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Original Research

Appraisal-Based Audit of Ideological Bias in Large Language Models Across Politics, Gender, Culture, and Technology

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Abstract. *This study examines how large language models construct evaluative meanings in response to political, gender, cultural, and technological issues. Using a qualitative-descriptive approach based on content analysis and Appraisal Theory frameworks, this study analyzed the outputs of ChatGPT, Gemini, and Claude to identify the patterns of Affect, Judgment, and Graduation in the framing of discourse. The results show that the AI response is not neutral, but contains systematic ideological biases. The emerging pattern shows a tendency to legitimize the liberal-Western paradigm through the strengthening of individual autonomy, criticism of state authority, and moral judgments that favor certain perspectives, while the Global South view is often given a more problematic framing of the Global South. In the gender realm, AI still reproduces a double bind to female leadership; in the cultural realm, AI tends to highlight anxiety over homogenization; and in the technological realm, AI displays strong epistemic insecurities. These findings confirm that AI output needs to be understood as a discursive practice that helps shape the legitimacy of meaning, so biased audits, algorithmic transparency, and critical AI literacy are needed in the use of generative systems.*

Keywords: *generative artificial intelligence; Appraisal Theory; ideological bias; discourse analysis; critical AI literacy*

1. Introduction

Development Generative Artificial Intelligence has made this system not only a tool for text production, but also a communication infrastructure that helps shape the way issues are understood by the public (Hashemi & Mahdavirad, 2023; White, 2025). In perspective Appraisal Theory, language always carries the judgment, position, and orientation of the speaker towards the object of discourse, so the AI output is not worthy of being considered neutral automatically (Alghazo et al., 2025; White, 2025). Recent studies have shown that AI-generated text has a pattern stance, Commitment, and Metadiscourse that differ from human texts, both in academic abstracts and argumentative essays (Berber Sardinha, 2024; Jiang & Hyland, 2025). At this point, analysis of AI responses becomes important because the lexical choices, intensity, and evaluations that emerge can lead readers to specific interpretations (Kong & Liu, 2024; White, 2025). AI outputs thus need to be read as text that produces points of view, not simply moving information (Alghazo et al., 2025; White, 2025).

This phenomenon is increasingly relevant when AI is used to discuss political, gender, cultural, and technological issues that are full of social importance (Motoki et al., 2025; Wei et al., 2025). Therefore, the study of the evaluative mechanism of AI is important to understand its influence on the formation of public opinion (Hashemi & Mahdavirad, 2023; White, 2025).

The main problem that emerges is that the bias in generative AI is present not only as factual errors, but also as political, gender, cultural, and ideological biases that are woven into the structure of language (Motoki et al., 2025; Wei et al., 2025). Recent research shows that generative models can reveal Politics bias and Value misalignment, as well as triggering different reactions from users depending on their political orientation (Messer, 2025; Motoki et al., 2025). In the realm of gender, AI still reproduces biases sourced from training data, algorithmic design, and user feedback, so women are often framed through a narrower evaluative lens (Ho et al., 2025). In the realm of communication, Source Disclosure does help improve transparency, but it doesn't automatically eliminate judgment bias against AI messages (Lim & Schmälzle, 2024; Schilke & Reimann, 2025). In fact, labeling an AI-generated text can lower trust and social legitimacy when audiences are skeptical of technology (Lim & Schmälzle, 2024; Schilke & Reimann, 2025). In terms of interpretability, Explainable AI can help recognize algorithmic biases, but its effectiveness depends heavily on the user experience and the design of the explanation given (Chuan et al., 2024). This condition shows that the issue of AI is not only technical, but also concerns power relations in the production of digital meanings (Francisco & Linnér, 2023; Monteiro & Singh, 2025).

The research gap can be seen from the tendency of previous research to more often examine only one domain, such as academics, health, or public communication, without mapping bias as a broader evaluative pattern (Alghazo et al., 2025; Jiang & Hyland, 2025). On the other hand, the study Appraisal Theory has shown that language evaluation can be systematically traced in journalistic, dissertation abstracts, and academic texts, but has not been largely directed to reading ideology in AI responses to contemporary socio-political issues (Hashemi & Mahdavirad, 2023; White, 2025). Therefore, the novelty of this research lies in the incorporation of Appraisal Theory with cross-thematic ideological bias audits, so that affect, Judgment, and Graduation can be mapped as an evaluative device that works simultaneously (Wei et al., 2025; White, 2025). This approach also expands on previous studies that compared human and AI texts, as the focus is not just on the quality of the language, but on the orientation of the values inserted in the text (Jiang & Hyland, 2025). By distinguishing Western and Global patterns South, this study highlights how definition, attribution, and intensification can function as mechanisms of meaning hegemony (Berber Sardinha, 2024; Francisco & Linnér, 2023). Another novelty lies in the reading of AI as an arena of epistemic contestation that produces legitimacy for one paradigm while delegitimizing another paradigm (Motoki et al., 2025; Wei et al., 2025). Thus, this research offers a new perspective in the study of language and artificial intelligence.

Based on this context, this study aims to identify the most prominent evaluative patterns in AI responses, explain emerging forms of attribution asymmetry, and map meaning-intensification strategies on political, gender, cultural, and technological issues (Hashemi & Mahdavirad, 2023; White, 2025). The results of the analysis are expected to show how AI can legitimize one paradigm while legitimizing another through word choice, focus, and strengthening certain values (Motoki et al., 2025; White, 2025). Practically, these findings are important for the development of critical AI literacy because users need to be equipped with the ability to more carefully assess the bias, transparency, and accountability of generative systems (Ma et al., 2025; Park, 2025; Veldhuis et al., 2025). Recent literature confirms that critical AI literacy, responsible AI literacy, and GenAI literacy needs to be explicitly designed so that users don't naively accept AI outputs (Anders & Dux Speltz, 2025; Ma et al., 2025; Veldhuis et al., 2025). In terms of governance, this study is in line with regulatory demands, Governance, and approach Explainable AI that is easier for the public to understand (Chuan et al., 2024; Francisco & Linnér, 2023; Monteiro & Singh, 2025). Theoretically, this study expands the use of Appraisal Theory From a mere linguistic evaluation analysis to an ideological reading of generative texts across domains (Hashemi & Mahdavirad, 2023; White, 2025). Ultimately, this study confirms that AI responses are text-loaded positions, so they need to be audited with the analytical prudence equivalent of human text (Alghazo et al., 2025; Wei et al., 2025).

2. Research Methods

This study uses a qualitative-descriptive design based on Content Analysis to read AI outputs as an evaluative practice, not just an informative response, as this approach allows researchers to organize, abstract, and interpret the meaning of the text systematically at the level Manifest or latent (Bengtsson, 2016; Erlingsson & Brysiewicz, 2017).

The analytical framework rests on Appraisal Theory which maps language evaluation into three main subsystems, namely Affect, Judgment, and Graduation, because this framework has proven to be effective in unraveling persuasive viewpoints, intensity, and orientations in academic and journalistic discourse (Hashemi & Mahdavirad, 2023; White, 2025).

The unit of analysis in this study is in the form of textual responses generated by three major language models, namely ChatGPT, Gemini, and Claude, to a set of topical questions politics, Gender, Culture, and Technology; any questions are asked in English, on a new conversation, using a new account, without a memory feature, to minimize Carryover context and maintain comparability across systems (Chen et al., 2025; Knoth et al., 2024). Preparation prompt Done with the principle Prompt Engineering which emphasizes instruction clarity, equality of meaning, and structural consistency, so that output differences can be interpreted as discursive variations between models, rather than the result of instructional irregularities (Chen et al., 2025; Knoth et al., 2024).

As a methodological foundation, this procedure is also aligned with qualitative research guidelines that emphasize the integration of assumptions, procedures, and analytical dilemmas in text-based studies, so that the data collection and reading process is directed to maintain analytical coherence from the beginning to the reporting stage. All answers are copied verbatim into the research corpus, then read over and over again to mark evaluative lexicons, intensifying or attenuating intensity, and focus markers; This stage follows the procedure Decontextualization, Recontextualization, Categorization, and compilation To keep analytical decisions searchable in a transparent manner (Bengtsson, 2016).

Coding is done manually by grouping each unit of meaning into subcategories Appraisal the most dominant, then compared between topics and between models to see asymmetrical patterns in affective tendencies, moral judgments, and narrative intensification; The focus of the analysis is directed at dominance, repetition, and distribution imbalances, not on mere statistical frequency (Hashemi & Mahdavirad, 2023; White, 2025).

The selection of four domains is carried out in a systematic manner Purposive Because these four represent a key arena of ideological bias that appears consistently in model output, the analysis is directed at cross-domain comparative readings to find stable and repeating evaluative patterns (Hashemi & Mahdavirad, 2023; White, 2025).

To keep trustworthiness, the researcher applies repeated reading, recording of analytical decisions, and checking the consistency between codes, so that the resulting interpretations can still be audited and accounted for academically (Bengtsson, 2016; Erlingsson & Brysiewicz, 2017). With this design, the study positions AI as an object of discourse that produces subtle evaluative biases, while allowing for a comparative reading of how seemingly small linguistic decisions can shape a broader ideological orientation (Chen et al., 2025; White, 2025).

3. Results and Discussion

The Results and Discussion section of this study presents empirical findings as well as analytical interpretation of the evaluative patterns that emerge in the response of large language models (LLMs) to political, gender, cultural, and technological issues. Departing from the framework of Appraisal Theory, the analysis is focused on how the subsystems of Affect, Judgment, and Graduation operate simultaneously in shaping the orientation of meaning, not only as linguistic representations, but as discursive mechanisms that produce specific ideological positions. Therefore, the results of the research are not treated as neutral data, but as a discourse practice that contains a structure of evaluation, intensification, and attribution that can be traced systematically.

Methodologically, this section integrates a descriptive reading of linguistic patterns with a critical interpretation of their ideological implications. Each finding is presented through a combination of visualization (images), categorical mapping (tables), and narrative elaboration to show consistency and evaluative asymmetry between domains and models. With this approach, the discussion not only explains "what was discovered," but also the "how" and "why" of those patterns in the context of global power relations, algorithmic bias, and the construction of meaning in the generative AI ecosystem.

For this, the visualization in Figure 1 reveals the asymmetric distribution of the affect category in the Large Language Model (LLM) response, which shows that the AI output is not a zero-value, but rather encodes a specific emotional resonance. The dominance of insecurity scores (9/10) in the political realm is closely related to the frequent use of the diction chilling effect, which tends to frame digital regulation as a systemic threat to freedom. A similar pattern was seen on the gender axis with a dissatisfaction score of (8/10). This reflects the double bind construction, where AI narratives still often evaluate women's leadership through an emotional lens that is biased rather than their strategic capabilities, thus reinforcing stereotypes of traditional social roles.

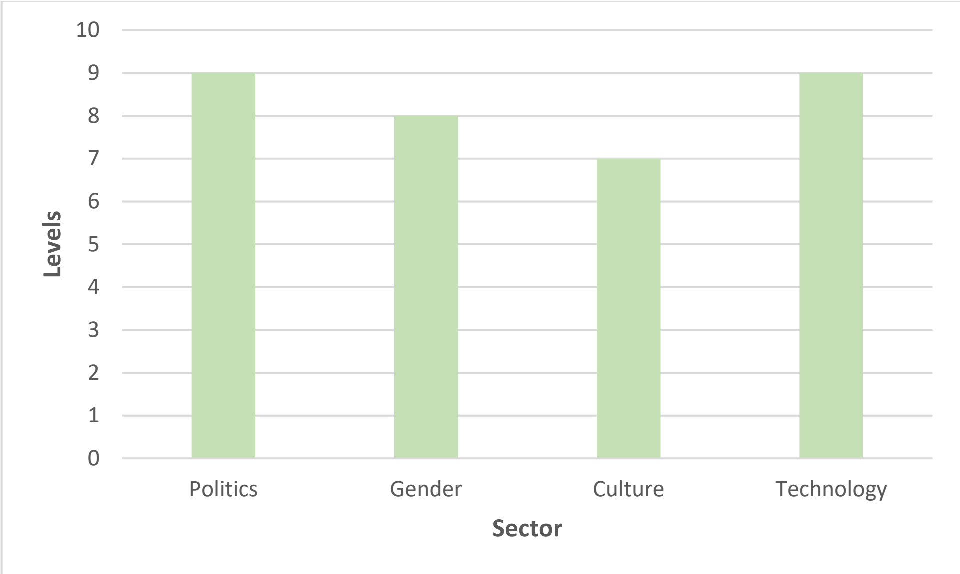

Figure 1. Affect Intensity Distribution in AI Responses to Key Global Issues.

This escalation of emotional resonance reaches its peak on the technological axis through the phenomenon of epistemic vertigo (9/10), which signals a crisis of trust in the veracity of information amid the dominance of private oligarchy. This phenomenon intersects with the cultural dimension (7/10) which highlights identity anxiety due to the process of homogenization or McDonaldization. Overall, this data confirms that an audit of ideological bias is crucial to mitigate the risk of "epistemic vertigo" that has the potential to dull people's critical reasoning. These findings reinforce the argument that information asymmetry in generative texts is a manifestation of technological hegemony that needs to be deconstructed through stricter algorithmic transparency.

3.1. Attitude Dynamics (Affect): Emotional Resonance in AI Global Discourse

Analysis of the Appraisal system at the Affect level reveals that the Big Language Model (LLM) does not simply process factual information, but encodes subtle emotional positions on crucial issues. In the realm of Politics and Public Policy, AI responses consistently show Affect in the form of "concern" for government authorities, especially through the use of chilling effect diction in English-language responses. This confirms the existence of an ideological tendency that views digital restrictions as a threat, which positions security not as a collective calm, but as a potential for emotional repression for the public.

On the topic of Gender and Inclusivity, the asymmetry of Affect is evident in the evaluation of women's leadership, which is often framed through an emotional lens. AI reproduces the perception that women in positions of authority face double binding, where expressions of assertiveness are often labeled as emotional instability (volatile or irrational), while empathy is seen as a gender default rather than a strategic skill. This phenomenon reflects a heavier burden of feelings (dissatisfaction) given to female subjects than to men in generative texts, which reinforces the traditional social role construct.

Turning to the discourse of Culture, Identity, and Globalization, the dimension of Affect manifests in the form of "nostalgia" and "cultural anxiety". Globalization is often framed as a threat to cultural security, which triggers a sentiment of uncertainty about local identity that is perceived as threatened by homogenization or "McDonaldization". On the other hand, diaspora discourse reflects a feeling of "ambivalence" or double consciousness, in which the subject feels torn between the idealized memory of the homeland and the demands of adaptation in the destination country that are often exclusive.

Finally, on the topic of Technology, AI, and Ethics, it was found that the content of Affect is in the form of systemic insecurity called epistemic vertigo. AI frames the risk of misinformation not only as data errors, but as a deep crisis of doubt. The emergence of Liar's Dividend creates an atmosphere of mass skepticism where the truth is suspect. In addition, the risk of academic dependency triggers concerns about the loss of human cognitive abilities in the face of massive automation.

Table 1. Cross-Topic *Affective* Manifestations

Main Topics	Dominant Affect Category	Emotional manifestations	Key Diction in Data
Politics	Insecurity	Fear of state censorship and repression.	"Chilling effect", "government abuse", "arbitrary".
Gender	Dissatisfaction	Biased emotional assessments of women's leadership.	"Emotional lens", "volatile", "double bind", "abrasive".
Culture	Unquiet/Nostalgia	Anxiety about the loss of identity due to globalization.	"Cultural security", "homogenization", "marginalized".
Technology	Insecurity	A crisis of trust due to AI misinformation.	"Deep doubt", "epistemic vertigo", "liar's dividend".

Overall, Affect's analysis proves that AI's multilingual responses contain emotional "spices" that are not neutral. AI tends to produce narratives that are emotionally in favor of liberal autonomy in the West, but insert structural anxiety when dealing with the policy realities of the Eastern or Global South. Thus, an audit of this dimension of feelings is crucial to unravel the control of discourse carried out by generative technologies on global public perception.

3.2. Judgment Dynamics: Capacity Construction and Moral Sanctions in AI Responses

An analysis of the Judgment sub-system in the source file reveals how the large language model (LLM) inserts an evaluation of human and institutional behavior through two main dimensions: Social Esteem and Social Sanction. Based on an audit of four main topics, it was found that AI implicitly constructs a hierarchy of values that benefits the liberal-Western paradigm while positioning reality non-Western in a more critical evaluation framework.

In the topic of Politics and Public Policy, the Social Esteem dimension is used to glorify "individual autonomy" and "citizens' capacity" in processing information independently, AI tends to give a positive assessment of policies that are "minimal" and "narrowly tailored", which indicates high confidence in the capacity of the subject in a democracy., AI provides a negative moral assessment of government intervention that is considered arbitrary or "draconian," especially in the context of policies in the Global South

In the realm of Gender and Inclusivity, there is a striking attribution asymmetry in the Social Esteem dimension. Women's leadership is often evaluated through the Double Bind, in which professional assertiveness is negatively constructed as "abrasive" or "cold" behavior, which is a form of social sanction. Meanwhile, similar behavior in men is consistently attributed as "strength" or "passion," which places men's capacity at a higher social estimation

In the discourse Culture, Identity, and Globalization, AI imposes social sanctions on the practice of "cultural commodification" that reduces living heritage to mere "commercial nostalgia" for the sake of tourism AI positions "originality" as a moral standard, but often fails to provide a fair social estimate of the cultural adaptation strategy (hybridity) carried out by local communities amid the pressure of globalization

Finally, on the topic of Technology, AI, and Ethics, AI vocally provides social sanctions against the phenomenon of "Private Oligarchy". Big tech companies are considered undemocratically accountable for delegating the moderation of public space to opaque "black box" algorithms This creates a crisis of legitimacy (veracity) in which AI itself warns of the risk of academic dependency that can dull human cognitive capacity.

Table 2. Typology of Judgment (Social Esteem & Sanction) in AI Response

Main Topics	Social Esteem Dimension	Social Sanction Dimension	Evaluative Focus
Politics	Upholding individual autonomy (Capacity)	Condemning the abuse of authority (Propriety)	Autonomy vs Authoritarianism
Gender	Attributing male capacity to "natural strength"	Sanctioning women's assertiveness as "negative"	Competency vs Gender Label

Main Topics	Social Esteem Dimension	Social Sanction Dimension	Evaluative Focus
Culture	Appreciate the adaptation of "Glocalization"	Condemning local identity loss (Veracity)	Authenticity vs Homogenization
Technology	Assess the high efficiency of the algorithm	Criticizing the lack of accountability of "Big Tech"	Innovation vs Private Oligarchy

Overall, this analysis of Judgment proves that AI is not neutral in providing moral judgment. By reinforcing social estimation of the values of individualism and imposing social sanctions on institutional control, AI subtly promotes global governance centered on the Western paradigm, while still inserting criticism of the ethics of the tech corporation itself.

3.3. The Dynamics of Graduation: Intensity and Focus in AI Narrative Control

An analysis of the Graduation subsystem in the response of large language models (LLMs) reveals how intensity (Force) and sharpness of focus (Focus) are used to reinforce or obscure ideological biases on four main topics. Graduation acts as a discursive volume regulator that determines how urgent or prototypical a phenomenon is described by AI. Through increasing intensity on certain diction, AI not only presents information, but also builds moral urgency that tends to favor certain value standards.

In the topic of Politics and Public Policy, the Force dimension is very dominant in English-language responses that use amplifications such as "fundamental," "essential," and "irreversible harm" to defend freedom of expression. In contrast, in the Indonesian-language response, intensity shifted to reinforce the concepts of "collective security" and "electoral integrity," reflecting a shift in focus from individual rights to systemic stability. This creates an asymmetry in which threats to democracy in the West are framed in a "louder" tone than similar threats in other regions.

In the realm of Gender and Inclusivity, graduation is used to sharpen the focus on traditional stereotypes. AI often uses sharpening strategies when labeling female leaders with diction that has a sharp negative charge such as "volatile," "irrational," and "abrasive." The use of the term "double bind" shows how sharp the boundaries of evaluation are for women, where the room for error is linguistically narrowed. In contrast, male capacity is often portrayed with a more softened focus or is considered an unquestionable normative standard.

In the discussion of Culture, Identity, and Globalization, the Force dimension emerges through intense metaphors such as "McDonaldization" and "cultural security" to describe the threat of cultural homogenization. This intensity builds a deep narrative of "cultural anxiety," in which globalization is positioned as an almost unstoppable force. Meanwhile, on the topic of Technology, AI, and Ethics, AI uses graduation to create the effect of "epistemic vertigo" and "deep doubt" through the concept of "wild's dividend". This diction has a high intensity designed to trigger systemic awareness of information risks, yet at the same time, AI maintains a strong focus on "efficiency" as a justification for its existence.

Table 3. Graduation Mapping (Force & Focus) Across Analysis Topics

Main Topics	Force Strategy (Intensity)	Focus Strategy (Sharpness)	Discursive Impact
Politics	Strengthening the urgency of civil rights ("fundamental", "essential").	Obscuration of state responsibility in censorship.	The legitimacy of the Western liberal paradigm.
Gender	Amplification of emotional burden in women.	Sharpening of negative labels of female leaders ("volatile").	Reproduction of the double bind stereotype.
Culture	The use of the metaphor of threat ("homogenization").	Strict categorization between "authentic" vs "nostalgic".	Construction of resistance to globalization.
Technology	Escalation of systemic risk ("epistemic vertigo").	Focus on corporate accountability ("black-box").	Normalization of supervision of Big Tech.

Qualitatively, these findings suggest that graduation is a very effective discourse control tool for AI. By regulating the volume and sharpness of terms, AI is able to direct user perception without having to explicitly state partisanship. This audit concluded that irregularities in cross-language and topical graduations are clear evidence of systemic biases that need to be watched out for to maintain information sovereignty in the digital age.

3.4. Audit of Ideological Bias: The Western Paradigm vs. Global South

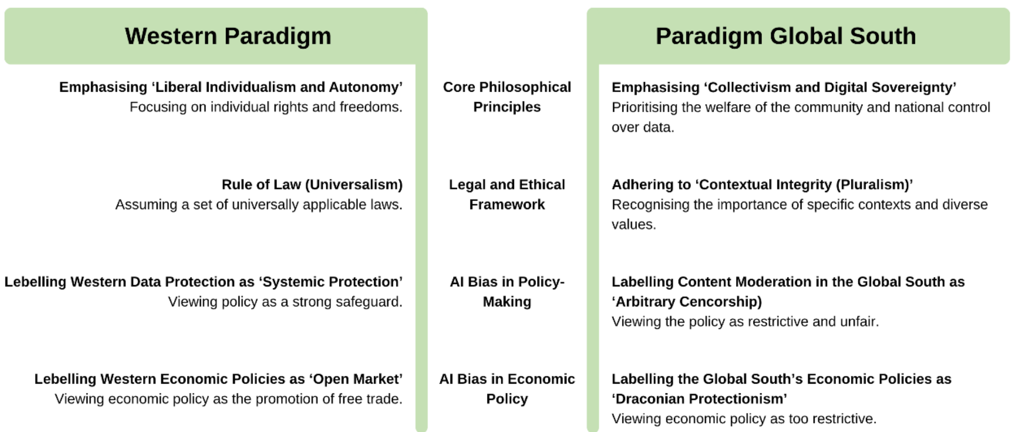

Figure 2. Epistemic Asymmetry: A Comparison of Western and Global South Paradigms in AI Narrative Construction.

The visualization in Figure 2 dissects the dichotomy of AI assessment that consistently positions the digital policies of the West and the Global South within contrasting evaluation frameworks. The Western paradigm tends to be legitimized through the terminology of systemic safeguarding and universalism, which assumes the standard of liberal autonomy as the ideal benchmark of data sovereignty. In contrast, the articulation of digital sovereignty in the Global South region is often delegitimized with pejorative labels such as arbitrary censorship or draconian protectionism. This labeling difference shows that the Appraisal system in AI does not simply process information, but reproduces a systemic bias that prioritizes individualistic structures over collective and pluralistic approaches to governance.

An in-depth analysis that covers political, gender, cultural, and technological ethics topics reveals the existence of non-uniform ideological mapping among large language models (LLMs). The audit identified three major currents in information processing: Rights Liberalism, Democratic Integrity, and Global South Perspectives. All three reflect how AI constructs sociopolitical realities based on training databases that tend to be biased towards certain standards.

In the Liberal Rights-Based paradigm, AI responses, particularly ChatGPT, consistently prioritize individual autonomy and civil liberties as the highest values. On political issues, content restriction is considered a major risk to pluralism, so any policy must be “minimal” and “narrowly tailored”. In the realm of gender and culture, this paradigm encourages self-representation and identity autonomy as a way to counter stereotypes, and favors “voter education” over content banning. This approach is very thick with the influence of the First Amendment of the United States which places freedom of speech above state intervention.

In contrast, the Democratic Integrity paradigm (Procedural Perspective), which often appears in Gemini responses, places more emphasis on systemic risk mitigation and collective protection. Its main focus is to keep democratic procedures from being distorted by technological manipulations, such as deepfakes or organized disinformation. In the topic of technology and ethics, this view supports strong regulations such as the EU Digital Services Act to force algorithm transparency and platform accountability. Here, the “digital shield” is considered a legitimate instrument for maintaining public order, even if it means placing slight restrictions on the flow of information.

The most contrasting difference is found in the Global South Perspective. The document shows that in this region, national stability and social order are often top priorities over procedural freedoms. AI acknowledges that developing countries often implement direct measures such as social media blackouts or harsh criminal penalties against “fake news” to prevent social fragmentation. However, there is an attribution bias where AI tends to label these security policies as “arbitrary” or “draconian,” while similar policies in the West are framed as transparent systemic protection efforts. Here is a table that summarizes the ideological mapping across topics.

Table 4. Ideological Paradigm Mapping in Multilingual AI Responses

Ideological Paradigm	Cross-Topic Key Focus	Regulatory Approach	Key Diction in Data
Liberalism of Rights	Individual autonomy, freedom of expression, and civil rights.	Minimalism, counter speech, and market autonomy.	Autonomy, narrowly tailored, minimal.
Democratic Integrity	Systemic stability, collective protection, and fair procedures.	Risk mitigation, algorithm transparency, and auditing.	Digital shields, safeguards, systemic risk.
Global South	National security, social stability, and information sovereignty.	Direct intervention, strict sanctions, and state control.	Stability, national security, order.

Qualitatively, these findings prove that AI does not simply present data, but rather curates discourse that positions the Western liberal paradigm as the ideal norm, while the sociopolitical reality of the Global South is often positioned as a subject that requires strict scrutiny or moral sanctions.

3.5. Hegemony of Definition: Standardization of Meaning in the Digital Space

Critical discourse analysis reveals the existence of the phenomenon of "Definition Hegemony," in which large language models (LLMs) tend to establish Western conceptual standards as universal truths. AI not only functions as a provider of information, but also as a curator of meaning that standardizes sensitive terms. This hegemony creates discursive boundaries that often marginalize sociopolitical and cultural nuances outside of the global mainstream narrative, especially those originating from the Global South or the Eastern region.

In the domain of Politics and Public Policy, this hegemony manifests in the definition of "freedom of expression" which is rigidly based on the First Amendment of the United States. AI tends to define the integrity of democracy through the lens of absolute individual autonomy, while national stability policies in developing countries are often defined pejoratively as "arbitrary" or "draconian" actions. By defining digital restrictions as an inherent threat to democracy, AI implicitly delegitimizes the sovereignty of the state in maintaining complex social order.

On the topic of Gender and Inclusivity, the hegemony of the definition emerges through the masculine construction of the term "leadership". AI consistently defines authority competencies through agentic traits (assertiveness, dominance) that have historically been associated with men. As a result, female leadership is defined in terms of "anomalies" or trapped in a double bind, where empathy is considered a weakness while assertiveness is considered aggressiveness.

Meanwhile, in Culture, Identity, and Globalization, AI tends to define local culture through the lens of "nostalgia" or "museumification". Cultural identity is often defined as a static object that needs to be protected from the currents of globalization, rather than as an adaptive living heritage. Finally, in the domain of

Technology, AI, and Ethics, the definition of "misinformation" relies heavily on Western technocratic standards such as the EU Digital Services Act. This has led to the control of information in the hands of Big Tech being defined as a legitimate protection measure, while the role of the state in regulating the digital space is often defined as a threat to freedom. The hegemony mapping of this definition is summarized in the following table.

Table 5. Hegemony of Cross-Topic Definitions in AI Response

Main Topics	Definition of Hegemonic (Western)	Marginal Perspective (Local/Eastern)	The Impact of Information Control
Politics	Freedom of expression is an absolute right.	National stability and collective security.	The delegitimization of the security policies of developing countries.
Gender	Leadership is based on agentic/masculine traits.	Collaborative and communal leadership.	Strengthening the double bind stereotype for women.
Culture	Culture as a nostalgic/static commodity.	Culture as an adaptive inheritance of life.	Museumification of local identity in the midst of globalization.
Technology	Misinformation by Western technocratic standards.	Information sovereignty and local political context.	Normalization of the power of private oligarchs (Big Tech).

Qualitatively, this definition hegemony proves that AI acts as an instrument of "closing" knowledge. By standardizing definitions of multidimensional issues, AI subtly directs users to adopt a single truth. This risks erasing local intellectual property and reinforcing the ideological dependence on a global paradigm dominated by the interests of big tech corporations.

3.6. Attribution Asymmetry: Evaluative Bias in Global Subject Construction

Critical discourse analysis of all topics reveals the phenomenon of "Attribution Asymmetry," which is the tendency of artificial intelligence (AI) models to provide different causal explanations and moral judgments of similar actions based on the subject's background. This phenomenon reflects information control in which AI acts as a value arbiter that validates dominant paradigms while positioning marginal perspectives as subjects that require more scrutiny.

In the dimension of Politics and Public Policy, this asymmetry is seen sharply in the narrative of digital content restrictions. AI tends to attribute restrictive policies in Western countries as "systemic protection measures" or digital shields to maintain election integrity. In contrast, similar policies in the East or Global South are often critically attributed as "arbitrary" or draconian measures aimed at political repression. This creates a double standard in which national security in the West is seen as a procedural necessity, while in the East is seen as a threat to freedom.

On the topic of Gender and Inclusivity, attribution asymmetry manifests in leadership evaluations. The success of male leaders is consistently attributed to internal capacity and strength of character, while the success of female leaders is often attributed to external factors or "soft skills". In addition, there is a pattern in which male failures are perceived as situational faults, but female failures are attributed to emotional temperament, which reinforces the double bind stereotype.

In the realm of Culture, Identity, and Globalization, AI tends to position local culture as a static object of "nostalgia", while Western globalization is attributed as a dynamic force of "innovation". This reduces living heritage to mere tourism commodities or "staged authenticity". Finally, on the topic of Technology, AI, and Ethics, technological efficiency is often attributed as scientific progress for developers, but the risk of academic dependency is attributed to the cognitive failure of individual users, rather than as the systemic responsibility of the developer company.

Table 6. Cross-Topic Attribution Asymmetry Mapping

Main Topics	Positive Attribution (Dominant/Western)	Negative Attribution (Marginal/East)	The Impact of Discourse
Politics	Systemic Safeguards .	Arbitrary/Draconian (Authoritarian Repression).	Legitimacy vs. Delegitimization of the State.
Gender	Agentic Traits (Male Capacity & Strength).	Emotional Lens (Women's Instability).	Glass Ceiling Reinforcement.
Culture	Global Innovation (Dynamic Progress).	Commercial Nostalgia (Static & Traditional).	Museumification of Local Identity.
Technology	Scientific Feat (Developer Innovation).	Cognitive Atrophy (User Dependence).	Individualization of systemic problems.

Qualitatively, these findings suggest that AI performs subtle but systemic "discourse sorting." This attribution asymmetry is not just a technical problem, but a form of hegemony that normalizes global power while disciplining local narratives. Thus, the results of this audit emphasize the importance of verification literacy for the public to recognize this evaluative bias so as not to get caught up in the "epistemic vertigo" generated by generative texts.

3.7. The "Private Oligarchy": Delegating Sovereignty and Algorithmic Control

In the contemporary digital communication landscape, the problem that is increasingly emerging is no longer just the existence of bias in AI texts, but how these biases are institutionalized through structured information control mechanisms. As the production and circulation of discourse increasingly relies on technological platforms, the authority in determining what is considered right, relevant, and worthy of display gradually shifts from public institutions to private entities. In this situation, previous findings—such as attribution asymmetry, definition hegemony, and graduation control—can no longer be read as separate linguistic phenomena, but rather as part of a broader and systemic configuration of power.

Within this framework, the concept of "Private Oligarchy" is key to understanding how this dominance works at a structural as well as discursive level. Private oligarchs not only monopolize digital infrastructure, but also regulate the visibility, intensity, and legitimacy of meaning through closed algorithms. Thus, before entering into a more detailed analytical description, Figure 3 is presented to comprehensively show how these control mechanisms operate across domains—politics, gender, culture, and technology—and their implications for the shift in information sovereignty on a global scale.

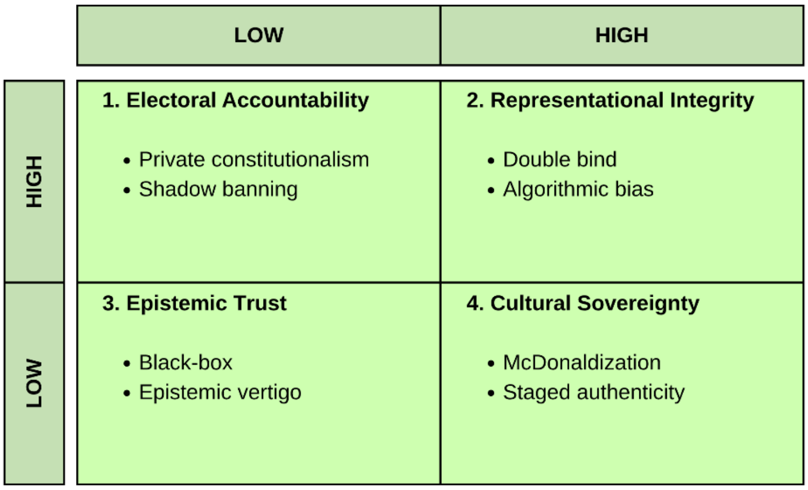

Figure 3. The Manifestation of Private Oligarchy: Mapping Information Control Mechanisms and Impacts on Global Sovereignty.

The visualization in Figure 3 maps the operationalization of "Private Oligarchy" in four crucial domains through an integrated information control mechanism. In the political and gender sectors, this control manifests as a shift of authority from the public sphere to private tech entities, where platforms unilaterally set standards of truth or amplify stereotypes through engagement metrics. The phenomenon of private constitutionalism and shadow banning shows the erosion of democratic accountability, where opaque algorithmic decisions replace transparent public deliberation processes, thus forcing global subjects to submit to norms programmed by a handful of tech corporations.

Critical discourse analysis of all dimensions reveals the phenomenon of "Private Oligarchy" as a new form of hegemony in global information governance. This phenomenon refers to the delegation of moderation authority of public space from democratic institutions to a handful of big tech companies (Big Tech) that have no public accountability. Through control of digital infrastructure, private oligarchs create "private constitutionalism" in which the rules of the platform (Terms of Service) often go beyond the legal sovereignty of the state in determining the boundaries of citizen expression.

In the topic of Politics and Public Policy, private oligarchs manifest through the role of platforms as arbiters of the sole truth during election periods. AI tends to frame information control by corporations as a systemic protection measure, but critically this holds the risk of shadow banning or suppression of dissenting voices that are not aligned with the platform's economic interests. This control creates a power asymmetry in which a "black box" algorithm determines democratic integrity in the absence of adequate procedural transparency.

In the realm of Gender and Inclusivity and Culture, Identity, and Globalization, the influence of private oligarchs can be seen in the standardization of representation driven by engagement metrics. AI reproduces algorithmic biases that prioritize dominant narratives, so female leadership is often trapped in emotional stereotypes in favor of maintaining a profitable algorithm. In the cultural context, these oligarchs are accelerating the "McDonaldization" or homogenization of global tastes, in which local identities are reduced to mere visual commodities or "commercial nostalgia" to meet the global target market.

Finally, in the domain of Technology, AI, and Ethics, there is a systemic effort to transfer ethical responsibility from technology producers to individual users. Private oligarchs dominate the innovation narrative by setting standards of "misinformation" centered on the interests of Western technocracy, while ignoring the risks of academic dependency and epistemic vertigo that dull the cognitive capacity of society. This reinforces the global ideological dependence on one opaque center of technological power.

Table 7. Manifestations of Private Oligarchy Across Analysis Topics

Main Topics	Information Control Mechanism	Impact on Sovereignty	Key Diction in Data
Politics	The sole authority over the "truth" of elections.	The erosion of democratic accountability.	"Private constitutionalism", "shadow banning".
Gender	Amplify stereotypes through engagement metrics.	Emphasis on alternative representation.	"Double bind", "algorithmic bias".
Culture	Homogenization of tastes through a global algorithm.	Museumification of local identity.	"McDonaldization", "staged authenticity".
Technology	Monopoly of ethical standards and data veracity.	Systemic epistemic dependence.	"Black-box", "epistemic vertigo".

Overall, this analysis concludes that the "Private Oligarchy" has transformed the information landscape into an asymmetrically controlled space. In the absence of strict biased audits and regulations that favor the public interest, AI will continue to act as an instrument of hegemony that strengthens corporate power over the sovereignty of citizens around the world.

3.8. Discussion

Theoretically, the findings of this study show that Appraisal Theory relevant to read AI outputs as an evaluation practice, not just the transmission of information (Hashemi & Mahdavirad, 2023; White, 2025). In the system, Affect, Judgment, and Graduation work together to shape readers' orientation towards political, gender, cultural, and technological issues (White, 2025). This can be seen from the dominance Insecurity, Dissatisfaction, and epistemic vertigo that do not appear randomly, but rather follow a pattern Framing consistent AI response (Alghazo et al., 2025). These findings are in line with research showing that viewpoints in public discourse are constructed through systematic and linguistically identifiable persuasive strategies (White, 2025). At the textual level, recent studies have shown that AI-generated texts tend to be less dialogical and have limitations in managing argumentative opposition than human writing (Kashiha, 2025). Thus, the bias identified is not a linguistic anomaly, but rather a discursive effect of a model that optimizes coherence while normalizing certain values (Alghazo et al., 2025). This reinforces the argument that AI output needs to be read as an ideological construct disguised in language choice (Hashemi & Mahdavirad, 2023).

The gender asymmetry found shows that AI still assesses women's leadership through a narrower emotional lens than men's (Newstead et al., 2023). Pattern Double bind, the use of labels such as Volatile or abrasive, as well as the attribution of emotional instability reflecting systemic evaluative biases in leadership representations (Ho et al., 2025). These findings are in line with studies showing that AI can reproduce gender bias in leadership and organizational contexts (Newstead et al., 2023). In addition, the source of bias comes not only from training data, but also from algorithm design and user interaction (Ho et al., 2025). Experimental evidence also suggests that gender attributes in AI agents can affect the level of trust and cooperation of humans (Bazazi et al., 2025). In the visual realm, AI-based representations still show the dominance of certain groups, which reinforces symbolic inequalities in the production of meaning (Currie et al., 2025). Overall, gender bias in AI is not only representational, but also evaluative and normative (Ho et al., 2025). Therefore, these findings can be understood as a reproduction of symbolic hegemony through lexical choices and assessment intensity (Newstead et al., 2023).

On the political and cultural dimensions, the results of the analysis show that AI distinguishes Western authorities and Global South through unequal diction. Terms such as chilling effect and systemic safeguards tend to legitimize individual freedom, while labels such as arbitrary or Draconian used to delegitimize other policies (Messer, 2025; Motoki et al., 2025). These findings are consistent with studies that show the existence of political bias and Value misalignment in generative AI. In addition, users' responses to AI bias are also influenced by their own ideological suitability (Messer, 2025; Motoki et al., 2025). From a theoretical perspective, generative AI can be understood as a shaper World A model that simultaneously limits the horizon of user knowledge (Amoore et al., 2024). In the context of power, algorithms serve as government technologies that move authority to private infrastructure (Kasapoglu et al., 2021; Whitehead & Collier, 2023). However, acceptance of algorithms is not always linear because it is influenced by phenomena

Algorithm Aversion and socio-cultural factors (Liu et al., 2023; Mahmud et al., 2022). Therefore, the ideological bias that emerges is the result of complex interactions between system design, data, and social context (Wei et al., 2025).

The practical implication of these findings is the need for AI literacy that is critical and reflective in nature. This literacy not only includes the ability to use AI, but also to understand, evaluate, and criticize Output produced (Ng et al., 2021). Advanced research shows that AI Literacy must integrate ethical, cognitive, and social aspects simultaneously (Chiu et al., 2024; Pinski & Benlian, 2024). In addition, critical literacy is needed to detect bias, misinformation, and manipulation in AI systems (Archambault et al., 2024; Veldhuis et al., 2025). In the context of transparency, the Explainable AI approach helps users understand the logic of algorithmic decisions (Chuan et al., 2024; Longo et al., 2024). However, its effectiveness depends on a design that users can access and understand (Chuan et al., 2024). On the other hand, the use of AI in education also has the potential to increase productivity while triggering cognitive dependency (Khalifa & Albadawy, 2024; Moorhouse et al., 2025). Therefore, strengthening AI literacy must go hand in hand with regulation and accountable governance (Stolpe & Hallström, 2024; Su et al., 2023).

4. Conclusion

In general, this study shows that the response of large language models cannot be understood as a neutral text, but rather as an evaluative practice that consistently produces a particular ideological position. Through the framework of Appraisal Theory, it is evident that Affect, Judgment, and Graduation work simultaneously to frame political, gender, cultural, and technological issues in a recurring pattern: individual freedom and procedural rationality tend to be legitimized, while perspectives that emphasize collective stability, local sovereignty, and the context of the Global South more often pushed into problematic positions. Thus, AI outputs operate as a discourse construct that helps determine the direction of legitimacy of meaning, not just presenting information. These findings reinforce the view that generative texts should be read as discursive products that carry evaluative bias, attribution asymmetry, and structured definition hegemony.

Implicitly, this study emphasizes the urgency of strengthening critical AI literacy, algorithmic transparency, and more systematic bias audits so that users do not naively accept AI outputs. Theoretically, this study extends the application of Appraisal Theory from language evaluation analysis to ideological readings of generative texts across domains. However, this study has limitations because it only examines three large language models, uses four specific domains, and relies on an English-speaking corpus with qualitative manual coding. Therefore, further research is recommended to expand the number of models, compare more languages and prompt genres, incorporate quantitative-mixed methods approaches, and test the consistency of bias in more diverse socio-political contexts. With this expansion, the reading of generative bias will become more comprehensive and more generalized in generalization.

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