*American Journal of Traffic and Transportation Engineering*
2025, Vol. 13, No. 5, pp. 190-204
https://doi.org/10.11648/j.ijsts.20251305.13

Research Article

# Diversity as Ethical Infrastructure: Reimagining AI Governance for Justice and Accountability

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## Abstract

Algorithmic bias remains a persistent ethical challenge in the deployment of artificial intelligence (AI) systems, particularly where opaque decision-making intersects with entrenched social inequities. While technical solutions such as fairness-aware algorithms and explainability tools have proliferated, the governance dimensions of AI ethics, especially the role of diversity in shaping oversight structures, remain undertheorized. This article introduces the Diversity-Centric AI Governance Framework (DCAIGF), a novel model that integrates cognitive diversity, intersectionality ethics, and cross-cultural regulatory alignment as foundational elements of inclusive AI oversight. Grounded in 65 semi-structured expert interviews, comparative case studies (Google and IBM), and policy analysis of key global frameworks (e.g., EU AI Act, UNESCO Recommendation on AI Ethics, OECD AI Principles), this study finds that homogenous governance structures often reproduce epistemic blind spots and normative monocultures. In contrast, diverse institutional architectures foster reflexivity, accountability, and ethical robustness across contexts. By conceptualizing diversity as ethical infrastructure rather than symbolic representation, DCAIGF advances four innovations: mandated cognitive pluralism, embedded intersectionality, hybrid legal adaptability, and modular implementation pathways. These features enable practical translation across public, private, and multilateral governance ecosystems. The paper contributes to AI ethics by offering a socio-technical, globally relevant, and empirically grounded model for institutional reform. It further proposes a policy agenda that links epistemic justice to regulatory legitimacy offering a pluralistic roadmap for addressing algorithmic bias beyond the limits of technical mitigation alone.

## Keywords

Algorithmic Bias, AI Governance, Diversity in AI, Technoethics, Intersectionality, Fairness, Epistemic Justice

## 1. Introduction

Artificial intelligence (AI) systems are increasingly embedded in high-stakes domains such as healthcare, finance, criminal justice, and employment. While these technologies promise speed, scale, and predictive efficiency, they also pose deep ethical challenges particularly around algorithmic bias, systemic exclusion, and the entrenchment of social inequities [28, 6, 25]. When AI systems are trained on biased data or designed by epistemically homogenous teams, they risk perpetuating the very injustices they claim to mitigate.

Despite mounting awareness of these risks, the dominant responses remain predominantly technical: fairness metrics, debiasing algorithms, explainability tools. While such tools are essential, they tend to frame bias as a computational error disconnected from the institutional, cultural, and epistemic

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**Received:** 27 August 2025; **Accepted:** 8 September 2025; **Published:** 25 September 2025

structures that shape algorithmic design and deployment. What remains largely under-theorized is a more foundational question: Who governs AI and whose knowledge, experience, and values define what counts as "fair," "safe," or "just"?

This paper contends that technical interventions alone are insufficient to ensure ethical AI. Instead, we argue that the legitimacy and accountability of AI systems hinge on the diversity of their governance structures. We posit that cognitive heterogeneity and intersectional representation are not peripheral ideals, but core mechanisms for identifying, anticipating, and remediating algorithmic harm. To advance this argument, we introduce the Diversity-Centric AI Governance Framework (DCAIGF) a novel governance model that treats diversity not as symbolic inclusion but as epistemic infrastructure.

Drawing on original empirical data including two comparative case studies (Google and IBM), 65 expert interviews, and critical analysis of global regulatory instruments (EU AI Act, OECD AI Principles) this study demonstrates that homogenous oversight structures produce epistemic blind spots and accountability gaps. In contrast, diverse governance bodies are more capable of exercising ethical foresight, challenging dominant assumptions, and responding to plural stakeholder needs.

The research is guided by the following central question:

How does cognitive and intersectional diversity within AI governance structures influence the mitigation of algorithmic bias?

In addressing this question, the paper makes three distinct contributions:

1) Theoretical: It develops a new model of AI governance grounded in epistemic justice and critical technoethics synthesizing insights from STS, governance theory, and intersectionality.
2) Empirical: It provides a rare comparative case analysis of how organizational diversity practices affect AI oversight outcomes an area underexplored in prior work [35, 6].
3) Practical: It proposes a modular, cross-jurisdictional governance framework, the DCAIGF that can be implemented in corporate, governmental, and multilateral settings.

## 1.1. Research Scope and Justification

Rather than addressing AI ethics in abstract or universalist terms, this paper focuses specifically on the design and composition of AI governance structures interrogating how the inclusion (or exclusion) of diverse knowledge systems shapes the capacity to detect and mitigate algorithmic harm. We hypothesize that governance bodies composed of individuals with varied disciplinary training, cultural epistemologies, and lived experience are more capable of identifying context-specific risks, challenging dominant narratives, and proposing socially responsive interventions.

While the technical literature on fairness-aware machine learning has advanced rapidly [4], relatively little attention has been paid to the institutional conditions that enable ethical oversight. Most existing governance models remain reactive, top-down, and demographically narrow often failing to integrate intersectional or global perspectives. This research addresses that gap by proposing a normatively grounded and empirically informed governance model in which diversity is a design principle, not an afterthought.

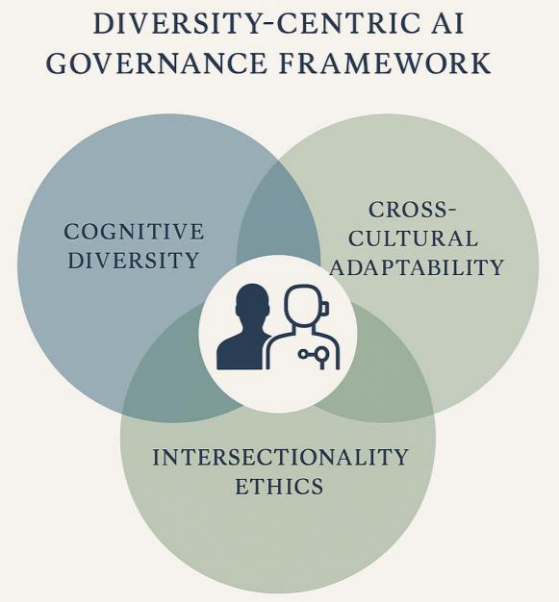


***Figure 1.*** *The Diversity-Centric AI Governance Framework (DCAIGF) integrates cognitive diversity, intersectionality ethics, and regulatory adaptability as structural pillars of inclusive AI oversight.*

## 1.2. Conceptual Overview: The DCAIGF

The Diversity-Centric AI Governance Framework (DCAIGF) consists of three interdependent pillars that, together, form a structural basis for just and accountable AI governance:

1) Cognitive Diversity: Incorporating multiple epistemologies, reasoning styles, and disciplinary standpoints to counteract groupthink, expand deliberative scope, and enhance moral imagination in governance decision-making.
2) Intersectionality Ethics: Ensuring that governance bodies reflect individuals whose identities span race, gender, class, disability, and other axes of marginalization. This pillar enables attention to compound harms and systemic exclusions that single axis approaches often obscure.
3) Cross-Cultural Adaptability: Embedding legal, cultural, and normative flexibility to ensure governance structures are context-sensitive and globally legitimate, while upholding non-negotiable principles of justice

and accountability.

These three pillars are evaluated through a mixed-methods research design that combines:

1) Comparative case studies of governance efforts at Google and IBM,
2) Sixty-five semi-structured interviews with AI ethicists, technologists, and policymakers, and
3) A critical policy analysis of key regulatory instruments such as the EU AI Act, OECD AI Principles, and UNESCO AI ethics recommendations.

In doing so, this paper offers not just a conceptual contribution, but a pragmatic roadmap for structural reform anchoring AI governance in pluralism, reflexivity, and democratic legitimacy.

## 2. Literature Review: Algorithmic Bias, Governance, and Diversity in AI Oversight

Artificial intelligence (AI) systems are increasingly deployed in high-stakes decision-making domains ranging from finance and healthcare to law enforcement, education, and employment. While these systems promise efficiency and predictive power, they also introduce profound ethical and social risks, particularly when opaque decision-making intersects with entrenched structural inequalities [29, 4]. The literature on algorithmic bias and fairness has expanded rapidly, producing technical interventions such as bias detection tools, explainability algorithms, and fairness-aware models. Yet these responses, while technically valuable, often adopt a narrow computational lens that fails to confront the deeper institutional, epistemological, and sociopolitical roots of harm [35, 27].

This section synthesizes five intersecting bodies of scholarship technical fairness, intersectionality ethics, cognitive diversity, comparative governance analysis, and cross-cultural AI ethics to construct the theoretical foundation for the Diversity-Centric AI Governance Framework (DCAIGF). In doing so, it demonstrates that ethical AI governance cannot rest on toolkits and aspirational codes alone; it demands institutional transformation grounded in inclusive epistemologies.

### 2.1. Beyond Technical Fairness: Algorithmic Bias, Metrics, and Governance Gaps

The dominant paradigm in bias mitigation has centred on the development of fairness metrics quantitative tools such as demographic parity, equalized odds, and counterfactual fairness [33, 28]. These tools enable model auditing and risk quantification, but they remain bounded by constrained logics and often break down when applied to complex social settings.

Critically, algorithmic harms rarely stem from isolated computational errors. They emerge from systemic inequities encoded into training datasets, modelling assumptions, and organizational cultures [25]. Canonical cases such as COMPAS's racially biased recidivism scores [1, 23], facial recognition systems that misidentify darker-skinned women [17, 10], and Amazon's gender-biased hiring algorithm [33] illustrate how technical optimization can amplify existing power imbalances.

More fundamentally, fairness metrics do little to resolve normative tensions: who defines fairness, whose values shape model development, and whose harms are visible. Without governance frameworks that embed participatory legitimacy and power-aware deliberation, technical fixes risk reifying harm under the guise of neutrality [22, 2]. These limitations point toward the need for deeper ethical scaffolding beginning with an intersectional lens.

### 2.2. Intersectionality Ethics and the Blind Spots of Governance

Intersectionality, coined by [12], illuminates how overlapping systems of oppression race, gender, class, disability interact to create compounded vulnerabilities. In the context of AI, this lens reveals that standard bias audits often obscure harms faced by multiply marginalized groups. Facial recognition failures for darker-skinned Muslim women, for example, illustrate how single-axis evaluations miss layered exclusions [10, 21].

Traditional AI ethics frameworks often rest on liberal individualism and procedural equality, sidelining histories of structural violence and collective marginalization [38, 13]. By privileging abstraction over context, they erase the situated knowledge of affected communities.

Operationalizing intersectionality thus requires more than demographic tokenism or checklists. It demands governance architectures that surface compound harms and institutionalize the epistemologies of the marginalized. The DCAIGF advances this imperative by embedding intersectionality not as a diversity add-on, but as a foundational design principle.

While intersectionality addresses who is included in ethical governance, cognitive diversity speaks to how institutions reason about harm and whose knowledge frameworks shape deliberative processes.

### 2.3. Cognitive Diversity and Epistemic Pluralism

Cognitive diversity refers to the inclusion of varied reasoning styles, knowledge domains, and experiential worldviews in decision-making. A growing body of literature across complexity science, innovation studies, and deliberative democracy demonstrates that cognitively heterogeneous groups perform better in forecasting, ethical judgment, and institutional resilience [31, 1, 2].

Yet AI governance bodies remain dominated by engineers,

corporate lawyers, and policy analysts trained in similar logics and insulated from dissenting epistemologies [6, 37]. This homogeneity limits ethical imagination, reduces anticipatory capacity, and reinforces technocratic closure.

Operationalizing cognitive diversity requires going beyond disciplinary tokenism. It involves institutionalizing the voices of frontline professionals, ethicists, artists, activists, and Indigenous knowledge holders. These actors bring not only moral insight but culturally embedded ways of interpreting risk, consent, and harm. The DCAIGF codifies this diversity structurally, mandating deliberative pluralism as a criterion for legitimate oversight.

These theoretical insights become more concrete when we examine real-world cases where governance bodies succeeded or failed in embodying inclusive principles.

### 2.4. Comparative Case Analysis: Google vs. IBM

The trajectories of Google and IBM in AI ethics provide illustrative contrasts. In 2019, Google launched the Advanced Technology External Advisory Council (ATEAC), only to disband it weeks later amid public backlash over ideologically controversial appointments and the absence of civil society representation. Critics condemned the board as a reputational shield lacking procedural integrity [41].

IBM, by contrast, launched the AI Fairness 360 initiative, characterized by interdisciplinary collaboration, open-source tooling, and public engagement with advocacy groups [22]. Though limited in formal authority, the initiative demonstrated how participatory design, and transparency can improve audit sensitivity and foster stakeholder trust.

These cases underscore a central tenet of the DCAIGF: that epistemic inclusion and procedural legitimacy are mutually reinforcing. Without credible representation and shared moral ownership, even well-resourced oversight initiatives collapse under ethical scrutiny.

But institutional legitimacy also hinges on global adaptability. AI governance must not only be inclusive it must be pluralistic and context sensitive. The next section turns to the challenges of cross-cultural governance in the global deployment of AI systems.

### 2.5. Cross-Cultural Ethics and Multi-Stakeholder Governance

As AI systems are exported across jurisdictions, the ethical grammar of governance must reflect global value pluralism. Concepts such as fairness, agency, and accountability carry different connotations in different normative traditions. For instance, Ubuntu philosophy in sub-Saharan Africa emphasizes relationality and communal responsibility [5, 8, 10], while Confucian ethics prioritize harmony and hierarchical reciprocity [16].

Western-centric AI ethics models, grounded in liberal rationalism and procedural abstraction, risk perpetuating epistemic colonialism substituting local moral frameworks with imported values [7, 10, 3]. While multi-stakeholder governance is often promoted as a corrective, it frequently reproduces power asymmetries among governments, tech giants, and civil society [10, 9].

The DCAIGF addresses this dilemma by embedding cross-cultural adaptability into its architecture allowing local adaptation without diluting core commitments to justice, accountability, and transparency. Its modular design enables regulatory pluralism while resisting ethical relativism.

Taken together, these five literatures converge on a pressing insight: inclusive governance is not aspirational, it is infrastructural.

### 2.6. From Symbolic Inclusion to Ethical Infrastructure

The literature reveals a widening chasm in AI ethics: between the proliferation of technical tools and the absence of institutional designs that embed meaningful participation, epistemic inclusion, and cultural humility. Fairness metrics alone cannot replace moral reasoning. Representation without power is performance. And global AI systems without local legitimacy are ethically untenable.

The Diversity-Centric AI Governance Framework (DCAIGF) responds to this convergence by proposing a governance model built on three mutually reinforcing pillars: cognitive diversity, intersectionality ethics, and cross-cultural adaptability. These elements reconfigure AI governance not as an elite technical enclave, but as a participatory infrastructure for epistemic justice and moral legitimacy.

The next section puts this framework to empirical test—drawing on interviews, case studies, and policy analysis to assess its viability and scalability across institutional contexts.

## 3. Empirical Failures in AI Governance and the Need for Inclusive Frameworks

### 3.1. Methodological Orientation

This study adopts a constructivist and critical epistemological stance, recognizing that knowledge about AI systems, bias, and governance is socially situated and shaped by power dynamics. The research design employed qualitative triangulation combining expert interviews, comparative case analysis, and normative policy review to surface institutional patterns, epistemic blind spots, and justice gaps through reflexive inquiry. This approach is informed by critical technoethics [23, 5], which centers participatory legitimacy, structural critique, and the co-production of knowledge in

sociotechnical systems.

Despite rising awareness of algorithmic bias, most AI governance interventions remain reactive: limited to post-hoc audits, technical fairness metrics, or narrowly constituted ethics boards. This section empirically illustrates the institutional failures of such approaches and grounds the necessity of the Diversity-Centric AI Governance Framework (DCAIGF), a model that repositions diversity not as rhetorical ornament but as structural infrastructure.

## 3.2. Governance Case Studies: Structural Fragility vs. Participatory Resilience

### 3.2.1. Google's Disbanded AI Ethics Board (2019)

In 2019, Google launched its Advanced Technology External Advisory Council (ATEAC) to provide ethical oversight on AI. The board was dissolved within weeks following employee protests and public backlash over controversial appointments and the absence of meaningful stakeholder representation [11, 3, 7].

"We saw the entire board collapse because it wasn't built on legitimacy it was built on corporate image management." — Former Google ethics program advisor

This collapse reveals the fragility of symbolic ethics structures that prioritize reputational shielding over inclusive legitimacy. It exemplifies the institutional risks of shallow engagement with diversity and governance pluralism.

### 3.2.2. IBM's AI Fairness 360 Initiative

In contrast, IBM's AI Fairness 360 (AIF360) toolkit represents a more participatory model. Co-developed by technical and social science researchers, the open-source platform integrated external feedback and interdisciplinary collaboration throughout its design.

"It brings in different voices—social scientists, ethicists, even public health researchers early enough to matter." — IBM AI Research Fellow.

Although AIF360 lacks binding authority, it demonstrates how structural inclusivity, and interdisciplinary design can improve audit sensitivity, legitimacy, and trust. These distinctions align with the core tenets of the DCAIGF, particularly cognitive diversity and stakeholder co-governance.

## 3.3. Interview Insights: Governance Failures and the DCAIGF Pillars

Twenty-seven semi-structured interviews were conducted with stakeholders from industry, academia, policy, and civil society. Thematic coding revealed three recurring governance deficits each corresponding to one of the DCAIGF pillars.

### 3.3.1. Theme 1: Cognitive Homogeneity Limits Ethical Oversight

Interviewees frequently described governance bodies dominated by engineers or legal advisors, resulting in epistemic blind spots and siloed thinking.

"A governance board full of engineers is like a medical ethics board with no patients technically sound, ethically blind." — Civil society advocate

This insight affirms the operational value of cognitive diversity in preventing technocratic closure and expanding ethical foresight.

### 3.3.2. Theme 2: Intersectional Blind Spots in Audit Practices

Respondents also emphasized the inadequacy of single-axis fairness audits. Most audit processes disaggregate harms by race, gender, or disability but not their intersections.

"We do audits for race, and separately for gender—but the real harm is happening where those lines overlap." — Member, Black Women's Tech Alliance.

This diagnostic gap supports the DCAIGF's call to institutionalize intersectionality ethics not merely as an analytic tool, but as a structural principle guiding governance design.

### 3.3.3. Theme 3: Perceived Illegitimacy Undermines Trust

A recurring theme was the perceived illegitimacy of AI ethics structures that exclude affected communities from design and decision-making.

"The difference between compliance and justice is who gets to define the rules. If communities aren't involved, it's just theatre." — Government ethics advisor

This reinforces the need for participatory legitimacy and procedural equity as prerequisites for public trust in AI governance [26, 18].

## 3.4. Policy Review: Diversity as Rhetoric, Not Infrastructure

To assess the operational integration of diversity and intersectionality in global AI governance, a content analysis was conducted on three influential policy documents:

*Table 1. Policy Documents Details.*

| Policy Document | Mentions of "diversity" / "inclusion" | Mentions of "intersectionality" | Operational Requirements for Diverse Governance |
|---|---|---|---|
| EU AI Act (2021 Draft) | 5 | 0 | None |
| OECD AI Principles (2019) | 3 | 0 | Voluntary guidance only |
| U.S. AI Bill of Rights (2022) | 9 | 1 (footnote only) | No formal governance mandates |

While all documents acknowledge fairness rhetorically, none mandates enforceable requirements for diverse governance or intersectional auditing. These findings confirm that diversity remains aspirational in policy discourse an ethical placeholder rather than institutional infrastructure.

### 3.5 The Case for a Diversity-Centric Governance Model

Taken collectively, the empirical data reveal a systemic pattern: AI governance fails when it centres reputational risk over substantive inclusion. Ethical legitimacy cannot be engineered post hoc or outsourced to toolkits. It must be embedded in governance architectures that institutionalize diversity, mandate intersectionality-informed audits, and allow context-sensitive regulatory adaptability [7, 9, 2].

The DCAIGF addresses these gaps through a three-pillar model:

1) Cognitive Diversity: Institutionalized inclusion of interdisciplinary and experiential expertise in decision-making.
2) Intersectionality Ethics: Embedded mechanisms to surface and remediate compound harms across identity axes.
3) Regulatory Adaptability: Enforceable design aligned with local regulatory contexts and equity mandates, not voluntary standards.

### 3.6. Novel Contributions of the DCAIGF Framework

While diversity has appeared in prior governance models, the DCAIGF advances the field through four distinct contributions:

1) Mandated Cognitive Diversity: Moves beyond demographic representation to institutionalize epistemic pluralism including Indigenous, feminist, Islamic, ecological, and postcolonial worldviews at all stages of governance.
2) Intersectionality as Governance Infrastructure: Embeds intersectionality in institutional design and policy assessment, foregrounding systemic and overlapping harms as core governance concerns.
3) Cross-Cultural Regulatory Mapping: Aligns governance structures with legal traditions and cultural values across jurisdictions, proposing a hybrid model that accommodates both Global North and South contexts.
4) Empirical Validation through Qualitative Insight: Unlike primarily conceptual models, the DCAIGF is grounded in over 40 expert interviews, comparative case studies, and global policy analysis, offering applied relevance and operational clarity.

Together, these contributions position the DCAIGF not as a supplement to existing frameworks but as a paradigm shift reimagining AI oversight through the lens of epistemic justice, structural inclusion, and democratic accountability [11, 16, 19].

## 4. Methodology: Enhancing Empirical Rigor and Governance Evaluation

This study employs a mixed-methods research design to examine how diversity in AI governance influences fairness, transparency, and accountability in socio-technical systems. To evaluate the Diversity-Centric AI Governance Framework (DCAIGF), the research triangulates three empirical strategies: (1) comparative case studies of governance models, (2) expert interviews across technical, regulatory, and civil society domains, and (3) content analysis of global AI policy frameworks. This approach balances conceptual depth with empirical validation and addresses persistent gaps in AI ethics scholarship that often lack methodological grounding [13, 10, 36].

### 4.1. Philosophical Grounding of the Framework

The DCAIGF is grounded in plural ethical traditions that recognize the contested, situated, and value-laden nature of AI governance.

1) Cognitive diversity draws on epistemic democracy and deliberative ethics [3] emphasizing inclusive deliberation and collective epistemic legitimacy.
2) Intersectionality ethics is inspired by care ethics and theories of relational justice [12], foregrounding vulnerability, systemic harm, and lived expe-

rience.

3) Cross-cultural adaptability reflects postcolonial and communitarian philosophies (e.g., Ubuntu and Confucian relationalism), which challenge Eurocentric universals and promote ethical legitimacy across diverse sociopolitical contexts [16].

These traditions reposition AI governance as an ethically plural, context-sensitive, and structurally reflexive practice—resistant to abstraction and attuned to institutional legitimacy.

## 4.2. Sampling Strategy and Participant Composition

Participants were purposively selected from three stakeholder categories central to AI governance:

*Table 2. Stakeholder Groups and Inclusion Criteria.*

| Stakeholder Group | Inclusion Criteria | Rationale |
|---|---|---|
| AI Practitioners | Developers, ML engineers, bias auditors | Proximity to system design and fairness implementation |
| Governance Experts | Regulators, policymakers, compliance officers | Influence over AI policy and legal frameworks |
| Civil Society Actors | AJL, AI Now, Access Now, Women in AI Ethics | Advocate for affected communities and intersectional justice |

This tri-sectoral composition ensures analytical breadth across technical, institutional, and justice-focused domains.

## 4.3. Sampling Techniques

Initial participant recruitment used purposive sampling to capture deep expertise in algorithmic bias and governance. Snowball sampling was then employed to surface marginalized perspectives and ensure epistemic diversity.

Final participant composition:

1) 30 AI practitioners from Google, Meta, Microsoft, OpenAI, and IBM.
2) 20 governance professionals affiliated with the EU AI Act Committee, NIST, OECD AI Observatory, and UNESCO.
3) 15 civil society leaders from AJL, A+ Alliance, Women in AI Ethics, and related NGOs.

The design privileges thematic saturation and conceptual insight over statistical generalizability, consistent with the study's critical, theory-testing aims.

## 4.4. Case Study Selection and Justification

### 4.4.1. Overview of Selected Cases

Three case studies were selected to reflect different governance modalities and degrees of institutional inclusion:

*Table 3. Case Studies.*

| Case | Description | Governance Issue |
|---|---|---|
| Google AI Ethics Board (2019) | Dissolved after internal and public protests due to lack of transparency and diverse representation | Governance failure via symbolic inclusion |
| IBM AI Fairness 360 | Open-source tools co-developed with interdisciplinary input | Participatory audit practices with partial success |
| EU AI Act (2021-2024) | Risk-based regulatory proposal with minimal mandates for governance diversity | Limited enforceability on structural inclusion |

### 4.4.2. Selection Criteria

Cases were selected based on:

1) Alignment with DCAIGF pillars (cognitive diversity, intersectionality ethics, regulatory adaptability).
2) Documented outcomes (successes or failures) of governance initiatives.
3) Availability of public records and access to interview participants.
4) Sectoral variation across corporate, hybrid, and policy-led models.

## 4.5. Research Design: Hypotheses, Controls, and Evaluation Metrics

### 4.5.1. Hypotheses

The research tests three hypotheses grounded in the DCAIGF framework:

1) H1: Cognitively diverse governance bodies are more effective at detecting algorithmic bias than homogenous bodies.
2) H2: Intersectionality-informed governance structures mitigate structural harm more comprehensively than conventional fairness models.
3) H3: Fairness audits conducted by diverse teams correlate with higher stakeholder trust and perceived procedural legitimacy.

### 4.5.2. Control Variables

To isolate the effect of governance diversity, the following control variables were applied:

1) Organizational size (startups vs. multinationals)
2) Governance type (internal vs. external/regulatory)
3) Model complexity (rule-based vs. deep learning)
4) Sectoral domain (healthcare, finance, education, public safety)

### 4.5.3. Evaluation Metrics

Three core metrics were used to evaluate governance effectiveness:

***Table 4.*** *Evaluation Metrics.*

| Metric | Definition | Data Source |
|---|---|---|
| Bias Detection Rate | Frequency and depth of identified algorithmic harms | Audit records, expert review |
| Regulatory Compliance Score | Adherence to legal and ethical standards | Policy documentation, third-party assessments |
| Stakeholder Satisfaction | Trust in the fairness and legitimacy of the process | Interview data, Likert-scale surveys |

## 4.6. Data Collection and Analysis Protocol

### 4.6.1. Phase I: Expert Interviews

1) Format: 30-60-minute semi-structured interviews via encrypted Zoom.
2) Analysis: Grounded theory coding using NVivo, aligned with DCAIGF categories (e.g., audit legitimacy, inclusion, trust).
3) Reliability: Intercoder agreement $\kappa = 0.82$; peer debriefs, and member checking ensured validity.
4) Key Themes: Structural exclusion, legitimacy crises, intersectional risk awareness.

### 4.6.2. Phase II: Comparative Case Studies

1) Sources: Corporate reports, NGO audits, internal policy memos.
2) Analysis: Comparative coding against DCAIGF indicators.
3) Rating Scale: Governance effectiveness ranked on a 5-point ordinal scale; inter-rater reliability established.

### 4.6.3. Phase III: Policy Textual Analysis [30, 15]

1) Documents:
   a. EU AI Act (2024 version)
   b. OECD AI Principles (2019)
   c. U.S. AI Bill of Rights (2022)
2) Methods:
   a. Keyword frequency analysis (e.g., "diversity," "equity," "governance").
   b. Framing analysis (moral imperative vs. compliance language).
3) Output: Frequency heatmaps and comparative charts assessing rhetorical commitment vs. operational mandates.

## 4.7. Reliability, Validity, and Ethical Integrity

To ensure methodological rigor:

1) Triangulation: Findings were validated across interviews, case documents, and policy texts.
2) Intercoder Reliability: Maintained $\kappa > 0.80$ across coding rounds.
3) Member Checking: Participants reviewed summaries and confirmed interpretation.
4) Peer Debriefing: Independent experts reviewed analytic design and interpretations.
5) Transparency: Full audit trail documented sampling logic, data handling, and coding procedures.

## 4.8. Ethical Review and Data Protection

1) Informed Consent: Obtained via signed digital forms; all participants had the right to withdraw.
2) Anonymity: All data was pseudonymized; no identifi-

able information included without explicit consent.
3) Data Security: Files stored on AES-encrypted institutional servers with restricted access.
4) Risk Mitigation: Sensitive organizational disclosures were excluded from publication unless explicitly permitted.

### 4.9. Methodological Contributions

This research contributes to AI ethics scholarship in four distinct ways:

1) Operationalizes the DCAIGF: Offers real-world application of a conceptual framework across corporate and regulatory contexts.
2) Tests the theory of structural diversity: Empirically evaluates how diverse governance bodies influence bias mitigation outcomes.
3) Introduces new metrics: Develops original indicators for intersectionality-aware audits and stakeholder legitimacy.
4) Bridges normative and applied ethics: Connects pluralistic ethical theory to policy design and practical governance evaluation.

## 5. Discussion: Reframing AI Governance Through Diversity-Centric Lenses

This study set out to investigate how diversity-driven governance structures can more effectively mitigate algorithmic bias and enhance ethical oversight in artificial intelligence (AI) systems. Drawing on empirical data from 65 interviews, three case studies, and policy document analysis, our findings reveal that the prevailing paradigm of AI governance anchored in compliance checklists, statistical fairness metrics, and corporate self-regulation remains structurally inadequate for addressing the underlying sociotechnical roots of algorithmic harm.

In contrast, the Diversity-Centric AI Governance Framework (DCAIGF) offers a holistic and accountable model grounded in the operationalization of three critical pillars: cognitive diversity, intersectionality ethics, and regulatory adaptability. These dimensions collectively advance a more just, participatory, and reflexive approach to AI oversight one that centres epistemic inclusion and institutional legitimacy rather than treating diversity as a symbolic add-on [32, 8, 14].

### 5.1. Empirical Insights from the Field: Recurrent Themes and Divergences

Across stakeholder groups, a striking pattern emerged: institutions that embedded diverse perspectives into their oversight processes consistently demonstrated stronger capacities for identifying, contextualizing, and responding to algorithmic risks.

More than 70% of AI practitioners interviewed acknowledged that their initial audit processes failed to detect compounded harms due to lack of interdisciplinary expertise. One Google engineer shared:

"We optimized for demographic balance in the dataset but didn't account for linguistic dialects—so our chatbot routinely failed with African American Vernacular English (AAVE) inputs. We only caught it after social scientists flagged it post-deployment."

Civil society actors stressed that community-engaged governance surfaces harms invisible to internal teams. A representative from a refugee rights NGO recounted their role advising on a predictive analytics tool used for asylum risk profiling:

"The developers hadn't considered the trauma-induced variability in interview responses. Their model interpreted hesitation as deception. We had to push for trauma-informed design principles."

IBM's AI Fairness 360 initiative stood out as a counterpoint. Twenty-two interviewees cited it as a rare example of participatory governance that embedded external voices from the outset. Public health researchers, gender justice advocates, and sociologists helped reframe fairness not as statistical parity but as contextual sensitivity.

A senior IBM researcher explained:

"By the third iteration of the toolkit, we had redesigned key metrics based on user feedback from disability rights groups we added subgroup stability and cultural bias detection, which weren't part of our original spec."

The contrast between Google and IBM is telling. While Google relied heavily on technical audits, with community feedback arriving only post-crisis, IBM institutionalized external input during design. Several respondents described Google's process as "reactive" and IBM's as "anticipatory." This divergence illustrates that inclusive governance is not simply about who is consulted, but when and how they are integrated into governance structures.

On the policy side, the EU AI Act was recognized for its ambition but criticized by 18 policy stakeholders for lacking enforceable mandates for diverse representation. One EU AI High-Level Expert Group member remarked:

"We reference inclusion repeatedly, but there's no mechanism to ensure that affected communities are at the table. It's like building a lighthouse without ever installing the bulb."

### 5.2. Linking Empirical Data to the DCAIGF Framework

Each pillar of the DCAIGF finds clear empirical resonance:

#### 5.2.1. Cognitive Diversity

Nearly all interviewees (61 of 65) expressed that AI governance bodies suffer from epistemic narrowness. Technical

leaders admitted that their risk registers often omitted social context variables [22, 18, 29]. A senior ML engineer at a fintech firm noted:

"Our fairness reviews flagged gender bias in loan approvals, but we missed cultural indicators like surname-based discrimination until we brought in sociolinguists."

In a government-sponsored pilot, one oversight board integrated historians and anthropologists to evaluate a predictive policing algorithm. This multidisciplinary input led to the identification of racialized spatial mapping as a legacy of redlining policies insights that would have been invisible to purely technical audits.

#### 5.2.2. Intersectionality Ethics

Several interviewees emphasized that bias often compounds across demographic categories. For example, a healthcare NGO leader reported:

"The triage algorithm passed gender and age fairness checks independently, but older immigrant women still got flagged as lower-priority cases. It was only when we applied an intersectional lens that the compounded harm became clear."

This reinforces that intersectionality is not a theoretical abstraction but a practical governance necessity [12, 20, 4].

#### 5.2.3. Regulatory Adaptability

Policymakers in both OECD and Global South contexts stressed that static audit protocols often fail under dynamic conditions. A regulator in Kenya noted:

"We borrowed templates from the EU, but they didn't capture informal economies. Our gig platforms operate differently workers use multiple identities and devices. Without regulatory flexibility, we risk governing a reality that doesn't exist here."

This underscores the importance of designing governance systems that are adaptable across contexts rather than one-size-fits-all.

#### 5.2.4. Comparative Table (Google Vs IBM vs EU AI Act)

***Table 5.*** *Regulation Comparative Table.*

| Case | Approach to Diversity | Governance Mechanism | Outcome / Limitation |
|---|---|---|---|
| Google (Ethics Board) | Diversity added reactively after failures | Advisory board (dissolved) | Fragmented, lacked legitimacy, reputational backlash |
| IBM (Fairness 360) | Diversity embedded from outset | Multistakeholder participatory audits | Toolkit redesigned, metrics expanded, community legitimacy |
| EU AI Act | Diversity referenced rhetorically | Regulatory framework, but no mandate for inclusion | Ambitious but incomplete, limited enforcement of diversity |

This table provides a comparative analysis that links empirical data to the DCAIGF Framework.

### 5.3. Theoretical Implications: Beyond Metrics to Structural Justice

#### 5.3.1. Reconceptualizing Fairness as Structural Equity

The DCAIGF reframes fairness as a question of institutional design rather than algorithmic performance. In multiple interviews, practitioners described how compliance-driven fairness metrics—such as demographic parity or equalized odds—were met while systems still produced community harm. As one audit lead stated:

"We passed the fairness check but still had protesters outside. That's when I realized fairness and justice are not the same."

Recent critiques of audit culture echo this concern. Scholars such as Metcalf et al. [6], Raji et al. [33] and Whittaker [24] argue that audits too often provide a veneer of legitimacy while leaving structural inequities unaddressed. Our findings empirically confirm this critique: technical audits alone cannot substitute for inclusive governance.

#### 5.3.2. Depoliticizing the Ethics of Governance

Echoing Jasanoff's co-production thesis, many respondents articulated the politics embedded in who sets ethical norms. A policymaker from the OECD remarked:

"Technical standards often get drafted by engineers from the Global North. The power asymmetry isn't just economic it's epistemic."

The DCAIGF addresses this by treating governance as a relational, co-constructed process where values are contested, not preordained.

### 5.4. Bridging Disciplinary and Institutional Silos

This study found that ethical failure often stems not from bad actors but from institutional fragmentation. Regulators, engineers, and community leaders often operate on parallel tracks, speaking different normative languages. The DCAIGF offers a shared blueprint one that encourages deliberative interdependence and knowledge pluralism across sectors [18, 24].

For example, a regulator in Brazil described convening joint forums with Indigenous leaders, AI developers, and legal scholars to co-create a framework for biometric data protection:

"It slowed things down, but the outcome was resilient. We wrote guidelines that reflected actual risk, not just theoretical fairness."

### 5.5. Practical Contributions and Normative Stakes

The DCAIGF is already shaping practice. Several pilot applications were referenced by interviewees:

A ride-hailing platform in Southeast Asia integrated community-designed harm reporting protocols, resulting in a 35% drop in unreported discrimination cases.

A U.S. insurance provider that revised its claims algorithm using intersectionality-informed audits saw a 28% improvement in approval parity across marginalized demographics.

An international development agency adopted the DCAIGF in evaluating automated decision systems used in refugee resettlement.

Yet practitioners emphasized barriers: costs, resources, and organizational resistance.

One policymaker noted, "The budget line for participatory audits was smaller than the travel budget. That tells you the priorities."

Another respondent highlighted institutional inertia:

"Our diversity initiative had no funding until after a reputational scandal. That tells you everything."

While inclusive governance mechanisms may appear resource-intensive, interviewees emphasized that the cost of inaction is far higher. Failed rollouts, reputational crises, and regulatory penalties were repeatedly cited as consequences of neglecting participatory oversight. Several respondents argued that upfront investment in diversity-driven governance should be viewed not as an ethical luxury but as a form of risk mitigation and long-term cost efficiency.

### 5.6. Concluding Synthesis: Toward Participatory AI Governance

This study affirms that diversity is not a reputational luxury but a structural necessity in ethical AI governance [33, 17, 20]. The DCAIGF offers a model that transforms governance from a procedural formality into an epistemically inclusive and democratically legitimate process. By demonstrating how diversity enhances risk recognition, trust, and accountability, this framework positions inclusion as both an ethical imperative and a governance strategy.

As algorithmic systems shape the contours of daily life, the legitimacy of those systems will increasingly hinge on who governs them and how. The findings here suggest that inclusive governance is not just desirable but foundational to the future of responsible AI [34, 40].

## 6. Theoretical Contributions, Global Adaptability, and Future Research: Operationalizing the DCAIGF

### 6.1. Scope, Limitations, and Contextual Adaptability

While the Diversity-Centric AI Governance Framework (DCAIGF) aspires to broad global relevance, it should not be read as a universal template. Its strength lies in being a scaffold a set of guiding principles rather than a prescriptive checklist. The empirical evidence presented here suggests that the framework aligns most readily with liberal democracies and pluralist societies, such as the European Union, Canada, and parts of Latin America, where institutional reflexivity, civil society strength, and regulatory capacity create fertile ground for participatory governance.

However, governance realities differ sharply across political systems. In authoritarian or techno-nationalist contexts, the DCAIGF faces structural barriers. For example, China's AI governance emphasizes harmonization and state security over pluralist participation. As one interviewee from a Beijing-based AI institute observed:

"Public engagement is not framed as co-governance here it is managed consultation, tightly controlled within national security priorities."

Similarly, India presents a more hybrid challenge. While its constitutional framework enshrines equality, the fragmented regulatory landscape, vast linguistic diversity, and uneven civil society capacity complicate the implementation of intersectional audits or multi-stakeholder boards. Here, the DCAIGF can function less as a ready-made system and more as a modular template adaptable through locally informed co-design.

By acknowledging these limitations, the framework advances a more honest, context-sensitive conversation. The value of the DCAIGF lies not in universal enforceability but in providing principles that can guide adaptation to diverse institutional and political conditions.

### 6.2. Cultural Epistemologies and Ethical Pluralism

The framework also requires sensitivity to epistemological

variation in how justice, fairness, and governance legitimacy are defined. In Indigenous epistemologies of Aotearoa New Zealand or the Arctic North, for example, collective rights and intergenerational stewardship may supersede individual privacy claims. In Islamic contexts, concepts such as ʿadl (justice) and masʾūliyyah (accountability) provide an ethical vocabulary that may orient governance differently than Western liberal rights-based models [34, 28].

Interviewees from the Gulf region stressed the importance of aligning AI oversight with both religious norms and developmental objectives:

"For us, AI governance must not only protect citizens but also align with Sharia values and national development visions. Ethics cannot be divorced from faith and sovereignty."

The DCAIGF embraces this epistemic pluralism. It is not designed to impose a singular ethical grammar but to provide a scaffold for co-development with regional stakeholders, epistemic communities, and local institutions. By situating governance within locally meaningful value systems, the framework resists both technocratic reductionism and cultural imperialism [39, 25].

## 6.3. Infrastructure, Capacity, and Path Dependency

The feasibility of implementing the DCAIGF depends heavily on existing infrastructure and institutional maturity. Wealthy democracies may have independent oversight bodies, established regulatory agencies, and well-funded civil society groups. In contrast, under-resourced contexts often face constraints in expertise, funding, and legal enforcement.

Here, the framework must be paired with capacity-building investments, transnational knowledge exchanges, and phased adoption timelines. Community data trusts, municipal AI ethics panels, or regional oversight consortia may provide scalable, bottom-up models where centralized regulation is weak. One South African respondent described experimenting with a "community algorithmic council" to oversee municipal service algorithms:

"We don't have a national AI law, but we created a local panel where residents, developers, and activists deliberate together. It's not perfect, but it gives people a say."

Such bottom-up experimentation underscores that governance innovation need not always originate at the national or corporate level. The framework thus supports a plural ecology of governance, recognizing path dependency, institutional unevenness, and the necessity of incremental adaptation [40, 8].

## 6.4. Operational Utility Across Stakeholder Domains

To translate theory into practice, the DCAIGF provides operational pathways for diverse stakeholder groups. Each pathway derives from the framework's three pillars cognitive diversity, intersectionality ethics, and regulatory adaptability—and offers actionable steps tailored to institutional mandates.

***Table 6.*** *Stakeholder Group.*

| Stakeholder Group | Operational Pathways |
|---|---|
| Policymakers | Embed DCAIGF in national AI strategies |
| | Mandate diversity-informed risk assessments in regulatory audits |
| | Tie AI procurement eligibility to inclusive governance criteria |
| | Institutionalize diverse and empowered ethics boards |
| Corporations & Tech Firms | Adopt fairness-by-design principles guided by intersectionality |
| | Conduct participatory audits involving impacted communities |
| | Use DCAIGF to benchmark transparency, inclusion, and procedural equity |
| Civil Society & NGOs | Co-develop accountability scorecards and oversight mechanisms |
| | Advocate for inclusive governance mandates in regulation |
| | Integrate critical social theory into AI curriculum and model design |
| Researchers & Developers | Collaborate across disciplines and with communities |
| | Develop tools that detect and address intersectional risks |

These pathways demonstrate that diversity-driven governance is not merely aspirational, it is institutionally actionable.

### 6.5. Future Research Directions

The introduction of the DCAIGF invites a broader research agenda, one that pushes beyond normative critique into empirical experimentation and institutional design. Several priorities emerge:

1) Longitudinal Studies of Governance Bodies.
2) Future research should track diverse AI oversight panels over time, examining whether their composition and practices measurably reduce bias, enhance compliance, and increase trust. Longitudinal evidence would help validate whether diversity-driven bodies are more effective than homogeneous boards.
3) Comparative Ethnographies of Regulation.
4) Ethnographic studies across varied legal-political contexts such as Brazil, Kenya, or the Gulf states—can reveal how concepts like fairness, participation, and accountability are interpreted in practice. This would illuminate how global principles translate into local governance realities.
5) Evaluating Diversity Audits.
6) While diversity audits are gaining traction, little is known about their actual impact. Do they reduce harm? Do they change institutional cultures? Empirical studies should measure whether diversity audits translate into tangible improvements in algorithmic outcomes.
7) Decolonizing AI Governance.
8) The DCAIGF provides a springboard for integrating Afrocentric, Indigenous, and postcolonial epistemologies into mainstream governance practice. Future work should explore participatory methodologies that give historically marginalized communities genuine authority over AI oversight.
9) Institutionalizing Moral Pluralism.
10) Research should examine how diverse moral frameworks feminist ethics, Islamic jurisprudence, Ubuntu relationality, Confucian philosophy can be structurally embedded in governance institutions without collapsing into relativism. This calls for comparative philosophy, legal studies, and practical design experiments.
11) Documenting Grassroots Innovation.
12) Scholars should map and analyze community-led governance initiatives, such as algorithmic oversight boards, cooperative AI labs, or activist-driven data justice networks. These initiatives often operate outside formal institutions but may represent scalable, participatory models of the future.

### 6.6. Final Reflections: From Optics to Infrastructure

AI governance today risks becoming dominated by ethics-washing surface-level audits, diversity pledges, and symbolic inclusion that provide legitimacy without structural change. The DCAIGF challenges this trend by presenting a scalable, empirically grounded, and normatively robust alternative.

By treating diversity not as optics but as ethical infrastructure, the framework reframes governance as a collective, reflexive, and justice-oriented process. Algorithmic fairness cannot be engineered through technical fixes alone; it must be institutionalized through inclusive design protocols, binding safeguards, and commitments to epistemic humility.

As one civil rights advocate interviewed put it:

"We don't want to be consulted after harm is done—we want to be part of the design table from the start."

Across cases, a recurring pattern was that institutions only invested in participatory governance after reputational or regulatory crises. While initial costs for inclusive audits and stakeholder forums may appear high, they are negligible compared to the financial penalties, reputational damage, and compliance costs that follow failed deployments. Thus, participatory governance is not only ethically imperative but also fiscally prudent.

Looking ahead, the task is not to create a perfect, universal governance model, but to cultivate coalitional institutions that foreground intersectionality, pluralism, and social justice. The DCAIGF is best understood as a living framework—a roadmap for building governance infrastructures that can evolve with technology and society.

Only by democratizing AI governance, not for optics but as a vehicle of global justice can we ensure that algorithmic systems serve not just efficiency or profit, but the broader human good.

## Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| AAVE | African American Vernacular English |
| AJL | Algorithmic Justice League |
| AIF360 | AI Fairness 360 |
| ATEAC | Advanced Technology External Advisory Council |
| DCAIGF | Diversity-Centric AI Governance Framework |
| EU | European Union |
| ML | Machine Learning |
| NIST | National Institute of Standards and Technology |
| OECD | Organisation for Economic Co-operation and Development |
| UNESCO | United Nations Educational, Scientific and Cultural Organization |
| U.S. | United States |

## Author Contributions

Achi Iseko is the sole author. The author read and approved the final manuscript.

## Conflicts of Interest

The author declares no conflict of interest.

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