Parameter-based analysis of AI ethics frameworks with regulatory and technological parameters

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Abstract
A method for operationalizing the artificial intelligence' ethical principles through analytical modeling of their regulatory and institutional parameters has been developed. A composite index of public welfare is proposed, integrating digital access indicators, innovation potential, and institutional justice, enabling a quantitative assessment of the ethical guidelines practical implementation degree in AI systems. Methods of multivariate data normalization, scenario modeling, and parametric analysis, as well as elements of hierarchical decision making, are applied to transform abstract normative concepts into computable parameters. The empirical base is formed based on international indices of digital development, innovation, and governance quality for various jurisdictions. The obtained results demonstrate that neither maximum openness nor strict regulatory protection ensures optimal ethical effects. The greatest public welfare is achieved with a balanced combination of regulatory flexibility, institutional quality, and data governance mechanisms, confirming the need for a parametric approach to AI.

Keywords
artificial intelligence ethics; computational modeling; digital governance; data-driven regulation; algorithmic fairness; socio-technical systems; composite indices; AI governance frameworks.

1. Introduction and Related Works

As AI becomes a common tool for creating and managing information, it has brought attention to ethical and social issues that were less visible before. AI improves access to information and offers strong analytical tools, but it also creates concerns about fairness, responsibility, and how much automation is acceptable. In addition, all of this is influenced by different national regulations and the self-regulation practices of digital platforms. These issues are becoming increasingly important as data-driven methods spread.

AI is not inherently positive or harmful; it mainly amplifies cultural and economic patterns that already exist [1]. Many recent studies now put ethical issues at the center of discussions about AI governance. Yet scholars consistently identify several structural gaps.

First, nearly all ethical guidelines repeat similar values [2; 3], while remaining largely declarative unless they are embedded within real mechanisms of accountability and law [4; 5]. At the same time, users rarely evaluate technologies through formal normative categories [6], which

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means that ethical assessment cannot be reduced to internal indicators alone; taken in isolation, such metrics do not guarantee any improvement in societal welfare [7].

Second, most AI-ethics documents are drafted by industrial and academic actors without meaningful involvement of independent regulators [8]. In practice, AI systems may even reinforce existing inequalities: when the volume of data expands without being redistributed, the broader system gradually loses openness and fairness [9; 10].

In reality, new technologies don't necessarily make society better unless the conditions around them also improve [11]. Scientific work today needs to focus on how digital ethics should be shaped and organized [12]. AI should be understood as a function of its specific social environment rather than as an abstract, universal entity [13]. But how, then, can we measure the actual integration of ethical concerns into AI development?

AI is not a "carrier" of ethics or a subject of rights; failures emerge not from the technology itself but from the contexts in which it is deployed [13]. Today, the dominant shift is toward building socio-technical systems within which algorithms operate [14], and such systems require rigorous justification and continual development.

In practice, these dynamics show that ethical questions cannot be examined in isolation from the broader conditions in which AI systems emerge. What may first look like a clear set of ethical rules turns out, on closer examination, to be a mix of legal, economic, and technical factors shaped by data access and unequal technological resources. Good intentions alone rarely change anything if the system does not support them. The final outcomes depend on how rules, institutions, and practical conditions of using AI work together.

In this sense, measuring "AI ethics" becomes an analytical challenge in its own right. It requires identifying the values that are formally declared as well as assessing how these values are implemented in practice, whether they are supported by enforceable mechanisms, and how they affect public welfare in environments marked by unequal access to data, computational resources, and regulatory authority. Recent research shows that the ethical quality of AI depends on how declared principles interact with real social and technical conditions.

The task of this study is to develop a methodology for conceptualizing and operationalizing the ethical parameters of AI through analytical models that make it possible to evaluate the degree to which ethical principles are integrated into AI development at the level of systems and digital platforms.

2. Methodology

This study uses a combination of normative analysis and quantitative modelling to examine how different regulatory settings influence the societal welfare produced by innovation. The central idea is that the ethical value of technological progress depends on how different legal approaches interact and on the overall fairness and quality of governance. To operationalize this concept, we constructed Societal Welfare Index (*Wsoc*) as an integrated composite indicator covering three functional dimensions: Access (*A*), Innovation (*I*), and Fairness (*F*).

The first level of the study focuses on three jurisdictions representing distinct regulatory paradigms of AI and knowledge governance:

(1) a case-law-driven system with flexible fair use principles and high reliance on judicial interpretation of text and data mining (TDM) (USA);

(2) a rule-based system with dual TDM exceptions and explicit opt-out mechanisms for right holders (EU);

(3) a radical model combining a narrow scientific TDM exception with the legal recognition of AI-generated outputs as protectable results (Ukraine).

These regimes were selected because they represent a wide range of legal approaches, from more open to more restrictive, which makes it possible to compare how different designs affect the ethics of innovation.

Empirical data were compiled from internationally recognized datasets published between 2022 and 2025 to ensure both temporal consistency and cross-country comparability. Each *Wsoc* component aggregates several publicly available indices:

- Access (*A*): Open Data Maturity Index [15], OECD Digital Government Index [16], Freedom on the Net [17], AI Readiness Index [18].
- Innovation (*I*): Global Innovation Index [19], World Digital Competitiveness Ranking [20], R&D Expenditure as a percentage of GDP [21–23], and Business R&D in ICT [24].
- Fairness (*F*): Rule of Law Index [25], Corruption Perceptions Index [26], Human Development Index [27], and Gini Index [28].

Not all indicators were available for each jurisdiction. For example, some digital competitiveness and OECD indices omit non-member states. To maintain comparability without arbitrary interpolation, subset normalization was applied: each country's sub-index (*A*, *I*, or *F*) was calculated as the arithmetic mean of all available metrics within that dimension. This method keeps the dataset consistent while recognizing that some countries simply have fewer indicators available.

Missing values were left blank rather than replaced by regional or global averages. This conservative method avoids inflating the apparent innovation potential in data-scarce environments. For the Gini coefficient, values from different years (2020–2023) were used without temporal correction, as short-term inequality shifts are statistically minor relative to cross-country differences.

All indicators were transformed to a common 0–1 scale using min–max normalization across the three jurisdictions for each variable:

$$X' = (X - X_{min}) / (X_{max} - X_{min}) \tag{1}$$

Data where X is the raw indicator and X' its normalized equivalent. For indices where lower values represent a more favorable outcome, such as corruption or Gini, the direction was inverted before normalization.

After normalization, sub-indices were computed as:

$$A = \left(\frac{1}{n_A}\right) \sum A_i \quad I = \left(\frac{1}{n_I}\right) \sum I_i \quad F = \left(\frac{1}{n_F}\right) \sum F_i \tag{2}$$

The baseline societal welfare potential (*Wsoc*) was then represented as a normalized composite indicator combining the three foundational dimensions (access (*A*), innovation (*I*), and fairness (*F*)). Given the absence of empirically validated weights or a theoretically dominant dimension, the model adopts an equal-weight aggregation approach. This approach keeps the model neutral, avoids arbitrary weighting, and offers a clear baseline for later adjustments.

To connect empirical data with normative evaluation, two regulatory parameters were introduced:
τ – freedom of text and data mining (TDM), representing openness of research ecosystems;
ρ – rigidity of proprietary rights for AI-generated results, reflecting the degree of legal exclusivity.

These parameters were assigned through expert calibration based on comparative analysis of copyright exceptions, AI governance frameworks, and judicial interpretation. The initial legal-adjusted model integrates both parameters:

The coefficient $(1 - 0.5\rho)$ introduces a moderate sensitivity of fairness to proprietary rigidity. A fully restrictive regime ($\rho = 1$) reduces the fairness component by half rather than eliminating it, reflecting that even strong intellectual property systems retain some public oversight. Division by three ensures equal weighting of the three *Wsoc* dimensions so that the index measures overall societal balance rather than dominance of any single factor.

To reflect the ethical dependency between openness and institutional integrity, the Access dimension was adjusted by Fairness.

The legal-adjusted *Wsoc* represents a version of the index in which legal parameters, such as TDM permissions and intellectual property rights, are incorporated without linking them to institutional performance. In this version, the model uses legal rules as they are written and does not consider how well they work in practice. It shows a situation where the legal framework is accepted as given, without checking whether it is actually enforced or produces real effects. It therefore reflects a scenario where the legal environment is taken at face value, without assessing whether legal rules translate into real enforcement or societal outcomes.

The legal-adjusted value of *Wsoc* is calculated as:

$$W_{soc}^{legal} = \frac{(A \cdot \tau + I + F(1 - 0.5\rho))}{3} \tag{3}$$

The institutionally-adjusted *Wsoc* integrates both legal parameters and the institutional environment. This version captures the realized effectiveness of legal norms by incorporating the quality of institutions that mediate their impact. The institutional context determines whether formal rights, such as TDM exceptions or intellectual property protections, translate into actual incentives for innovation or remain only declarative.

Accordingly, the institutionally-adjusted *Wsoc* reflects a configuration in which the effect of legal rules on access, innovation, and fairness depends on institutional performance. This allows the index to approximate the marginal contribution of legal frameworks under real-world institutional constraints.

The institutionally-adjusted value is calculated as:

$$W_{soc}^{inst} = \frac{(A \cdot \tau \cdot F + I + F(1 - 0.5\rho))}{3} \tag{4}$$

Put simply, TDM openness helps only when the institutional framework is strong enough to support it.

Given the small sample size of jurisdictions, statistical outlier detection was not applicable. The relative ranking of models remained consistent, confirming that cross-jurisdictional differences are driven by institutional and regulatory structures rather than arbitrary parameterization.

3. Results

To enable a comparative assessment of structural differences across countries, the following tables present key indicators of access, innovation capacity, and institutional fairness for the United States, the EU average, and Ukraine (Tables 1–3).

Table 1
Access and Digital Openness Indicators (Access)

Index	US	EU	Ukraine
Open Data Maturity Index	–	83%	97%
OECD Digital Government Index	0.59	0.61	–
Freedom on the Net	76	≈82	61
AI Readiness Index	87.03	69.60	56.03

Table 2
Innovation Capacity and Competitiveness Indicators (Innovation)

Index	US	EU	Ukraine
Global Innovation Index	61.7	≈51.0%	29.7
World Competitiveness	99.29	≈83.0	–
R&D Expenditure	3.4%	2.22%	0.33%
Digital Economy Value Added	10%	8%	4%

Table 3
Fairness, Governance, and Institutional Quality Indicators (Fairness)

Index	US	EU	Ukraine
Rule of Law Index	0.68	0.73	0.48
Corruption Perception Index	65	66	35
Gini Index	41.3%	29.4%	≈23.0
Human Development Index	0.938	≈0.915	≈0.771

To assess internal consistency and robustness, two non-parametric validation tests were conducted. Concordance of rankings across indicators within each dimension was measured using Kendall's W, yielding 0.71 for Access, 0.92 for Innovation, and 0.28 for Fairness. These results indicate strong alignment of innovation metrics and moderate coherence for digital access, while fairness indicators remain heterogeneous. Robustness was further evaluated through a leave-one-out procedure: recalculating the overall $Wsoc$ after sequentially excluding each indicator produced a maximum deviation of 0.07–0.09 across jurisdictions, confirming that no single metric disproportionately influenced the final results. In subsequent stages of modeling, the legal and licensing variables (τ, ρ, λ) were introduced precisely in the Access and Fairness dimensions, where lower coherence revealed structural and normative asymmetries requiring theoretical adjustment.

To illustrate how different legal traditions shape the ethical-institutional performance of data and AI governance, the table below compares three jurisdictional model types across the core parameters and the resulting aggregated welfare scores (Table 4).

Table 4
Comparative Evaluation of Jurisdictional Model Types

Model Type	A	I	F	τ	ρ	$Wsoc$	$Wsoc\_legal$	$Wsoc\_inst$
Case-law (US)	0.57	1.00	0.69	0.70	0.20	0.753	0.673	0.632
Rule-based (flexible) (EU)	0.61	0.49	0.88	0.80	0.40	0.660	0.561	0.541
Rule-based (radical)	0.33	0.00	0.25	0.65	0.70	0.193	0.126	0.072

(Ukraine)

Overall, the data point to a clear pattern shaped mainly by institutional and economic factors: jurisdictions with higher innovation capacity and lower regulatory rigidity generate substantially greater levels of societal welfare. Introducing legal parameters lowers the *Wsoc* values because formal rules create certain limitations. Adding the institutional adjustment reduces them even more, as it reflects how data and AI governance actually works in practice. Overall, the *Wsoc* model confirms that institutional quality and legal flexibility are decisive factors shaping a jurisdiction's ability to produce societal value in the digital economy.

4. Discussion

4.1. Structural Findings and Cross-Parameter Dynamics

Although many international indices can be used to assess innovation, access, and fairness, the aim of this study is not to highlight any specific dataset. The goal is to show the usefulness of modeling based on regulatory parameters. Regardless of which indicators are chosen, the structural relationships revealed by the *Wsoc* framework remain consistent and theoretically meaningful.

The numbers show that the parameters influence each other in ways that aren't always straightforward: even small shifts in rigidity or licensing influence generate disproportional changes in the fairness-adjusted welfare scores, revealing structural sensitivities that would remain hidden without formal modeling.

The results highlight several insights. First, innovation outcomes emerge from the interaction between access and institutions: freedom of TDM alone does not generate societal benefit unless supported by transparent, fair, and stable institutional conditions that enable equitable participation in innovation processes.

Second, regulatory models embody different ethical logics of openness and control – flexible interpretative systems facilitate experimentation, codified rule-based regimes enhance predictability while constraining creativity, and hybrid or sui generis frameworks extend proprietary boundaries in ways that redefine the moral circulation of knowledge. The models confirms that legal overprotection reduces experimentation and limits the social diffusion of knowledge [29].

Third, institutional strength essentially determines whether the rules work as intended: the gap between legal potential and realized welfare reflects the limiting effect of corruption, inequality, or low administrative capacity on the ethical materialization of innovation. Even strong legal or ethical frameworks fail to increase welfare when not backed by real institutions of accountability [30].

Fourth, societal welfare depends on the equilibrium among access, innovation mechanisms, and fair institutions; only when these components align does technological progress translate into collective ethical value.

Finally, the link between access and fairness plays an important ethical role: when governance is strong, even moderate openness brings real benefits, but when governance is weak, more open rules lose much of their value.

Building on these insights, the analysis then turns to the redistributive dimension of AI ecosystems. Societal welfare is shaped by law and institutions and also by the contractual allocation of rights within platform-based environments.

4.2. Scenario Modeling Under Platform-Mediated Intellectual Property Regimes

Today we observe the growing importance of contractual governance, which increasingly functions as a substitute for statutory law [31]. Technological innovation is outpacing the law, transforming ownership and value into fluid, contract-based constructs [32]. Recent developments in AI governance show that licensing agreements increasingly substitute or neutralize the effect of national copyright law. Across major generative AI platforms such as OpenAI, Midjourney, and Runway, the terms of service often provide the platform with broad rights to use, modify, or commercially exploit user-generated outputs, irrespective of whether national law treats such results as protectable works. As a result, platform licensing operates like a separate layer of rules which can effectively supersede or diminish the statutory rules on authorship and ownership. In the contemporary digital environment, proprietary control is often expanded beyond the limits of traditional law [33; 34], in particular, through contractual and technical mechanisms.

This situation creates ethical and structural imbalances. On one hand, global licensing rules make access more uniform across countries. On the other hand, they shift control from individual creators to platform operators. As a result, platforms start to function like separate regulators that decide how rights and benefits are distributed.

To represent this interaction in the model, licensing is treated as a factor modifying the effective rigidity of property rights. Licensing frameworks redistribute control: they determine how strongly proprietary structures dominate over public-interest principles. The corresponding parameter λ (licensing influence) interacts with the baseline rigidity coefficient ρ to produce an adjusted value of rights rigidity:

$$\rho_{eff} = \rho + \alpha \cdot s \cdot \lambda \tag{5}$$

where s (sign parameter) ∈ {−1, +1} and α (sensitivity coefficient) ≈ 0.5.

The value of α was set at 0.5 to represent a balanced sensitivity level, ensuring that institutional quality influences, but does not dominate, the legal components of the model; this midpoint allows the adjustment to reflect structural differences without overpowering the underlying legal parameters.

Accordingly, fairness becomes:

$$F' = F \cdot (1 - 0.5 \cdot \rho_{eff}) \tag{6}$$

And the platform-adjusted model of societal welfare is defined as:

$$W_{soc}^{plat} = \frac{(A \cdot \tau \cdot F + I + F \cdot (1 - 0.5 \cdot \rho_{eff}))}{3} \tag{7}$$

For this part of the analysis, we consider abstract models grounded in well-known philosophical approaches to intellectual property [35–42] (Table 5).

Table 5
Scenario Models Based on Philosophical Theories

Scene	Theoretical foundation	τ	ρ	λ	s
Epistemic Openness	public-good, open science	0.90	0.10	0.20	-1
Regulated Utilitarianism	pragmatic, balanced regulation	0.75	0.35	0.40	-1
Economic Incentivism	intellectual capital, incentive theory	0.65	0.55	0.60	+1
Data Sovereignty	national control, digital realism	0.55	0.70	0.80	+1

AI Proprietarianism	proprietary, rights-based radicalism	0.45	0.85	0.90	+1

Because the variables presented in Table 5 are derived from abstract conceptual approaches rather than empirical statistical data, scenario-based forecasting is the most appropriate method for this type of modeling.

The scenario-based framework makes it possible to evaluate how different configurations of TDM freedom (τ), rights rigidity (ρ), licensing influence (λ), and directional effect (s) shape societal welfare. Once the criteria were ranked and weighted, each scenario could be compared within a unified parameter space. This enables an assessment of how far each model deviates from an ethically balanced configuration of openness, innovation capacity, and fairness.

To operationalize these theoretical parameters, Decision Making Helper program [38; 39] was applied once to transform abstract variables into structured pairwise comparisons. The analysis revealed that the influential factor differentiating the scenarios is the effective rigidity coefficient ρ_eff, which incorporates the corrective effect of licensing. Because ρ_eff depends on formal rights as well as on the sign of regulatory direction (s), two scenarios with identical nominal rigidity (ρ) may produce substantially different fairness scores (F'). This is particularly evident where licensing either counteracts or reinforces proprietary control.

Scenarios grounded in openness, such as Epistemic Openness and Regulated Utilitarianism, initially show strong potential due to high τ and low ρ. However, their resulting welfare values decrease once the negative directional parameter ($s = -1$) is applied, which lowers adjusted fairness. In practical terms, this means that legal openness alone does not guarantee higher societal welfare if the licensing environment introduces uncertainty or weakens the effectiveness of governance mechanisms. These models therefore lose part of their theoretical advantage when fairness is corrected through ρ_eff.

Scenarios characterized by high rigidity (Data Sovereignty and AI Proprietarianism) display the lowest welfare values. Their elevated ρ and λ, combined with a positive directional effect ($s = +1$), sharply increase ρ_eff, resulting in significant reductions of F'. Although such models may enhance control over data in the short term, their structural configuration leads to a substantial decline in adjusted welfare. The drop in F' across these scenarios illustrates how intensified rights rigidity disproportionately suppresses overall societal benefit.

The scenario that produced the most balanced and favorable outcome is Economic Incentivism. Its medium τ, moderate ρ, and relatively high λ, together with a positive directional parameter, create a configuration in which proprietary rigidity is partially offset by licensing redistribution, while openness remains sufficient to support innovation. As a result, this scenario outperforms all others. This finding demonstrates that neither maximal openness nor maximal control is optimal; instead, societal welfare is highest under a moderate equilibrium between them.

The tabular and 3D visualization further (Figure 1) confirms the central position of Economic Incentivism within the parameter landscape.

The scenario tests show that ethical and legal factors affect each other in complex ways. Small increases in rigidity or licensing influence may produce disproportionately large shifts in welfare outcomes once certain parameter boundaries are crossed. This sensitivity highlights the importance of maintaining balanced regulatory ecosystems in which institutional quality, access conditions, and proprietary rules remain aligned. It also demonstrates that ethical trade-offs are embedded within structural design choices: shifts toward either extreme (high-control or high-openness) destabilize overall welfare more rapidly than incremental changes in moderate configurations.

The use of this software tool represents a scientifically grounded approach, as it applies the analytic hierarchy process developed by Thomas Saaty and relies on systematic pairwise comparison of criteria [38; 39]. Its computational procedure evaluates weights, checks internal consistency, and aggregates heterogeneous indicators into a coherent decision model, ensuring that the scenario outcomes are derived from a transparent and reproducible mathematical method. This transforms abstract parameters into rigorously processed analytical results, reinforcing the reliability of the modelling framework.

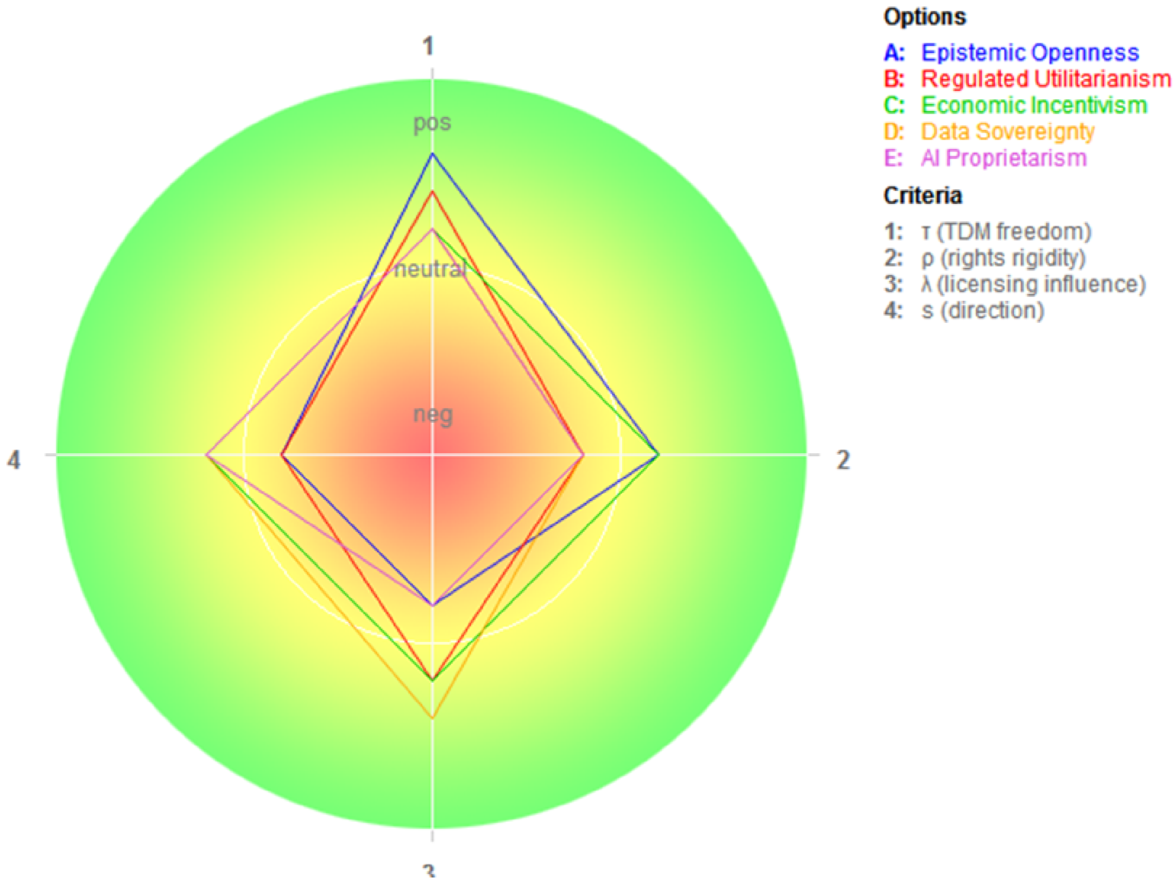

Figure 1: 3D Visualization of Scenario Intersections.

The strongest scenario is the one that stays in a balanced middle zone, where no single parameter dominates and none of the indicators reach extreme values. This geometric stability across dimensions explains why the scenario maintains its lead even when fairness and rigidity parameters are adjusted. It also shows that welfare decreases non-linearly when models move toward maximal restriction or maximal openness, underscoring the value of a balanced regulatory architecture.

5. Conclusions

The study shows that ethical evaluation becomes more informative when ethical categories are approached as adjustable parameters that can be combined and tested in different ways. By using relevant contemporary parameters we showed how different ethical configurations behave under analytical conditions. This approach illustrates that ethical principles can be explored dynamically.

Through systematic variation of the parameters, the study highlighted the complexity of ethical integration in AI development. Some configurations that appear normatively attractive in theory became less effective once fairness adjustments were applied; others performed better only when licensing counterbalanced rigidity. These findings indicate that the ethical behavior of AI systems is shaped by how various legal and ethical factors interact within a broader socio-technical context. The model thus reveals patterns that would remain hidden without parameter-level experimentation.

The scenario analysis indicates that moderately balanced approaches deliver the most stable ethical results. The exploration of contrasting scenarios, ranging from high-openness models to highly proprietary ones, allowed us to observe how societal welfare reacts when ethical parameters are pushed to their limits. The fact that the strongest result emerged from a scenario positioned between extremes shows that ethical AI governance is an exercise in calibration.

A key limitation of this study lies in the heterogeneous and evolving nature of the underlying data. Many of the indicators used to construct the Access, Innovation, and Fairness dimensions are updated annually and may shift considerably over short periods of time, which affects longitudinal stability. In addition, the number of available indicators differs across jurisdictions. As a result, each jurisdiction is assessed on a slightly different subset of criteria, which introduces structural asymmetry. The model mitigates this through subset normalization, but it cannot fully compensate for the uneven availability and granularity of empirical data. Finally, any scenario-based modeling inevitably abstracts away contextual nuances; therefore, the results should be interpreted as indicative patterns rather than fixed or exhaustive representations of real-world institutional dynamics.

Overall, the study's central contribution lies in demonstrating that ethical parameters can be operationalized through analytical modeling and stress-tested through controlled variation. By experimenting with these variables we created a methodological pathway for evaluating the degree to which ethical principles are actually embedded in AI development. This approach opens the door to more empirical, adaptive, and evidence-based research on AI ethics, where ethical concepts can be measured, compared, and refined through iterative modeling.

Future research may expand this framework in several directions. First, the parameter set itself can be refined by incorporating additional ethical and regulatory variables, such as transparency requirements, model accountability mechanisms, or data provenance standards. Second, the methodology could be extended to a larger and more diverse set of jurisdictions once more consistent datasets become available, enabling robust cross-country comparisons. Third, integrating temporal dynamics (tracking how changes in law, licensing practices, or institutional conditions modify welfare outcomes over time) would allow the model to function as an early diagnostic tool for emerging regulatory trends. Finally, empirical validation through case studies, industry datasets, or real-world regulatory interventions would help determine how accurately the modeled interactions reflect the practical integration of ethical principles into AI development.

Beyond its conceptual contribution, the framework can also support practical assessments of regulatory initiatives, national AI strategies, and the governance models implemented by digital platforms and eco, offering a structured method for evaluating how ethical principles are operationalized in real policy environments.

Declaration on Generative AI

Generative AI tools (ChatGPT 5.1) were used to assist in verification of statistical information collected by the authors, language editing, paraphrasing, and stylistic refinement of the manuscript. All conceptual contributions, data selection, methodological decisions, modelling design, interpretations, and conclusions were developed entirely by the authors. The authors reviewed and validated all AI-generated suggestions and takes full responsibility for the content of the final text.

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