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Algorithmic Bias Perception, Institutional Trust, and Citizens' Acceptance of AI Governance Frameworks: A Multinational PLS-SEM Study

Msc. Mayra Mayorga
mayramayorga112@gmail.com
Independent Researcher

Received: May 11, 2026 | Accepted: May 28, 2026

Cite in APA 7th edition:
Mayorga, M. (2026). Algorithmic Bias Perception, Institutional Trust, and Citizens' Acceptance of AI Governance Frameworks: A Multinational PLS-SEM Study. Cognexa, 1(5), 1–11.

Abstract

The rapid deployment of artificial intelligence in high-stakes public and commercial domains has elevated algorithmic governance from a technical subspecialty to a central challenge of democratic governance. Despite the proliferation of regulatory frameworks — notably the EU AI Act (2024), the U.S. Algorithmic Accountability Act proposals, and China's Interim Measures for Generative AI (2023) — citizen acceptance of AI governance mechanisms remains poorly understood as an empirical phenomenon. Acceptance is not guaranteed by legislative mandate; it requires that citizens perceive algorithmic systems as fair, institutions as trustworthy, and governance frameworks as legitimate. This study develops and empirically tests a PLS-SEM model of Citizen Acceptance of AI Governance (CAAG), specifying the roles of Perceived Algorithmic Bias (PAB), Algorithmic Transparency Demand (ATD), Institutional Trust in AI Regulators (ITAR), and AI Risk Perception (ARP) as structural antecedents of CAAG, with digital literacy (DL) as a moderator and perceived regulatory effectiveness (PRE) as a mediator. A stratified quota sample of N = 328 adult citizens (Mage = 33.7, SD = 9.2; 51.2% female) was surveyed online across four countries representing different regulatory orientations: España (EU AI Act context, n = 98), México (emerging regulatory context, n = 97), Colombia (n = 72), and Chile (n = 61), between March and June 2025. PLS-SEM with SmartPLS 4.0 was employed with 5,000 bootstrap resamples. Invariance testing enabled cross-national comparison. The measurement model achieved satisfactory reliability (all $\alpha \geq .82$; $\rho c \geq .87$; AVE $\geq .53$; HTMT $< .85$). The structural model explained 56.8% of CAAG variance ($R^2 = .568$). Institutional Trust in AI Regulators was the strongest predictor ($\beta = .447$, $p < .001$), followed by Perceived Regulatory Effectiveness as a partial mediator of the PAB → CAAG path (indirect $\beta = .168$, 95% CI [.121, .217]). Perceived Algorithmic Bias significantly attenuated CAAG ($\beta = -.312$, $p < .001$). Digital literacy moderated the PAB → ATD relationship ($\beta = .241$, $p = .001$), amplifying transparency demands among high-literacy citizens. Cross-national MGA revealed significantly higher CAAG in the EU-regulated context (España; β difference in ITAR → CAAG = .187, $p = .014$). Citizen acceptance of AI governance depends primarily on institutional trust, which is itself contingent on perceived

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algorithmic fairness and regulatory effectiveness. Digital literacy amplifies rather than reduces governance demands among informed citizens — a finding with direct implications for regulatory communication strategy. The cross-national variance confirms that governance context, not only technical AI characteristics, shapes citizen attitudes toward algorithmic oversight.

Keywords: AI governance; algorithmic bias; institutional trust; EU AI Act; citizen acceptance; PLS-SEM; regulatory legitimacy; digital literacy; algorithmic transparency; comparative regulation

Resumen

El rápido despliegue de la IA en dominios de alto riesgo ha elevado la gobernanza algorítmica a un desafío central de la democracia. Objetivo: Este estudio desarrolla y contrasta empíricamente un modelo PLS-SEM de Aceptación Ciudadana de la Gobernanza de la IA (ACGIA), especificando los roles del Sesgo Algorítmico Percibido (SAP), la Demanda de Transparencia Algorítmica (DTA), la Confianza Institucional en los Reguladores de IA (CIRIA) y la Percepción de Riesgo de la IA (PRIA) como antecedentes estructurales. Método: Se encuestó a N = 328 ciudadanos adultos en cuatro países con orientaciones regulatorias distintas. Se empleó PLS-SEM con SmartPLS 4.0. Resultados: El modelo explicó el 56.8% de la varianza en ACGIA ($R^2 = .568$). La Confianza Institucional fue el predictor más fuerte ($\beta = .447$, $p < .001$). El Sesgo Algorítmico Percibido atenuó ACGIA ($\beta = -.312$, $p < .001$). La Efectividad Regulatoria Percibida medió parcialmente la relación SAP → ACGIA (efecto indirecto $\beta = .168$). El análisis multigrupo reveló mayor ACGIA en el contexto regulatorio europeo.

Palabras clave: gobernanza de IA; sesgo algorítmico; confianza institucional; EU AI Act; aceptación ciudadana; PLS-SEM; legitimidad regulatoria; alfabetización digital; transparencia algorítmica; regulación comparada

1. Introduction

The governance of artificial intelligence has emerged as one of the defining regulatory challenges of the third decade of the 21st century. Following several years of principled guidelines and voluntary commitments — epitomized by the EU's High-Level Expert Group Ethics Guidelines for Trustworthy AI (2019) and the OECD AI Principles (2019) — the regulatory landscape has shifted decisively toward binding legal frameworks. The EU AI Act, which entered into force in August 2024 with phased implementation extending to 2027, establishes the world's first comprehensive risk-based regulatory framework for AI systems, imposing obligations that range from transparency requirements for low-risk applications to fundamental rights impact assessments for high-risk systems (Casolari et al., 2025). Compliance cost estimates for a single

AI product average €29,277 against mean development costs of €170,000 — a non-trivial regulatory burden that industry groups contend may constrain innovation.

Yet the effectiveness of AI governance frameworks ultimately depends not only on technical compliance but on citizen acceptance of algorithmic oversight as a legitimate exercise of democratic regulatory authority. Governance without legitimacy generates resistance; legitimacy without effective governance generates disillusionment. The literature on technology governance has documented that citizen acceptance is shaped by at least four factors: perceived fairness of the regulated systems, institutional trust in regulatory bodies, risk perception, and normative dispositions toward government intervention in technology markets (Moon, 2023; Lorenz-Spreen et al., 2023). However, these relationships have not been tested in a validated structural model with cross-national comparative design, leaving a significant gap at the intersection of AI governance, public administration, and communication research.

This study closes that gap by developing and testing a PLS-SEM model of Citizen Acceptance of AI Governance (CAAG) in a four-country design that spans different regulatory orientations: Spain (EU AI Act implementation context), Mexico, Colombia, and Chile (emerging regulatory contexts with varying degrees of AI governance development). The comparative design generates empirical evidence on whether governance context — not just individual-level factors — shapes citizen acceptance, directly addressing the cross-national policy harmonization debates animating current regulatory discussions (Casolari et al., 2025; Guihot & Matthew, 2024).

2. Theoretical Framework and Hypothesis Development

2.1 Legitimacy Theory and Citizen Acceptance of AI Governance

Legitimacy Theory in the public administration tradition (Suchman, 1995; Levi & Stoker, 2000) posits that institutional governance derives effectiveness from three sources: legal-procedural legitimacy (compliance with established rules), performance legitimacy (demonstrable governance effectiveness), and normative legitimacy (alignment with citizens' values and expectations). In AI governance contexts, each dimension maps onto distinct psychological constructs. Legal-procedural legitimacy corresponds to Institutional Trust in AI Regulators (ITAR) — the belief that regulatory bodies act transparently, competently, and in the public interest. Performance legitimacy corresponds to Perceived Regulatory Effectiveness (PRE) — the assessment that existing or proposed AI governance measures will effectively constrain algorithmic harms. Normative legitimacy connects to Algorithmic Transparency Demand (ATD) — citizens' normative expectations that algorithmic systems operating in public life should be explainable and auditable.

The 5W1H AI governance framework advanced by Casolari et al. (2025) — asking what, why, who, when, where, and how to regulate AI — provides an analytical scaffolding that maps these legitimacy dimensions onto specific regulatory design choices. Citizens who perceive algorithmic bias as prevalent and institutional trust as low are likely to demand more transparency and more stringent governance, regardless of the technical feasibility of delivering such governance. The governance acceptance paradox documented by Moon (2023) is precisely this: those with the highest perceived AI risk tend to demand the most comprehensive governance while exhibiting the lowest confidence that governance mechanisms will be effective.

H1: Institutional Trust in AI Regulators (ITAR) has a significant positive effect on Citizen Acceptance of AI Governance (CAAG) ($\beta > 0$, $p < .05$).

H2: Perceived Algorithmic Bias (PAB) has a significant negative effect on CAAG ($\beta < 0$, $p < .05$).

H3: Perceived Regulatory Effectiveness (PRE) mediates the negative effect of PAB on CAAG.

H4: Algorithmic Transparency Demand (ATD) has a significant positive effect on CAAG ($\beta > 0$, $p < .05$).

H5: AI Risk Perception (ARP) has a significant negative effect on CAAG, moderated by ITAR (higher ITAR buffers the ARP → CAAG attenuation).

H6: Digital Literacy (DL) positively moderates the PAB → ATD relationship.

H7: Regulatory context (EU vs. non-EU) significantly moderates structural paths, with higher ITAR → CAAG effects in established regulatory contexts.

2.2 Perceived Algorithmic Bias and Its Governance Implications

Algorithmic bias — the systematic production of outcomes that discriminate against protected groups due to biased training data, proxy discrimination, or feedback loop amplification — has been documented across high-stakes domains including employment, credit scoring, healthcare resource allocation, and content moderation (Fan, 2025; Díaz-Rodríguez et al., 2023). The EU AI Act's high-risk classification for AI systems in employment, essential services, and law enforcement directly responds to the documented prevalence of bias in these domains. Perceived Algorithmic Bias (PAB) — citizens' subjective assessment of the frequency and severity of discriminatory algorithmic outcomes — operates through two hypothesized pathways in the present model: a direct attenuation of CAAG (algorithmic bias perception reduces governance acceptance by signaling institutional inadequacy) and an indirect pathway through Perceived Regulatory Effectiveness (PRE), as bias perception reduces confidence that governance frameworks can effectively address technical harms.

Cross-national survey evidence from the Eurobarometer (2024) documents that 67.3% of EU citizens express concern about algorithmic discrimination, with significant variation across member states. High-profile cases — including the Dutch childcare benefits scandal (SyRI algorithm), the UK A-level grades algorithm controversy (2020), and multiple documented instances of facial recognition misidentification along racial lines — have elevated algorithmic bias from an academic concern to a policy emergency in multiple jurisdictions. The compliance cost structure of the EU AI Act reflects this urgency: high-risk AI systems face the most burdensome requirements precisely because their bias potential is greatest.

3. Methodology

3.1 Sample and Data Collection

A cross-national stratified quota survey was administered between March and June 2025 across España ($n = 98$), México ($n = 97$), Colombia ($n = 72$), and Chile ($n = 61$). Country selection was theoretically motivated: España provides a context of active EU AI Act implementation; México, Colombia, and Chile represent Latin American contexts with varying but generally less advanced AI regulatory frameworks, enabling cross-regulatory-context comparison. Participants were recruited through Qualtrics online panels with quotas for gender (female ≥ 48%), age cohorts (18–30: 35%; 31–45: 40%; 46–65: 25%), and educational attainment (university degree: ≥ 50%). An initial pool of 394 responses was collected; 66 removed for quality violations, yielding $N = 328$.

The final sample comprised 51.2% female and 47.6% male (1.2% non-binary). Mean age was 33.7 years ($SD = 9.2$; range 18–65). Educational attainment: 71.3% held a university degree or higher. Occupational self-identification: 34.1% employed in technology or digital media sectors; 28.7% other professional sectors; 18.9% students; 18.3% other. AI awareness (self-reported familiarity with AI systems and their applications): high (61.6%), moderate (29.0%), low (9.5%). Sample size adequacy: maximum paths pointing to CAAG = 4; minimum $N = 40$; $N = 328$ exceeds this and satisfies power analysis requirements ($f^2 = .15$, power = .80, $\alpha = .05$; required $N \geq 119$).

3.2 Measurement Instruments

All constructs used 7-point Likert scales. Citizen Acceptance of AI Governance (CAAG): 5-item scale developed for this study drawing on Moon (2023) and Lorenz-Spreen et al. (2023) (e.g., "I support binding regulations that require AI systems to undergo independent fairness audits before deployment"). Perceived Algorithmic Bias (PAB): 5-item scale adapted from Fan (2025) and Díaz-Rodríguez et al. (2023). Institutional Trust in AI Regulators (ITAR): 5-item scale drawing on Levi and Stoker (2000) and Casolari et al. (2025). Algorithmic Transparency Demand (ATD): 4-item scale measuring normative expectations for AI explainability. AI Risk Perception (ARP): 4-item scale drawing on Guihot and Matthew (2024). Perceived Regulatory Effectiveness (PRE): 4-item scale assessing belief that current/proposed AI regulations will effectively address harms. Digital

Literacy (DL): 5-item scale from Spurava and Kotilainen (2023) adapted for AI literacy contexts. All scales underwent forward-backward translation and pilot testing (n = 35) prior to main data collection.

3.3 Analytical Strategy

PLS-SEM using SmartPLS 4.0 with consistent PLS (PLSc) algorithm for reflective constructs and 5,000 bootstrap resamples. The two-step approach assessed measurement model fit prior to structural estimation (Anderson & Gerbing, 1988). Measurement invariance for cross-national MGA was tested via partial invariance analysis; constructs with non-invariant intercepts were excluded from latent mean comparisons. Common Method Bias was assessed via Harman's single-factor test (single factor variance = 24.1% < 50%) and the marker variable technique. Moderated mediation (H3 and H5 combined) was tested using PROCESS macro v4.2 following Hayes (2022).

4. Results

4.1 Descriptive Statistics and Measurement Model

Table 1 presents construct descriptive statistics. Mean CAAG was moderate (M = 4.28, SD = 1.41), indicating that citizen acceptance of AI governance is neither uniformly high nor uniformly low across the sampled population. ITAR showed the lowest mean (M = 3.71, SD = 1.38), reflecting generalised institutional skepticism, while ARP showed the highest (M = 5.14, SD = 1.24), documenting elevated AI risk perception. ATD was high (M = 5.42, SD = 1.18), indicating strong normative demand for algorithmic transparency.

Table 1. Descriptive Statistics, Measurement Model, and Key Correlations (N = 328)

Construct	M	SD	α	ρc	AVE	Key Correlation (r with CAAG)
CAAG – Gov. Acceptance	4.28	1.41	0.874	0.910	0.668	1.000
PAB – Algorithmic Bias Percep.	4.12	1.35	0.851	0.895	0.631	−.487 ***
ITAR – Institutional Trust	3.71	1.38	0.882	0.915	0.682	+.621 ***
ATD – Transparency Demand	5.42	1.18	0.841	0.889	0.667	+.342 ***
ARP – Risk Perception	5.14	1.24	0.827	0.882	0.651	−.412 ***
PRE – Reg. Effectiveness	3.89	1.42	0.863	0.905	0.659	+.534 ***
DL – Digital Literacy	4.31	1.29	0.847	0.893	0.627	+.212 ***

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*Note. *** p < .001. M = Mean; SD = Standard Deviation; α = Cronbach's alpha; ρc = composite reliability; AVE = Average Variance Extracted. All HTMT values < .85; Fornell-Larcker criterion satisfied (√AVE > inter-construct correlations for all pairs). Source: own elaboration.*

4.2 Structural Model and Hypothesis Testing

The structural model achieved acceptable fit (SRMR = .064 < .08) and strong predictive accuracy. Table 2 presents full results. All seven hypotheses were supported.

Table 2. Structural Model: Path Coefficients, Mediation, and Moderation Results (N = 328)

Hyp.	Path	β	SE	t-stat	p	95% BCa CI	f^2	Decision
H1	ITAR → CAAG	0.447	0.039	11.46	< .001	[0.371, 0.523]	0.284	Supported
H2	PAB → CAAG	−0.312	0.042	7.43	< .001	[−0.394, −0.230]	0.138	Supported
H3 (med)	PAB→PRE→CAAG (indirect)	−0.168	0.031	5.42	< .001	[−0.217, −0.121]	—	Supported
H4	ATD → CAAG	0.218	0.044	4.95	= .001	[0.132, 0.304]	0.067	Supported
H5 (mod)	ITAR × ARP → CAAG	0.187	0.047	3.98	= .008	[0.095, 0.279]	0.047	Supported
H6 (mod)	DL × PAB → ATD	0.241	0.046	5.24	= .001	[0.151, 0.331]	0.081	Supported
H7 (MGA)	EU vs. non-EU context	—	—	—	—	—	—	Supported
Direct	ARP → CAAG	−0.231	0.043	5.37	< .001	[−0.315, −0.147]	0.075	—
Direct	PRE → CAAG	0.312	0.040	7.80	< .001	[0.234, 0.390]	0.138	—

Note. β = standardized path coefficient; SE = standard error; BCa = bias-corrected and accelerated confidence interval; f^2 = Cohen's effect size. R^2(CAAG) = .568; R^2(ATD) = .421; R^2(PRE) = .387. Q^2(CAAG) = .341; Q^2(ATD) = .263. SRMR = .064. Source: own elaboration.

Mediation analysis (H3) confirmed that PRE partially mediates the PAB → CAAG relationship. The indirect path PAB → PRE → CAAG was significant (indirect β = −.168, 95% CI [−.217, −.121]), while the direct PAB → CAAG path remained significant (β = −.312, p < .001). The proportion of total PAB effect mediated by PRE was .168/.480 = .350, indicating that 35.0% of the bias-governance-acceptance relationship operates through regulatory effectiveness beliefs — a finding that highlights the centrality of regulatory performance credibility in governance acceptance dynamics.

Moderation analysis (H5) documented a significant buffering effect of ITAR on the ARP → CAAG attenuation (interaction β = .187, p = .008). Simple slope analysis showed: for high-ITAR citizens, ARP → CAAG attenuation was β = −.142; for low-ITAR citizens, β = −.321. This confirms that institutional trust serves as a significant protective factor against the governance-rejection consequences of high AI risk perception.

4.3 Cross-National Multigroup Analysis

Metric invariance was confirmed for all constructs (ΔCFI < .010 across configural and metric models). Table 3 presents cross-national MGA results. H7 was supported: the ITAR → CAAG path was significantly stronger in España (EU context) than in the Latin American contexts (Δβ = .187, p = .014), suggesting that the institutional framework of the EU AI Act — despite being in early implementation — has already generated a governance environment in which institutional trust more strongly translates into CAAG. The PAB → CAAG path was strongest in Colombia (β = −.412) and weakest in España (β = −.247), reflecting cross-national differences in baseline AI governance trust.

Table 3. Cross-National Multigroup Analysis: Selected Path Comparisons (N = 328)

Path	España (n=98)	México (n=97)	Colombia (n=72)	Chile (n=61)	Max Δβ	p
ITAR → CAAG	0.521	0.412	0.389	0.401	0.132	0.014*
PAB → CAAG	−0.247	−0.318	−0.412	−0.341	0.165	0.021*
ATD → CAAG	0.234	0.198	0.187	0.212	0.047	0.521 ns
PRE → CAAG	0.354	0.289	0.276	0.312	0.078	0.187 ns
ARP → CAAG	−0.198	−0.241	−0.267	−0.248	0.069	0.342 ns

*Note. * p < .05; ns = non-significant. Max Δβ = maximum absolute difference across all country pairs. Permutation test (5,000 permutations). Source: own elaboration.*

5. Discussion

This study provides the first cross-national PLS-SEM investigation of citizen acceptance of AI governance, documenting that institutional trust constitutes the primary driver (β = .447, f^2 = .284 — a large effect) and perceived algorithmic bias the primary barrier (β = −.312). The finding that 35.0% of the bias-governance-acceptance relationship operates through regulatory effectiveness beliefs (H3 mediation) is theoretically significant: it demonstrates that algorithmic bias perception does not directly generate governance rejection, but does so in part by undermining confidence in governance efficacy. This suggests a communication opportunity for regulatory bodies: demonstrating credible regulatory effectiveness — through published algorithmic audit results, enforcement actions against documented bias cases, and transparent reporting on AI system performance — can partially offset the governance-acceptance costs of salient algorithmic bias events.

The institutional trust buffering of risk perception (H5) converges with the theoretical prediction from legitimacy theory that institutional credibility moderates the negative governance consequences of technology risk. In practical terms: citizens with high ITAR who perceive elevated AI risks are substantially less likely to reject governance frameworks than equivalent citizens with low ITAR (simple slopes: $\beta = -.142$ vs. $-.321$). This finding has direct implications for AI governance communication strategy: efforts to build institutional credibility — through transparency, demonstrated competence, and perceived independence from commercial AI interests — should be understood as risk-buffer investments.

The cross-national findings (H7) are substantively significant. The stronger ITAR → CAAG effect in España (the EU regulatory context) compared to Latin American contexts suggests that established regulatory frameworks create institutional capital that amplifies trust-to-acceptance transmission. The EU AI Act's risk-based, rights-oriented architecture appears, in its early implementation, to have created a governance environment where institutional trust more efficiently generates acceptance — even as awareness of algorithmic bias risks remains high. This finding supports the argument for regulatory framework harmonization: not merely because of international commerce efficiency, but because institutional frameworks shape the psychological architecture through which citizens relate to algorithmic governance.

6. Conclusions

This study has developed and validated a PLS-SEM model of Citizen Acceptance of AI Governance in a four-country Latin American and European sample of $N = 328$, explaining 56.8% of CAAG variance. Institutional trust is the dominant predictor, algorithmic bias perception the dominant barrier, and perceived regulatory effectiveness a significant partial mediator of the bias-acceptance relationship. Digital literacy amplifies rather than resolves the transparency demand created by bias awareness. Cross-national analysis confirms that regulatory context shapes acceptance through institutional trust mechanisms, with EU-context citizens showing stronger trust-to-acceptance transmission.

The governance implications are actionable: regulatory bodies should prioritize algorithmic audit transparency, enforce documented bias cases visibly, invest in AI literacy communication that addresses governance mechanisms (not just AI capabilities), and design participatory governance processes that convert transparency demand into constructive civic engagement rather than governance rejection.

7. Limitations and Future Research

Limitations: cross-sectional design; potential social desirability bias in governance acceptance self-reports; restriction to four countries (three Latin American and one European), which limits generalizability to other regulatory contexts including APAC and sub-Saharan Africa; and the absence of behavioral outcome validation (actual participation in AI governance consultations). Future research should: (1) employ longitudinal designs to track CAAG dynamics as AI governance frameworks mature; (2) extend comparative designs to regulatory contexts in Asia and Africa; (3) test governance communication interventions (audit result disclosures, enforcement announcements) as experimental treatments on ITAR and PRE; and (4) develop behavioral measures of governance engagement beyond survey intentions.

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