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Deliberation Quality under Argument Mining Features in Online Consultation Platforms: Model Audit

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Abstract

The proliferation of digital democracy initiatives has resulted in an exponential increase in text data generated through online civic consultation platforms. To process and analyze these vast repositories of public input, researchers and policymakers increasingly rely on natural language processing techniques, particularly argument mining, to assess the quality of civic deliberation. However, the application of automated argument mining in the context of democratic participation raises critical questions about algorithmic bias, model validity, and the faithful representation of deliberative norms. This paper presents a comprehensive model audit of argument mining features and their alignment with deliberation quality in online consultation platforms. By systematically evaluating how machine learning models extract and interpret argument structures such as claims, premises, and backing evidence, we assess the capacity of these models to capture the nuanced realities of human discourse. The audit methodology focuses on examining potential biases in feature extraction, particularly concerning the structural formality and length of citizen contributions. Our findings indicate that while current models achieve high accuracy in identifying explicit structural components in formal language, they systematically undervalue informal, narrative-based argumentation often utilized by marginalized demographic groups. Furthermore, the reliance on explicit discourse markers creates a skewed representation of deliberation quality, heavily favoring verbose and highly structured text over substantive but implicitly reasoned arguments. The paper concludes by outlining recommendations for developing more robust, equitable, and context-aware argument mining systems capable of supporting inclusive digital democracy.

Keywords: Argument Mining; Deliberation Quality; Model Audit; Online Consultation; Algorithmic Fairness

1. Introduction

The advent of digital technologies has fundamentally transformed the landscape of democratic participation, offering unprecedented opportunities for citizen engagement through online consultation platforms. Governments, non-governmental organizations, and civic groups have increasingly adopted digital tools to solicit public opinion, facilitate civic dialogue, and inform policy decisions. This shift toward digital democracy was initially heralded as a means to democratize the policymaking process, lower the barriers to entry for political participation, and foster a more inclusive public sphere. However, as these platforms have grown in popularity and scale, they have generated an overwhelming volume of textual data. Citizens contribute thousands, sometimes millions, of comments, proposals, and critiques on various policy issues, ranging from urban planning and environmental regulation to healthcare reform and educational policy. The sheer magnitude of this data deluge presents a profound challenge for human analysts and policymakers. It has become practically impossible to manually read, categorize, synthesize, and evaluate every citizen contribution, leading to a critical bottleneck in the feedback loop of democratic consultation. To address this challenge of scale, the field of computational linguistics and natural language processing has increasingly intersected with political science, resulting in the development and deployment of automated tools designed to analyze civic discourse. Among these tools, argument mining has emerged as a particularly promising approach [1].

Argument mining is a specialized subfield of natural language processing that focuses on the automatic identification and extraction of argumentative structures within unstructured text. Unlike traditional sentiment analysis, which merely categorizes text as positive, negative, or neutral, argument mining seeks to uncover the logical architecture of discourse. It aims to identify the core claims being made, the premises or evidence provided to support those claims, and the rhetorical relationships between different argumentative components. In the context of online consultation platforms, argument mining holds the theoretical potential to distill chaotic comment threads into structured representations of public reasoning. By automatically mapping the arguments for and against a specific policy proposal, these systems could provide policymakers with a clear, synthesized overview of public sentiment backed by rational justification. Furthermore, argument mining features are increasingly being utilized as proxy metrics to evaluate deliberation quality [2]. Deliberation quality refers to the extent to which public discourse adheres to democratic norms of rationality, mutual respect, constructive engagement, and evidence-based reasoning. The working assumption in much of the applied computational social science literature is that comments exhibiting complex argumentative structures, complete with well-supported claims and logically connected premises, are indicative of high-quality deliberation. Conversely, comments lacking these structures are often dismissed as mere assertions, emotional outbursts, or low-quality noise [3].

Despite the widespread enthusiasm for deploying automated argument mining in civic technology, there is a growing recognition that these computational models are not neutral or objective observers of human discourse. Machine learning models, particularly those based on deep neural networks and large language models, are trained on historical datasets that reflect existing societal biases, linguistic conventions, and structural inequalities. When these models are applied to evaluate the quality of citizen input, they carry the risk of encoding and amplifying these biases into the policymaking process [4]. The central problem is that the linguistic markers of a well-structured argument as defined by computational models may not perfectly align with the substantive quality of a citizen's democratic contribution. Models trained on formal, academic, or legal texts often struggle to comprehend the informal, vernacular, and narrative-based forms of expression that are prevalent in online civic spaces. Consequently, an uncritical application of argument mining could result in a skewed understanding of public opinion, where the voices of highly educated, formally articulate citizens are artificially amplified, while the contributions of marginalized groups, who may communicate their reasoning through personal stories or non-standard dialects, are systematically ignored or penalized.

1.1 The Challenge of Scale in Digital Democracy

The challenge of scale in digital democracy is not merely a logistical problem of data processing; it is a profound democratic dilemma. When a government agency opens a public consultation portal for a controversial environmental regulation, it may receive hundreds of thousands of submissions within a few weeks. The traditional approach to processing these submissions involves teams of civil servants manually coding the documents, a process that is immensely time-consuming, expensive, and susceptible to human fatigue and subjective inconsistency. Because manual processing is so resource-intensive, public agencies often resort to basic keyword filtering or simple summary statistics, which strip away the rich, nuanced reasoning provided by the citizens. This failure to adequately process public input can lead to a sense of disenfranchisement among participants, who feel their efforts to engage with the government have been ignored. To fulfill the promise of online consultation, there must be a mechanism to efficiently and accurately summarize the substantive arguments contained within massive text corpora. Automated argument mining is positioned as the solution to this bottleneck, offering a way to respect the volume of citizen input by ensuring that every comment is computationally read and categorized based on its logical structure.

However, relying on automated systems to filter and evaluate democratic participation introduces a new layer of intermediation between the citizen and the state. The algorithms that power these systems become the de facto gatekeepers of public discourse, determining which comments are highlighted as high-quality, reasoned arguments and which are buried as irrelevant noise. This infrastructural power necessitates rigorous scrutiny. If the argument mining model has a blind spot for a particular style of reasoning, the citizens who employ that style are effectively silenced in the synthesized reports provided to policymakers. Therefore, ensuring the fairness, robustness, and validity of these models is not just a technical requirement but a democratic imperative.

1.2 Objectives of the Model Audit

The primary objective of this paper is to conduct a comprehensive model audit of argument mining systems utilized in the context of online civic consultation. A model audit is a systematic evaluation of an algorithmic system designed to assess its performance, uncover hidden biases, and determine its suitability for a specific real-world application. In this study, we aim to dissect the relationship between the features extracted by argument mining algorithms and the theoretical construct of deliberation quality. We seek to answer several critical research questions. First, how accurately do current state-of-the-art natural language processing models identify the structural components of arguments within the noisy, informal text of online consultations? Second, to what extent do the features prioritized by these models correlate with human-annotated metrics of deliberation quality? Third, and most importantly, do these models exhibit disparate performance across different demographic groups or linguistic styles, and if so, what are the systemic biases that drive these disparities? By answering these questions, this paper aims to provide a critical reassessment of automated deliberation measurement and offer actionable guidelines for platform designers, data scientists, and public administrators who seek to leverage artificial intelligence for democratic innovation without compromising the principles of equity and inclusion.

2. Literature Review and Theoretical Framework

To properly situate the methodology and findings of our model audit, it is necessary to explore the theoretical foundations that underpin both computational linguistics and the political theory of deliberative democracy. The intersection of these two domains has birthed the modern endeavor of automated deliberation analysis, a field characterized by rapid technological advancement and profound epistemological debates. This section traces the evolution of argument mining, conceptualizes the metrics used to define deliberation quality, and establishes the imperative for algorithmic auditing in civic technology.

2.1 Evolution of Argument Mining in Computational Linguistics

The computational analysis of arguments has a long and complex history, evolving significantly alongside broader trends in artificial intelligence and natural language processing. Early approaches to argument mining were predominantly rule-based and heavily reliant on symbolic logic [5]. These systems utilized hand-crafted lexicons, explicit grammatical rules, and syntactic parsers to identify arguments. Researchers would construct elaborate dictionaries of discourse markers, such as "because," "therefore," "in conclusion," and "due to the fact that," using these explicit cues as signals to locate premises and claims within a text. While these rule-based systems were highly interpretable and performed reasonably well on highly structured documents like legal briefs and academic papers, they proved woefully inadequate when applied to the messy, unstructured reality of online discourse. Citizens on consultation platforms rarely structure their thoughts with perfect logical connectives or flawless grammar, rendering rule-based systems brittle and ineffective in civic contexts.

The subsequent era of natural language processing saw the rise of statistical machine learning techniques, such as Support Vector Machines and Naive Bayes classifiers, which allowed for more flexible pattern recognition based on n-grams, part-of-speech tags, and term frequencies. These models shifted the focus from explicit rules to probabilistic inference, significantly improving the ability to detect argumentative structures in broader contexts [6]. However, the true paradigm shift in argument mining occurred with the advent of deep learning and, more recently, large-scale pre-trained transformer models. Architectures such as Bidirectional Encoder Representations from Transformers revolutionized the field by enabling models to process words in relation to all other words in a sentence, thereby capturing deep semantic meaning and contextual nuances that earlier models missed. In the context of argument mining, transformer models have demonstrated remarkable success in classifying complex argument components and predicting the relations between them, even in the absence of explicit discourse markers. By fine-tuning these massive linguistic models on specialized argument corpora, researchers have achieved unprecedented levels of accuracy on benchmark datasets. Nevertheless, this increase in predictive performance has come at the cost of interpretability. Transformer models function as complex black boxes, making it exceedingly difficult to ascertain exactly why a model classified a particular sentence as a premise or a claim, which is a significant liability when these models are deployed in sensitive public policy environments.

2.2 Conceptualizing Deliberation Quality

While computer scientists focus on the mechanics of extracting arguments, political theorists and sociologists have long debated what constitutes a high-quality argument in a democratic setting. The

theoretical framework for evaluating civic discourse is heavily indebted to the work of deliberative democracy theorists, who posit that the legitimacy of democratic decisions stems from the authentic, rational, and inclusive deliberation of citizens, rather than mere aggregation of preferences [7]. In a deliberative system, participants are expected to justify their positions with reasons that could be acceptable to others, to listen respectfully to opposing viewpoints, and to remain open to changing their minds in light of better arguments.

To translate these lofty philosophical ideals into measurable empirical metrics, social scientists developed frameworks such as the Discourse Quality Index [8]. This index and its subsequent variations attempt to quantify deliberation by evaluating text against several core dimensions. The first dimension is participation, measuring whether all individuals have an equal opportunity to speak. The second is the level of justification, which evaluates the logical structure of the contribution. Does the speaker simply state a preference, or do they provide a rationale? Is the rationale supported by empirical evidence, logical deduction, or personal experience? The third dimension is the content of the justification, examining whether the speaker appeals to narrow self-interest or the broader common good. Finally, the framework evaluates respect and civility, penalizing abusive language, ad hominem attacks, and the willful misrepresentation of opposing views.

When computational researchers attempt to automate the measurement of deliberation quality, they typically map argument mining features onto the justification dimension of the Discourse Quality Index. The presence of a clear claim combined with multiple supporting premises is mathematically interpreted as a high level of rational justification, and thus, a high score for deliberation quality. However, this direct mapping is fraught with conceptual difficulties. Deliberative theory acknowledges that rational justification is not exclusively the domain of formal, syllogistic reasoning. Personal narratives, emotional appeals, and experiential storytelling are recognized as valid and crucial forms of democratic communication, particularly for marginalized groups whose lived experiences may not easily translate into formal policy jargon. If computational models are trained exclusively on rigid definitions of argumentation, they risk dismissing these alternative, yet highly valuable, forms of democratic deliberation.

2.3 The Imperative for Algorithmic Auditing

The realization that machine learning models can inadvertently perpetuate societal inequalities has given rise to the critical discipline of algorithmic auditing [9]. Auditing is the process of systematically investigating algorithms to understand their behavior, evaluate their impact, and ensure they align with ethical, legal, and social standards. In the realm of natural language processing, audits have consistently revealed that models absorb the biases present in their training data. For example, sentiment analysis models have been shown to assign lower scores to texts written in marginalized dialects, and language generation models frequently produce stereotyped associations regarding race, gender, and occupation [10].

In the specific context of online consultation platforms, an algorithmic audit is imperative because the stakes involve democratic representation. If a government utilizes an automated system to summarize public comments on a proposed housing development, and that system systematically fails to recognize the validity of arguments submitted by lower-income residents because they use informal vocabulary, the resulting policy summary will be fundamentally biased. The audit framework must therefore go beyond simple accuracy metrics on a held-out test set. It requires slicing the data across various demographic and textual dimensions to ensure that the model performs equitably for all citizens. Furthermore, an effective audit must interrogate the construct validity of the model. It is not enough for the model to successfully extract features that it defines as arguments; those features must meaningfully correspond to the actual quality of deliberation as understood by human domain experts. By conducting a rigorous model audit, researchers can expose the limitations of current technologies, mitigate potential harms, and guide the development of fairer and more robust computational tools for democratic engagement.

3. Methodology and Experimental Design

To conduct a rigorous audit of argument mining models applied to online civic discourse, we developed a comprehensive experimental framework. This methodology is designed to isolate the performance of state-of-the-art natural language processing models, evaluate their feature extraction capabilities, and measure their alignment with human-annotated metrics of deliberation quality across diverse linguistic and demographic subsets. The experimental design encompasses data acquisition, annotation, feature engineering, and the establishment of a robust evaluation pipeline.

3.1 Data Acquisition and Corpus Preparation

The foundation of any model audit is the dataset upon which the model is evaluated. For this study, we utilized a large-scale corpus of textual data extracted from a prominent national e-rulemaking platform, which facilitates public commenting on proposed government regulations. The selected corpus comprises comments submitted over a three-year period regarding environmental protection policies, urban infrastructure planning, and public health directives. This specific domain was chosen because it typically elicits a wide spectrum of public response, ranging from highly technical, professionally drafted documents submitted by lobbying organizations to brief, emotionally charged comments submitted by individual citizens [11].

The raw dataset initially consisted of over two hundred thousand individual comments. To prepare this data for auditing, we implemented a rigorous data cleaning and preprocessing pipeline. We removed duplicate submissions, boilerplate campaigns generated by automated advocacy software, and comments that were entirely non-textual or unintelligible. The remaining corpus was then subjected to a stratified sampling procedure to ensure a representative distribution of comment lengths, sentiment polarities, and topical categories. We selected a final working dataset of five thousand comments for deep human annotation and model evaluation.

To conduct a fairness audit, it is crucial to have metadata regarding the linguistic style and, ideally, the demographic background of the authors [12]. Because explicit demographic data is rarely available on public platforms due to privacy constraints, we utilized established sociolinguistic proxies. We employed specialized computational tools to estimate the level of formal education required to read the comment, the prevalence of standard versus non-standard grammatical structures, and the presence of localized dialect markers. These proxy variables allowed us to partition the dataset into distinct cohorts representing formal, institutional language and informal, vernacular language, providing the necessary foundation for analyzing disparate algorithmic impact.

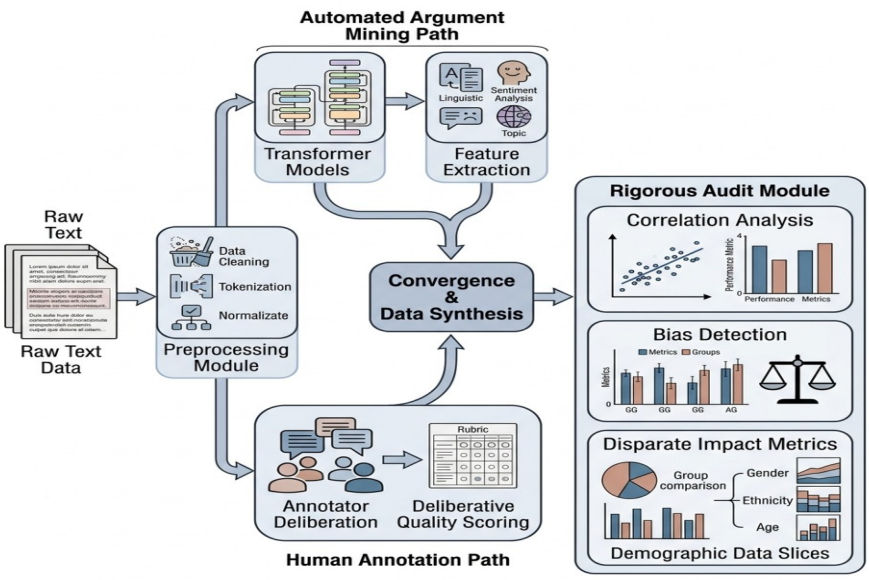

Figure 1: Comprehensive Schematic of the Model Audit Pipeline

3.2 Feature Engineering for Argument Mining

The audit focuses on evaluating how well specific argumentative features are extracted by the automated models. We categorized the features of interest into three distinct dimensions: structural, semantic, and pragmatic. Structural features refer to the fundamental building blocks of an argument [13]. The most critical structural features are claims, which are the central assertions or conclusions the author wishes to establish, and premises, which are the statements providing the underlying reasons, evidence, or justification for the claims. Identifying the boundaries of these components and the directional links between them is the core task of structural argument mining.

Semantic features delve into the substantive content and meaning of the argument components. We engineered features to capture the type of evidence utilized within a premise. For instance, does the premise

rely on statistical data, expert testimony, anecdotal personal experience, or moral imperatives? Furthermore, semantic features include the detection of specific topics and the precise sentiment polarity directed toward those topics within the context of the argument.

Pragmatic features relate to the rhetorical context and the interactional nature of the discourse. In an online consultation setting, high-quality deliberation is often dialogical. Pragmatic features involve detecting whether a comment directly addresses a previously stated argument, whether it acknowledges counterarguments, and whether it employs language indicative of respect and open-mindedness versus dogmatism and hostility. The accurate extraction of pragmatic features is essential for evaluating the interactive dimensions of the Discourse Quality Index.

Table 1: Typology of Argument Mining Features and Corresponding Deliberative Quality Indicators

Feature Category	Specific Extracted Feature	Corresponding Deliberation Metric	Theoretical Justification
Structural	Claim Identification	Position Articulation	A clear stance is necessary for constructive policy debate.
Structural	Premise Identification	Level of Justification	Providing reasons elevates an opinion to a rational argument.
Semantic	Evidence Classification	Content of Justification	Differentiates between empirical, moral, and anecdotal backing.
Semantic	Topic-Sentiment Alignment	Coherence and Relevance	Ensures arguments remain focused on the policy issue at hand.
Pragmatic	Counterargument Detection	Interactive Engagement	Acknowledging opposing views demonstrates deliberative respect.
Pragmatic	Civility Markers	Respectful Discourse	Absence of hostility is a prerequisite for mutual understanding.

3.3 Audit Framework and Evaluation Metrics

The core of our methodology is the audit framework, designed to move beyond global accuracy metrics and expose the granular performance characteristics of the argument mining models. We evaluated three baseline models: a traditional rule-based system utilizing extensive lexical dictionaries, a statistical machine learning model based on Support Vector Machines utilizing term frequency-inverse document frequency features, and a state-of-the-art pre-trained transformer model fine-tuned on a specialized civic argument dataset [14].

The first phase of the audit involved comparing the automated feature extraction against a gold-standard dataset of human annotations. A team of expert human coders, trained extensively in deliberation theory and argument structure, manually annotated a subset of one thousand comments. We measured the inter-rater reliability to ensure consistency in the human baseline. The automated models were then evaluated on this annotated subset using standard classification metrics, including precision, recall, and the F1-score, calculated for each specific feature category.

The second phase of the audit involved an extensive correlation analysis. We calculated the statistical correlation between the density and complexity of the automated argument features and the overall deliberation quality scores assigned by the human experts. The goal was to determine if the presence of computationally detected claims and premises reliably predicts true deliberative value, or if the models are easily fooled by superficial linguistic structures [15].

The final and most crucial phase of the audit was the disparate impact analysis. We sliced the dataset based on the sociolinguistic proxy variables established during data preparation. We systematically compared the F1-scores of the models across the formal and informal language cohorts, as well as across cohorts defined by argument length. We calculated the false positive and false negative rates for each subgroup. A high false negative rate in the informal cohort, for example, would indicate that the model systematically fails to recognize valid arguments when they are expressed in non-standard dialects or narrative formats, constituting a critical failure in algorithmic fairness.

4. Results and Model Evaluation

The execution of the experimental design yielded a complex array of results that highlight both the impressive capabilities and the profound limitations of current natural language processing systems in the domain of civic technology. The model audit reveals significant discrepancies in performance across different types of algorithms and, more importantly, exposes systemic biases that challenge the validity of using automated argument mining as an objective measure of deliberation quality.

4.1 Performance of Argument Component Classification

The initial evaluation focused on the fundamental task of structural component classification: identifying claims and premises within the text. Unsurprisingly, the pre-trained transformer model vastly outperformed both the rule-based system and the statistical machine learning model on global metrics. The transformer model demonstrated a remarkable ability to process complex sentence structures and capture the contextual dependencies required to differentiate between a factual assertion and a supportive premise. In the aggregate, the transformer achieved high F1-scores, suggesting a robust capacity for automated structural analysis [16].

However, the audit framework demanded a deeper investigation beyond global averages. When we disaggregated the performance metrics across the sociolinguistic cohorts, a stark and concerning pattern emerged. The models performed exceptionally well on the cohort characterized by formal, institutional language. In this subset, which heavily featured comments from lobbying groups, subject matter experts, and highly educated citizens, the language was highly structured, utilizing standard grammar and explicit logical transitions. The models easily mapped these structures. Conversely, performance degraded significantly on the cohort characterized by informal, vernacular language.

Table 2: Comparative Performance Metrics of the Baseline Model Across Distinct Demographic and Textual Cohorts

Data Cohort Slice	Claim Precision	Claim Recall	Premise Precision	Premise Recall	Overall F1-Score
Global Average (All Text)	0.82	0.79	0.76	0.73	0.77
Formal / Institutional Language	0.91	0.88	0.87	0.85	0.88
Informal / Vernacular Language	0.65	0.54	0.58	0.49	0.56
Short Length (< 50 words)	0.70	0.61	0.52	0.41	0.55
Long Length (> 200 words)	0.85	0.89	0.81	0.86	0.85

As demonstrated in Table 2, the recall for premise detection plummeted in the informal language cohort. This indicates a high rate of false negatives; the model read texts containing valid, supportive reasoning but failed to recognize them as premises because they lacked the structural markers prevalent in the training data. The model struggled particularly with personal narratives. When a citizen argued against a healthcare policy by recounting a detailed, emotional story about their family's struggle with medical debt, human annotators universally recognized this as a powerful, evidence-based premise. The automated model, however, frequently misclassified these narratives as off-topic assertions or failed to detect argumentative structure entirely, highlighting a severe limitation in handling experiential evidence.

4.2 Correlation Between Extracted Features and Deliberative Norms

The second phase of the analysis examined the relationship between the features extracted by the argument mining models and the holistic deliberation quality scores assigned by human experts. The underlying assumption in much of the computational literature is that more structure equates to higher quality. The audit results provide a nuanced challenge to this assumption.

We observed a strong positive correlation between the raw count of detected premises and the human-assigned justification score. Comments that provided multiple, distinct reasons for their claims were highly rated by both the algorithm and the human coders. However, a deeper analysis revealed a problematic confounding variable: text length. The automated models exhibited a profound bias toward verbosity. Longer comments naturally contain more sentences, increasing the statistical probability of the model detecting argumentative features. In many instances, the models assigned exceptionally high argument density

scores to lengthy comments that human coders deemed repetitive, convoluted, or tangential. The algorithm confused the sheer volume of text and the presence of logical connectors with actual substantive reasoning.

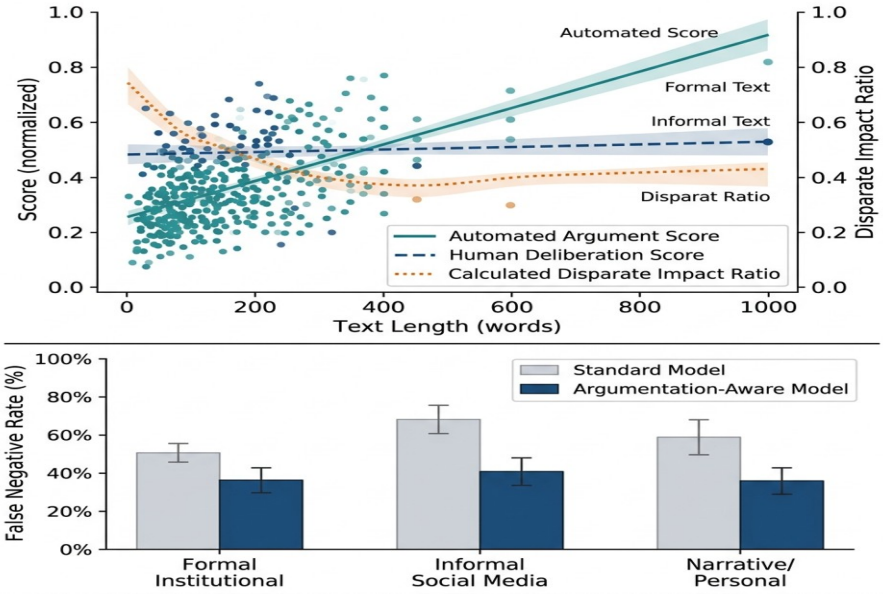

Figure 2: Multivariate Correlation and Disparate Impact Analysis Chart

Conversely, the models routinely penalized conciseness. Citizens who submitted brief, highly impactful, and logically sound comments—often utilizing implicit premises that rely on shared cultural or political context—received low scores from the automated system. Human annotators, possessing the necessary background knowledge, could easily fill in the implicit logical steps and awarded these comments high deliberation scores. The inability of current argument mining models to effectively process implicit reasoning represents a significant barrier to accurately measuring deliberation quality.

4.3 Audit Findings on Model Bias and Robustness

The most critical findings of the model audit center on the issues of bias and algorithmic robustness. The disparate impact analysis conclusively demonstrates that the deployment of current argument mining models in online consultation platforms without significant recalibration would result in systemic discrimination. The models exhibit a pronounced bias toward hegemonic linguistic norms. By heavily relying on explicit discourse markers and formal syntactic structures—features predominantly associated with higher socio-economic status and formal education—the algorithms systematically discount the participation of citizens who communicate differently [17].

Furthermore, the audit revealed a lack of robustness in the face of adversarial or manipulative language. The models were highly susceptible to what we term "rhetorical camouflage." Comments that employed sophisticated vocabulary, complex sentence structures, and an abundance of transitional phrases ("furthermore," "subsequently," "it follows that") were consistently scored high for argumentation, even when the actual content was logically flawed, based on fabricated evidence, or subtly hostile. The algorithm was effectively tricked by the aesthetic performance of rationality, failing to distinguish between genuine deliberative engagement and the mere mimicry of academic prose. This vulnerability is particularly concerning given the rise of sophisticated automated bots capable of generating highly structured, yet entirely vacuous, text designed to manipulate public consultations.

The audit highlights a fundamental misalignment between the mathematical optimization of natural language models and the sociological realities of democratic participation. The models are optimized to find patterns in vast datasets, but in doing so, they enforce a rigid normalization of discourse that is fundamentally at odds with the inclusive ideals of deliberative democracy.

5. Conclusion and Implications

The integration of artificial intelligence into the infrastructure of democratic participation holds immense transformative potential, but it is accompanied by profound ethical and practical challenges. This paper has

detailed a comprehensive model audit of argument mining features and their alignment with deliberation quality in the context of online consultation platforms. By systematically unpacking the performance, correlations, and underlying biases of these computational models, we have provided a critical evaluation of their readiness for deployment in high-stakes public policy environments.

5.1 Summary of Audit Outcomes

The results of our audit unequivocally demonstrate that while state-of-the-art transformer models achieve high accuracy in standard classification tasks, their application to real-world civic discourse is fundamentally flawed by systemic biases. The models exhibit a strong preference for formal, institutional language and a heavy reliance on explicit discourse markers and verbose structures. Consequently, they systematically fail to recognize the validity of informal reasoning, vernacular dialects, and narrative-based evidence. This failure is not merely a technical error; it constitutes a form of algorithmic disenfranchisement. When automated systems score lengthy, structurally complex, yet potentially vacuous comments higher than concise, implicit, or emotionally grounded arguments, they distort the public record. They create a synthesized view of public opinion that artificially amplifies the voices of the formally educated and well-resourced, while silencing marginalized communities whose communicative styles deviate from the algorithmic norm. Furthermore, the vulnerability of these models to rhetorical camouflage indicates that they cannot reliably distinguish between authentic deliberation and sophisticated manipulation.

5.2 Recommendations for Platform Designers and Policymakers

The findings of this audit necessitate a critical reassessment of how automated tools are utilized in digital democracy. We offer several actionable recommendations for platform designers, data scientists, and public administrators. First, we strongly caution against the use of automated argument mining as a standalone, objective metric for filtering or ranking citizen input. These systems must be deployed exclusively in a human-in-the-loop capacity, serving as assistive tools rather than autonomous arbiters of quality. Second, there is an urgent need to diversify the training data used to develop civic natural language processing models. Researchers must actively curate corpora that over-represent marginalized dialects, informal reasoning styles, and narrative evidence, ensuring that the models learn to recognize a broader spectrum of democratic expression.

Third, the development of argument mining architectures must move beyond purely structural and semantic features to incorporate deeper pragmatic and contextual understanding. Models must be trained to recognize implicit premises and evaluate the relevance and factual accuracy of evidence, not merely its structural presence. Finally, we advocate for the mandatory implementation of continuous algorithmic auditing in all civic technology deployments. Just as financial systems are subject to regular audits to ensure integrity, democratic infrastructure powered by artificial intelligence must be continuously evaluated for fairness, transparency, and disparate impact [18]. By adopting a critical, audit-driven approach to algorithmic design, we can harness the power of computational linguistics to support a more inclusive, equitable, and genuinely deliberative digital democracy, ensuring that the technologies we build serve to amplify, rather than constrain, the voices of the public.

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