiracist efforts is limited. Washington (RCW 28A.415.445) provides professional learning on cultural competency but requires deeper, systemic integration of equity. While each state demonstrates strengths, such as California's culturally responsive education or Washington's professional development, gaps in systemic integration, notably in CR and AR, remain. Policies often focus on procedures rather than transformative strategies, limiting progress. States should clarify implementation, embed systemic equity, and promote collaboration for greater impact.

Bridging Theory and Practice

The CARE rubric, integrated with AI-supported analyses, provides a practical and research-driven framework for embedding justice-oriented practices into educational policy. Gaps in culturally responsive (CR) and antiracist (AR) dimensions underscore the need to integrate equity-driven principles to address policies that perpetuate inequities and exclusion. The rubric serves as both a diagnostic and guiding tool, enabling policymakers to transition from procedural practices to CARE-aligned systems.

Implications for Policy Improvement

The CARE rubric offers a scalable framework for inclusive education policies. Its integration with AI showcases technology's role in promoting equity-driven policymaking. Policymakers should prioritize supporting capacity building with resources and collaboration, embedding culturally responsive and equity-focused principles into policy to address long-standing inequities, and using AI insights alongside educator expertise to enable dynamic, evidence-based policy adjustments aligned with CARE principles and emerging needs.

Conclusion

Ultimately, bridging state policy analysis with school-level implementation requires tools that both reveal equity gaps in policy language and support practitioners in anticipating barriers before they become entrenched. We demonstrate how AI-assisted methods can be translated into accessible frameworks that enable school and district leaders to conduct equity audits within their contexts. As policy complexity continues to increase across multilevel governance structures (Pont, 2020), such approaches offer promising pathways for ensuring that equity commitments embedded in state policies reach all students.

Limitations

Several limitations merit transparent acknowledgment. Policy selection was purposive rather than systematic, with nine documents across five jurisdictions representing a small, non-random sample; findings describe these specific texts and cannot be generalized to broader state or national policy landscapes. VADER was developed and validated for social media text (Hutto & Gilbert, 2014), and cross-domain validation data from the original study show notably reduced performance on formal prose. In the study, the F1 accuracy drops from 0.96 on social media text to 0.55 on opinion editorials, the closest published analogue to policy language. VADER's sensitivity to formal, procedural language, where ideologically neutral wording may encode inequity structurally, is therefore limited (Besigomwe, 2025), and sentiment scores should be interpreted as indicators of tonal orientation rather than definitive measures of equity commitment. Word counts were not normalized for document length, meaning longer documents produce higher raw counts regardless of thematic emphasis. Rubric scores were assigned collaboratively by the research team without inter-rater reliability testing by independent coders. Finally, from a critical policy analysis perspective, the absence of a keyword or aspirational tone in policy text does not confirm the absence of equity intent. Implementation guidance, funding mechanisms, and regulatory structures operating beneath the statutory level were outside the scope of this analysis.
As equity infrastructure faces active dismantling at the federal level, the stakes of procedural policy language are urgent. Policy determines which students receive support and which are excluded. The CARE rubric and the methodology presented here offer practitioners a justice-centered entry point into policy evaluation that does not require technical expertise. Procedural language is a design choice, and this analysis demonstrates it can be redesigned. The framework is adaptable, reproducible, and grounded in the principle that AI is most valuable when it serves researcher judgment without replacing it.

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References

Agarwal, R., & Bhatnagar, A. (2025). Transforming Education: Harnessing the Power of AI to Empower Educators. *Productivity, 66*(1), 54–62. https://doi.org/10.32381/PROD.2025.66.01.7

Ball, S. J. (2015). What is policy? 21 years later: reflections on the possibilities of policy research. *Discourse: Studies in the Cultural Politics of Education, 36*(3), 306–313. https://doi.org/10.1080/01596306.2015.1015279

Barnes, E., & Hutson, J. (2024). Navigating the ethical terrain of AI in higher education: Strategies for mitigating bias and promoting fairness. In *Forum for Education Studies* (Vol. 2, No. 2). https://doi.org/10.59400/fes.v2i2.1229

Besigomwe, K. (2025). Using natural language processing (NLP) to analyze education policies: A systematic review. *Cognizance Journal of Multidisciplinary Studies, 5*(7), 440–454. https://doi.org/10.47760/cognizance.2025.v05i07.036

California Legislature. (2021). *Senate Bill No. 224*. https://leginfo.legislature.ca.gov

Chatterjee, R. (2025, September 19). Their teenage sons died by suicide. Now, they are sounding an alarm about AI chatbots. *NPR*. https://www.npr.org/sections/shots-health-news/2025/09/19/nx-s1-5545749/ai-chatbots-safety-openai-meta-characterai-teens-suicide

Coburn, C. E. (2004). Beyond decoupling: Rethinking the relationship between the institutional environment and the classroom. *Sociology of education, 77*(3), 211–244. https://doi.org/10.1177/003804070407700302

Crenshaw, K. (1989). Demarginalizing the intersection of race and sex. *University of Chicago Legal Forum, 1989*(1), 139–167.

Datnow, A., & Park, V. (2009). Conceptualizing policy implementation: Large-scale reform in an era of complexity. In G. Sykes, B. Schneider, & D. N. Plank (Eds.), *Handbook of education policy research* (pp. 348–361). Routledge.

Davies, B., Gottsche, M., & Bansel, P. (2011). Critical approaches to education policy and leadership. *Management in Education*, *25*(2), 47–49. https://doi.org/10.1177/0892020611404802

Diem, S., Welton, A. D., & Brooks, J. S. (2022). Antiracism education activism: Theoretical frameworks for understanding and promoting racial equity. *AERA Open*, *8*(1), 1–14. https://doi.org/10.1177/23328584221126518

Every Student Succeeds Act (ESSA), Pub. L. No. 114-95, 129 Stat. 1802 (2015). https://www.congress.gov/bill/114th-congress/senate-bill/1177

Foucault, M. (1977). *Discipline and punish: The birth of the prison.* Pantheon Books.

Foucault, M. (1991). Governmentality. In G. Burchell, C. Gordon, & P. Miller (Eds.), *The Foucault effect: Studies in governmentality* (pp. 87–104). University of Chicago Press.

Freire, P. (1970). *Pedagogy of the Oppressed.* Continuum International Publishing Group.

Gay, G. (2010). *Culturally responsive teaching: Theory, research, and practice* (2nd ed.). Teachers College Press.

Green, T. L., Trautmann, K., Clarida, K., Anglin, K., & Horne, J. D. (2026). Virtue signaling or substantive solidarity? A discourse analysis of school districts' positioning in equity-oriented policies and

resolutions. *Educational Administration Quarterly, 62*(2), 199–236. https://doi.org/10.1177/0013161X251400755

Gupta, S., Modgil, S., Lee, C. K., & Sivarajah, U. (2022). The Future Is Yesterday: Leveraging AI/ML in SCM to Build Organizational Resilience and Competitive Advantage. *Production Planning & Control*, *33*(16), 1457–1472. https://doi.org/10.1080/09537287.2021.1882689

Hagen, L. (2025, July 9). Elon Musk's AI chatbot, Grok, started calling itself "MechaHitler." *NPR*. https://www.npr.org/2025/07/09/nx-s1-5462609/grok-elon-musk-antisemitic-racist-content

Hoca, M., & Nuredin, L. (2025). Algorithmic Bias in AI-Enhanced Education: Cultural Dimensions and Pedagogical Impact. https://doi.org/10.55843/ISL2025symp163h.

Hooks, b. (1994). *Teaching to transgress: Education as the practice of freedom.* Routledge.

Hutto, C.J., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media*, 216–225. https://doi.org/10.1609/icwsm.v8i1.14550

Isoaho, K. (2021). Topic modeling and text analysis for qualitative policy research. *Policy Studies Journal*, *49*(1), 300–324. https://doi.org/10.1111/psj.12343

Joshi, S. (2025). Strategic integration of artificial intelligence in U.S. K–12 education: A comprehensive review and policy roadmap. *International Journal of Computer Applications, 187*(24), 21–38.

Kendi, I. X. (2019). *How to be an antiracist*. One World.

Khalifa, M. A., Gooden, M. A., & Davis, J. E. (2016). Culturally responsive school leadership: A synthesis of the literature. *Review of Educational Research*, *86*(4), 1272–1311. https://doi.org/10.3102/0034654316630383

Kowsari, K., Jafari Meimandi, K., Heidarysafa, M., Mendu, S., Barnes, L., & Brown, D. (2019). Text classification algorithms: A survey. *Information*, *10*(4), 150. https://doi.org/10.3390/info10040150

Kuang, H., Tian, P., & Liang, X. (2024). Policy analysis combining artificial intelligence and text mining technology in the perspective of educational informatization. *Humanities and Social Sciences Communications, 11*(1), 1–15. https://doi.org/10.1057/s41599-024-04076-0

Kumar, S., Kar, A. K., & Ilavarasan, P. V. (2021). Applications of text mining in services management: A systematic literature review. *International Journal of Information Management Data Insights*, *1*(1), 100008. https://doi.org/10.1016/j.jjimei.2021.100008

Ladson-Billings, G. (1995). Toward a theory of culturally relevant pedagogy. *American Educational Research Journal, 32*(3), 465–491. https://doi.org/10.3102/00028312032003465

Lee C. & Lim, C. (2021). From technological development to social advance: A review of Industry 4.0 through machine learning. *Technological Forecasting and Social Change*, *167*, 120653. https://doi.org/10.1016/j.techfore.2021.120653

Lipsky, M. (2010). *Street-level bureaucracy: Dilemmas of the individual in public services* (30th anniversary expanded ed.). Russell Sage Foundation.

Menon, S., & Chen, Y. (2023). *Analyzing US Federal Action on Artificial Intelligence Education Using a Process Governance Framework.* DOI: 10.1145/3598469.3598546

Mitchell, R. (2018). *Web scraping with Python: Collecting more data from the modern web* (2nd ed.). O'Reilly Media.

North Carolina State Board of Education. (2024, November 7). *Policy GRAD-009: High school transcript standards*. North Carolina Department of Public Instruction. https://www.dpi.nc.gov/districts-schools/classroom-resources/academic-standards/standard-course-study/nc-graduation-requirements

Oregon Legislative Assembly. (2019). ORS 418.529: *Child Welfare Services—Training standards and certifications*. Retrieved from https://www.oregonlegislature.gov

Olavsrud, T. (2022). 7 famous analytics and AI disasters. *CIO*. https://www.proquest.com/trade-journals/7-famous-analytics-ai-disasters/docview/2678812441/se-2

Ouedraogo-Thomas, R., Rummage Massey, S., & Bullins, L. M. K. (2025). Equity in North Carolina's SHLT-003: Gaps and Recommendations for Inclusive Trauma-Informed Education. Journal of Trauma-Sensitive Education, 4(3). https://doi.org/10.70085/jtse.v4i3.322

Ouedraogo-Thomas, R. (2026). *From Tool to Digitized Co-Conspirator: A Reflective Analysis of GPT-Based Engagement with Educational Equity.* American Journal of STEM Education. https://doi.org/10.32674/jxz8hn16

Pont, B. (2020). A literature review of school leadership policy reforms. *European Journal of Education*, *55*(2), 154–168. https://doi.org/10.1111/ejed.12398

Powell, j., Menendian, S., & Ake, W. (2019). *Targeted universalism: Policy & practice primer*. Othering & Belonging Institute, UC Berkeley. https://belonging.berkeley.edu/sites/default/files/2022-12/Targeted%20Universalism%20Primer.pdf

Shields, C. M. (2010). Transformative leadership: Working for equity in diverse contexts. *Educational Administration Quarterly, 46*(4), 558–589. https://doi.org/10.1177/0013161X10375609

Washington State Legislature. (2017). RCW 28A.415.445: *Professional learning days—Mental health topics—Cultural competency, diversity, equity, and inclusion*. Retrieved from https://www.leg.wa.gov

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*, 1–18. https://doi.org/10.1155/2021/8812542