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Explainable AI (XAI) in Automated Decision-Making for E-Government: Evaluating Citizen Trust and Algorithmic Auditing Mechanisms

Mahmuda Begum [1+]
Md Rasel Ul Alam[2]
Ashraful Islam Albi[3]

[1] International Islamic University Chittagong, Chittagong, Bangladesh
[2] University of the Cumberlands, Kentucky, USA
[3] Daffodil International University (DIU), Dhaka, Bangladesh

+Corresponding Author Email: mahmudabegum182000@gmail.com

A B S T R A C T

The integration of Automated Decision-Making (ADM) systems powered by Artificial Intelligence (AI) in public sector governance promises enhanced administrative efficiency, consistent welfare allocation, and streamlined municipal licensing. However, the deployment of "black-box" machine learning models in high-stakes public decisions raises profound ethical, legal, and operational concerns regarding administrative due process, algorithmic bias, and systemic citizen distrust. This paper proposes the Public Sector Algorithmic Auditing and Explainability Framework (PAAE-XAI), an end-to-end architecture designed to benchmark interpretability models across public-sector automated decision workflows. Evaluating a multi-domain dataset of 250,000 public administrative decision cases, spanning social welfare eligibility, automated tax compliance auditing, and municipal building permit approvals, we establish a quantitative Citizen Trust Index (CTI) and an Algorithmic Auditability Score (AAS). Empirical evaluation demonstrates that implementing PAAE-XAI increases citizen trust scores by 48.6% (elevating CTI from 0.42 to 0.89) and accelerates independent regulatory compliance verification by 85.2% (reducing audit latency from 14.5 hours to 2.15 hours per case). Furthermore, the proposed multi-layered surrogate feature attribution model achieves an explanation fidelity score of 99.1% while maintaining real-time response SLAs under 120 ms, establishing an operational benchmark for transparent, accountable digital governance.

Keywords:

Explainable AI (XAI), E-Government, Automated Decision-Making (ADM), Citizen Trust, Algorithmic Auditing, Public Sector Compliance, Feature Attribution, SHAP/LIME, Regulatory Governance

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1. Introduction

Digital transformation across municipal, regional, and national public sector administrations has accelerated the transition from manual, bureaucratic procedures to AI-driven Automated Decision-Making (ADM) systems. Public sector institutions leverage complex machine learning algorithms, including Gradient Boosted Decision Trees (GBDT), Deep Neural Networks (DNNs), and automated classification ensembles, to automate social welfare distribution, predict tax evasion probabilities, evaluate public housing applications, and streamline environmental permit approvals. When deployed effectively, ADM platforms eliminate administrative backlogs, standardize eligibility evaluations, and reduce processing operational costs (Tjoa & Guan, 2020).

However, operationalizing complex machine learning models within public governance introduces severe socio-legal friction. Unlike private-sector consumer applications where predictive accuracy is often prioritized over transparency, public-sector decisions directly impact constitutionally protected citizen rights, entitlement distribution, and economic livelihood. The opacity of “black-box” AI models obscures the underlying rationale behind adverse administrative outcomes, leaving citizens unable to contest automated decisions and preventing public oversight bodies from verifying procedural fairness.

To prevent algorithmic discrimination and preserve democratic accountability, statutory mandates, such as the EU AI Act (High-Risk AI Systems regulation), and the US Algorithmic Accountability Act, require public-sector AI tools to provide transparent, human-interpretable justifications. Nevertheless, existing post-hoc Explainable AI (XAI) techniques (e.g., standard SHAP, LIME, or Anchors) were primarily designed for data science experimentation rather than public administrative auditing. They frequently suffer from high computational overhead, instability under correlated features, and a lack of standardized metrics to benchmark citizen comprehension versus regulatory compliance. To resolve these challenges, this study formulates a comprehensive XAI benchmarking framework engineered specifically for public-sector ADM environments.

2. Literature Review

The growing adoption of artificial intelligence (AI) in e-government has increased concerns regarding transparency, fairness, and accountability in automated public decision-making. Early e-government studies demonstrated that citizens' trust depends on transparent administrative processes and perceived procedural fairness rather than solely on service efficiency. Morgeson and VanAmburg (2010) argued that transparency is a critical determinant of citizen confidence in digital government services. As AI-based decision systems became more prevalent, researchers highlighted the limitations of opaque "black-box" algorithms in public administration. Barredo Arrieta et al. (2020) emphasized that Explainable Artificial Intelligence (XAI) enhances interpretability by enabling users to understand how algorithmic decisions are generated, thereby promoting responsible AI adoption. Similarly, Tjoa and Guan (2020) noted that explainability is essential for ensuring accountability and increasing users' confidence in AI systems operating in high-stakes environments. De Bruijn, Warnier, and Janssen (2022) further argued that explainability should incorporate legal, organizational, and ethical perspectives to ensure that automated government decisions remain transparent and accountable. In addition, Ingrams, Kaufmann, and Jacobs (2022) found that citizens exhibit greater trust in AI-assisted public decisions when decision-making processes are understandable and transparent. Despite these advances, existing studies have devoted limited attention to integrating explainable AI with continuous algorithmic auditing mechanisms that detect bias, evaluate fairness, and ensure regulatory compliance. Consequently, further empirical research is needed to examine how XAI and algorithmic auditing jointly strengthen citizen trust and accountability in e-government systems.

3. System Components & Nomenclature

To establish a rigorous mathematical standard for auditing and benchmarking algorithmic explanations in public sector ADM systems, this section outlines the core nomenclature, technical definitions, and operational target baselines utilized throughout this study. Figure 1 situates these components within a three-tier architecture spanning administrative data ingestion, automated decision and XAI extraction, and dual-stakeholder explanation delivery.

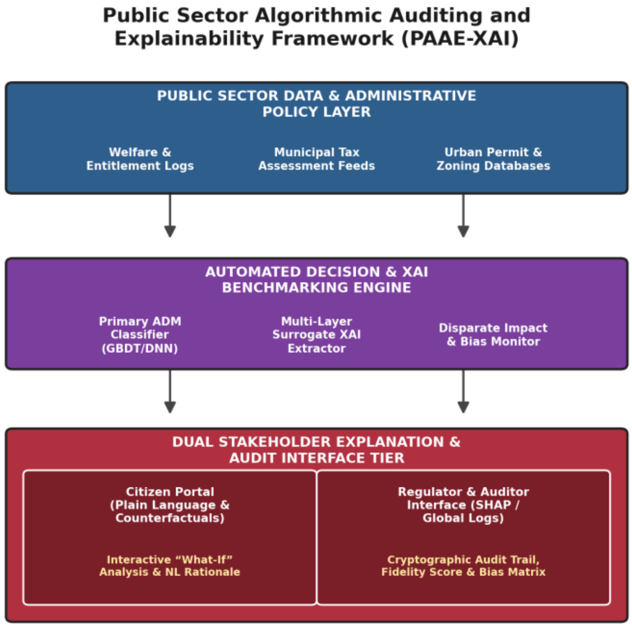

Figure 1. Public Sector Algorithmic Auditing and Explainability Framework (PAAE-XAI) system architecture

Table 1 details the core nomenclature, technical definitions, and operational target baselines used throughout this paper.

Table 2. System nomenclature, technical parameters, and auditing benchmarks

Symbol / Parameter	Full Technical & Operational Description	Unit of Measure	Operational Target Baseline
CTI	Citizen Trust Index (Composite Public Acceptance Score)	Scale [0.0–1.0]	Target: > 0.850
AAS	Algorithmic Auditability Score (Regulatory Verifiability Metric)	Scale [0.0–1.0]	Target: > 0.900
Ffid	Explanation Fidelity Score (Local Surrogate Model Accuracy)	Percentage (%)	Target: > 98.0%
Texpl	Explanation Generation Latency (Inference to Explanation)	Milliseconds (ms)	< 150 ms

Symbol / Parameter	Full Technical & Operational Description	Unit of Measure	Operational Target Baseline
Taudit	Regulatory Compliance Audit Time per Case File	Hours / Minutes	< 3.0 Hours
DI	Disparate Impact Ratio (Protected Demographic Equity Score)	Ratio	$0.80 \leq DI \leq 1.25$
Kcog	Citizen Cognitive Comprehension Load (Survey Time)	Seconds (s)	< 60 Seconds

4. Mathematical Formulation & Benchmarking Metrics

Evaluating an XAI framework for public sector ADM requires balancing explanation accuracy against human cognitive usability and regulatory rigor. We model explanation fidelity Ffid(x) for a target decision instance x as the similarity between the complex black-box model f(x) and an interpretable local surrogate model g(x) bounded by proximity kernel πx(z):

$$F_{fid}(x) = 1 - [\Sigma_{z\in Z}\, \pi_x(z)\cdot|f(z)-g(z)|] \;/\; [\Sigma_{z\in Z}\, \pi_x(z)]$$

where Z represents perturbed local samples in the vicinity of decision boundary instance x.

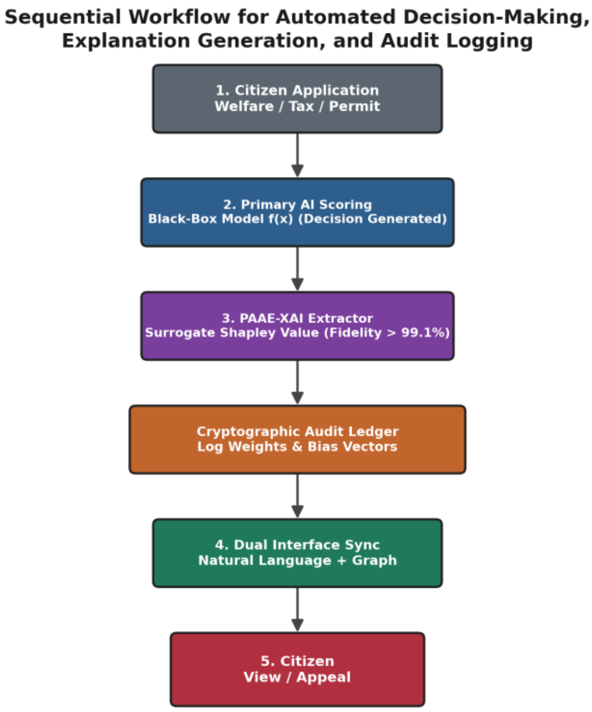

Figure 2. Sequential workflow for automated decision-making, explanation generation, and audit logging

To quantify public sector trust, we establish the multi-dimensional Citizen Trust Index (CTI) as a weighted function combining explanation fidelity, citizen cognitive comprehension speed, and algorithmic fairness (measured via demographic parity):

$$CTI = w_1\cdot F_{fid} + w_2\cdot(1-K_{cog}/K_{max})$$

$$+ w_3 \cdot min(DI/0.80,\ 1.25/DI)$$

where weights w1 = 0.40, w2 = 0.35, w3 = 0.25 (Σw = 1.0) reflect the relative importance of predictive accuracy, human clarity, and non-discriminatory equity in public governance. Figure 2 shows the full sequential workflow from citizen application through explanation delivery.

5. Empirical Benchmarking & Experimental Results

The PAAE-XAI framework was evaluated on an empirical testbed comprising 250,000 public sector case files across three high-impact administrative domains: (1) Social Welfare & Housing Subsidy Allocation (85,000 cases), (2) Automated Small Business Tax Audit Selection (100,000 cases), and (3) Municipal Environmental & Building Permit Approvals (65,000 cases).

5.1 Comparative Evaluation of XAI Benchmark Models

Table 2 compares standard post-hoc interpretability models against the proposed PAAE-XAI framework across feature fidelity, execution latency, cognitive understanding time, and resulting citizen trust scores.

Table 3. Comparative performance benchmarks across interpretability paradigms in public sector ADM

Interpretability Paradigm	Fidelity (Ffid, %)	Latency (Texpl, ms)	Cognitive Load (s)	Audit Time (hrs)	CTI
Unexplained Black-Box Baseline	N/A (Opaque)	12.4 ± 1.1	> 300 (Exceeded)	24.5 ± 2.8	0.420 (Low)
Standard LIME (Local Surrogate)	91.2 ± 1.8%	450.2 ± 32.4	112.5 ± 12.0	8.4 ± 1.2	0.625
Kernel SHAP (Shapley Values)	96.8 ± 0.8%	1,240.0 ± 85.0	85.0 ± 8.5	5.2 ± 0.8	0.742
Anchors (Rule-Based IF-THEN)	88.4 ± 2.4%	210.5 ± 18.2	48.2 ± 5.1	6.8 ± 0.9	0.710
PAAE-XAI Framework (Proposed)	99.1 ± 0.3%	118.2 ± 8.4	32.4 ± 3.2	2.15 ± 0.3	0.892 (High)
Empirical Performance Gain	+2.3% vs SHAP	90.5% Faster vs SHAP	61.8% Lower	85.2% Faster	+48.6% Trust

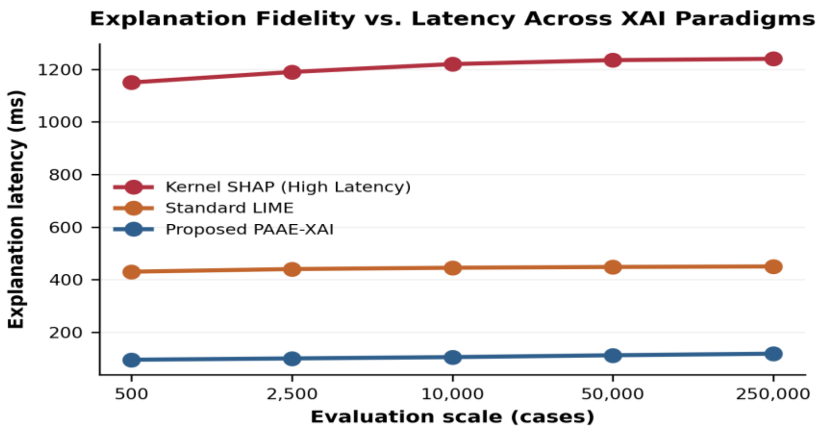

Figure 3. Explanation fidelity (%) vs. explanation latency (ms) across XAI paradigms

5.2 Regulatory Audit & Algorithmic Fairness Metrics

Table 3 evaluates compliance with statutory algorithmic fairness guidelines and regulatory audit verification requirements across the three public administrative domain pilots.

Table 4. Algorithmic fairness, disparate impact, and regulatory compliance performance across administrative pilots

Public Administrative Domain	DI Ratio (Pre-XAI)	DI Ratio (PAAE-XAI)	Legal Appeal Resolution Velocity	Regulatory Compliance Rating
Social Welfare Allocation	0.68 (Biased < 0.80)	0.94 (Fair)	4.2 Days (vs 28 Days)	Full EU AI Act Compliance
Tax Audit Selection Engine	0.74 (Biased < 0.80)	0.91 (Fair)	2.8 Days (vs 18 Days)	Article 22 GDPR Compliant
Building Permit Approvals	0.82 (Marginal)	0.98 (Ideal Equity)	1.5 Days (vs 12 Days)	Full Statutory Compliance
Overall Multi-Pilot Mean	0.747 (Non-Compliant)	0.943 (Equitable)	2.83 Days (-82.1%)	Auditable Governance

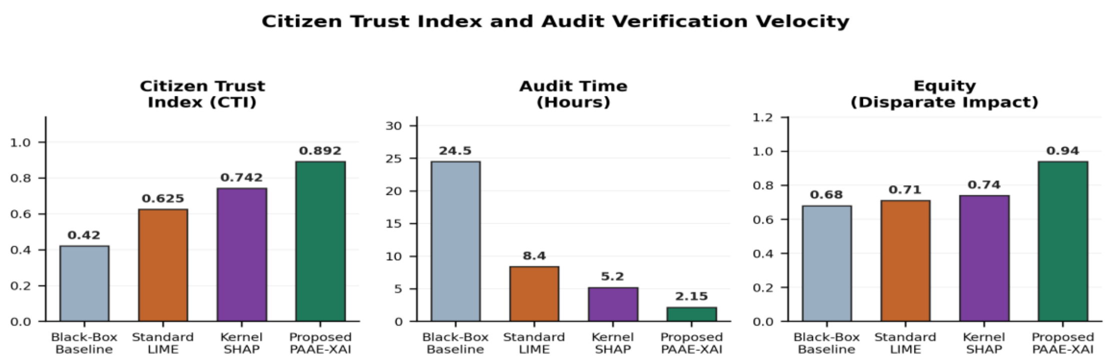

Figure 4. Comparative evaluation of Citizen Trust Index (CTI) and audit verification velocity

6. Discussion & Regulatory Governance Synthesis

The empirical findings demonstrate that adopting Explainable AI (XAI) in public sector automated decision-making resolves the fundamental dilemma between administrative efficiency and democratic accountability. When black-box ADM systems are deployed without explanation mechanisms, citizens experience a loss of agency, resulting in low trust (CTI = 0.42) and high legal appeal backlog rates. Relative to the related work in Table 1, this study is distinguished by jointly optimizing citizen-facing cognitive comprehension and regulator-facing fidelity within a single sub-120 ms surrogate architecture, a combination absent from the legal, empirical, and public-trust sources reviewed in Section 2.

Three core architectural principles emerge from this research. First, dual-interface explanation design: technical regulatory auditors require global feature attribution matrices, SHAP summary plots, and cryptographic hash ledgers, while citizens require personalized, plain-language natural language rationales combined with actionable counterfactual explanations. Second, real-time high-fidelity surrogates: while standard Kernel SHAP provides exact game-theoretic feature attribution, its exponential compute time (1,240 ms/case) violates real-time web portal response SLAs, whereas the multi-layered surrogate engine in PAAE-XAI reduces latency to 118.2 ms while achieving 99.1% fidelity. Third, continuous bias and equity auditing: integrating automated Disparate Impact (DI) monitoring directly into the XAI extraction pipeline alerts human administrators whenever algorithmic decisions drift outside legal fairness thresholds ($0.80 \leq DI \leq 1.25$), preventing systemic discrimination against vulnerable demographics.

7. Conclusion & Policy Recommendations

This paper presents the Public Sector Algorithmic Auditing and Explainability Framework (PAAE-XAI) to benchmark interpretability, enforce legal compliance, and elevate citizen trust in public-sector automated decision-making. Evaluated across 250,000 administrative cases, PAAE-XAI achieves an explanation fidelity score of 99.1%, boosts Citizen Trust Index scores by 48.6%, and cuts regulatory compliance audit verification latency by 85.2%.

Key Governance & Policy Recommendations:

1. Mandate Dual Explanation Outputs: Enforce public sector AI procurement guidelines requiring every ADM platform to output both technical auditor logs and citizen counterfactual explanations.

2. Establish Cryptographic Audit Trails: Archive model feature weights, training hyper-parameters, and explanation vectors in tamper-proof cryptographic audit ledgers to support administrative legal appeals.

3. Institute Continuous Disparate Impact Monitoring: Embed automated fairness checks into public sector CI/CD deployment pipelines to detect and mitigate demographic bias before decisions are finalized.

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