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(Review Article)

From black box to glass box: A survey on explainable AI for accountable e-governance

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Abstract

While Artificial Intelligence (AI) is rapidly transforming e-governance by enhancing efficiency and enabling data-driven policymaking, its prevalent "black box" nature poses significant risks to transparency, fairness, and public trust. Opaque algorithmic decisions in the public sector can undermine accountability and challenge principles of due process. This paper provides a systematic survey of the literature on Explainable AI (XAI) applications within the e-governance sector. We aim to map the current landscape, categorize existing work, and identify key trends and challenges to guide future research. We reviewed 42 papers sourced from key academic databases, including IEEE Xplore, ACM Digital Library, and Scopus, published between 2018 and 2024. Our survey organizes applications into a novel taxonomy based on the governance domain and the XAI techniques used. We identify key trends, such as the prevalence of post-hoc explanation methods like SHAP and LIME over intrinsically interpretable models, and highlight significant research gaps, particularly in the co-design of explanations with non-expert stakeholders. This survey serves as a foundational resource for researchers, policymakers, and practitioners aiming to develop trustworthy AI systems for the public sector. By structuring the field and outlining critical challenges, we provide a roadmap for advancing the development of accountable and transparent AI in governance.

Keywords: Explainable AI; XAI; e-Governance; Algorithmic Accountability; Interpretable Machine Learning; Public Sector AI.

1. Introduction

The convergence of big data, increased computational power, and advanced algorithms has catalyzed a paradigm shift in public administration. Governments worldwide are increasingly adopting Artificial Intelligence (AI) and machine learning to modernize service delivery and enhance operational efficiency [1]. This transformation, often termed "e-governance," moves beyond simple digitization to the active use of intelligent systems for complex decision-making. Examples are widespread and growing in sophistication, from optimizing public transport routes and managing energy grids in smart cities [2] to deploying predictive policing models to allocate law enforcement resources. In public finance, AI is used to identify complex patterns of tax and welfare fraud [3], while in citizen services, AI-powered chatbots provide 24/7 support, answering queries and guiding users through bureaucratic processes. The overarching promise of these technologies is a more agile, responsive, and data-informed government capable of addressing societal challenges with greater precision.

Despite this transformative potential, the adoption of advanced AI models—particularly deep neural networks and ensemble methods like gradient boosting—introduces a critical challenge: opacity [4]. These models often operate as "black boxes," where the intricate, non-linear relationships learned from data are too complex for human comprehension. This lack of transparency is fundamentally at odds with the core tenets of democratic governance. In

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the public sector, decisions that directly affect citizens' rights and livelihoods—such as determining eligibility for social benefits, assessing criminal recidivism risk [5], or prioritizing patients for medical care—must be fair, auditable, and contestable [6]. An opaque decision-making process erodes public trust, creates risks of undiscovered algorithmic bias against vulnerable populations [7], and makes it impossible to provide meaningful recourse for citizens who wish to appeal an adverse outcome. This accountability gap is a significant barrier to the ethical and widespread deployment of AI in government.

Explainable AI (XAI) has emerged as a vibrant and essential field of research dedicated to dismantling this black box problem [8, 9]. XAI encompasses a suite of methods and models designed to make AI systems more interpretable and transparent. The central goal is to provide human-understandable justifications for AI-driven decisions, answering fundamental questions such as: "Why was this specific outcome reached?", "Which factors were most influential in this decision?", and "How would the outcome change if certain inputs were different?". By exposing the internal logic of AI systems, XAI aims to build stakeholder trust, facilitate model debugging and validation, ensure fairness and equity, and support compliance with legal and regulatory frameworks [10].

While the need for XAI in e-governance is widely acknowledged in principle, the landscape of practical applications remains fragmented and lacks a cohesive overview. As governments accelerate their investment in AI, a systematic understanding of the state-of-the-art is urgently needed. This survey aims to fill that gap by providing a structured and comprehensive review of existing XAI applications, a novel taxonomy to classify them, and a critical analysis of trends and challenges to guide future work.

2. Survey Methodology

Our systematic review was designed to identify, evaluate, and synthesize research on the application of XAI in e-governance with methodological rigor. This survey was guided by three research questions: (RQ1) What are the primary application domains of XAI within e-governance? (RQ2) Which XAI techniques are most commonly used in these applications, and why? (RQ3) What are the main challenges and limitations identified in the literature regarding the practical deployment of XAI in the public sector?

We conducted a systematic search of four major academic databases: IEEE Xplore, ACM Digital Library, Scopus, and Google Scholar. The search was performed using a structured query: ("Explainable AI" OR "XAI" OR "Interpretable ML") AND ("e-governance" OR "public sector" OR "digital government" OR "public administration"). To ensure the quality and relevance of the surveyed literature, we included only peer-reviewed journal and conference papers published in English between January 2018 and May 2024 that described a concrete application of XAI in an e-governance domain. We excluded papers that only mention XAI in passing, purely theoretical works, non-peer-reviewed sources, and papers not in English. Our initial search yielded 150 papers. After removing duplicates and screening titles and abstracts, 75 papers were selected for full-text review. Applying our criteria resulted in a final corpus of 42 papers for in-depth analysis.

3. A Taxonomy of XAI in e-Governance

We propose a two-dimensional taxonomy to classify the reviewed literature: by the e-Governance Application Domain and by the XAI Technique Employed.

3.1. e-Governance Application Domain

Our analysis revealed five primary domains where XAI is being actively researched:

- **Social Welfare & Public Services:** This was the most prominent category, reflecting the high-stakes nature of decisions in this area. Applications focus on bringing transparency to automated systems that determine eligibility for social benefits, unemployment assistance, and public housing [11, 12]. XAI is used to provide caseworkers with justifications for an AI's recommendation and to generate simplified explanations for citizens.
- **Judicial and Legal Systems:** XAI is explored to address controversy surrounding algorithmic tools in the justice system, particularly in explaining outputs from recidivism risk assessment tools to judges and parole boards [5]. The goal is to ensure these tools are used as transparent aids and to audit them for bias [7].
- **Urban Planning & Smart Cities:** Here, XAI is used to help planners and residents understand the outputs of complex models governing urban life, such as explaining traffic flow predictions to manage congestion [2] and justifying algorithmic recommendations for zoning.

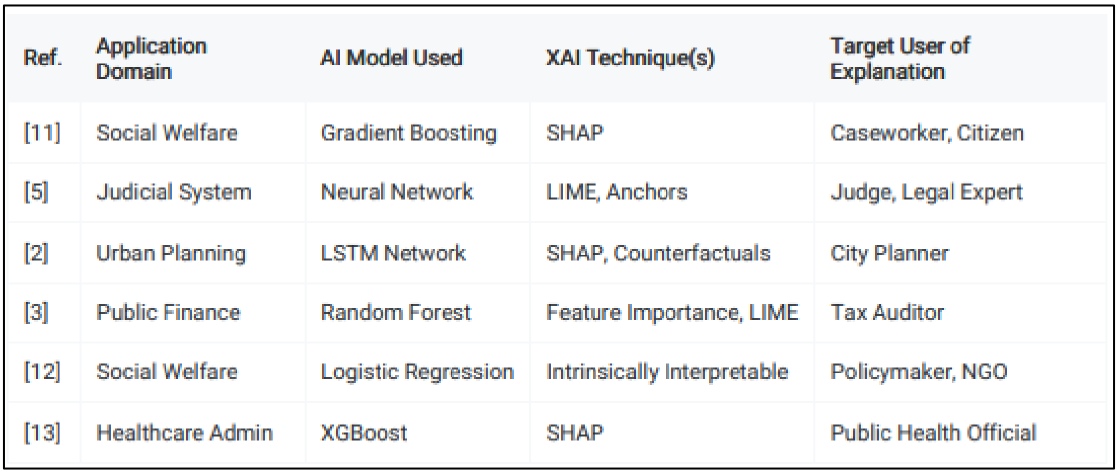
- **Public Finance & Taxation:** Governments are deploying XAI to enhance fairness in financial administration. The primary application is in developing explainable models for tax fraud detection [3], allowing auditors to conduct more targeted and justified investigations.
- **Healthcare Administration:** This domain focuses on the transparent management of public health resources. Interest has grown in using explainable models to predict disease outbreaks and guide the equitable allocation of critical medical supplies during emergencies [13].

3.2. XAI Techniques Employed

The surveyed papers employed two primary categories of XAI techniques:

- **Model-Agnostic Post-hoc Methods:** This was the most common approach (over 75% of papers). These methods can be applied to any machine learning model after it has been trained. The most prevalent were LIME (Local Interpretable Model-agnostic Explanations), which explains an individual prediction by creating a simpler local "surrogate" model [9], and SHAP (SHapley Additive exPlanations), which uses game theory to calculate the contribution of each feature to the prediction [14].
- **Intrinsically Interpretable Models:** These models are transparent by their very structure. While sometimes sacrificing predictive performance, their inherent transparency makes them valuable in high-stakes contexts. Examples include Linear Models, where feature importance is represented by coefficients, and Decision Trees, which provide a clear, flowchart-like representation of rules. Some research advocates strongly for their use in areas like justice [15].

Table 1 A synthesis of representative papers from our review, mapping them across our taxonomy to illustrate how these domains and techniques intersect in practice.



Ref.	Application Domain	AI Model Used	XAI Technique(s)	Target User of Explanation
[11]	Social Welfare	Gradient Boosting	SHAP	Caseworker, Citizen
[5]	Judicial System	Neural Network	LIME, Anchors	Judge, Legal Expert
[2]	Urban Planning	LSTM Network	SHAP, Counterfactuals	City Planner
[3]	Public Finance	Random Forest	Feature Importance, LIME	Tax Auditor
[12]	Social Welfare	Logistic Regression	Intrinsically Interpretable	Policymaker, NGO
[13]	Healthcare Admin	XGBoost	SHAP	Public Health Official

4. Discussion

Our systematic analysis reveals several key trends and persistent challenges. A dominant trend is the use of post-hoc explanation methods for existing high-performance black-box models, reflecting a pragmatic "accuracy-first" approach. The domain of social welfare is the most researched area, likely due to the direct impact of its decisions on citizens' lives. However, a significant gap exists in the human-centered design and evaluation of explanations. Most studies focus on technical implementation, with a lack of rigorous user studies assessing if explanations are understandable and useful for non-expert audiences.

Several open challenges must be addressed. First is the Explanation-Fidelity Trade-off, where simple, intuitive explanations may not accurately reflect the model's complex reasoning, potentially providing a misleading justification [16]. Second is the need for Stakeholder-Specific Explanations; a one-size-fits-all approach is ineffective, as the needs of a data scientist, a manager, and a citizen differ dramatically. Third is the challenge of Evaluating Explanation Quality. There is no standardized metric for a "good" explanation, making it difficult to compare XAI methods rigorously. Finally, Regulatory and Legal Integration remains a hurdle, as legal frameworks like the GDPR allude to a "right to explanation," but the requirements are ambiguous and often misaligned with technical realities [6].

Based on these gaps, future research should focus on three areas. First, the development of Interactive and Contestable Explanation Systems that allow users to ask follow-up questions and explore "what-if" scenarios. Second, conducting In-depth, Real-world User Studies with caseworkers, judges, and citizens to measure the impact of XAI on decision quality, fairness, and trust. Third, the Integration of XAI with Fairness and Ethics Auditing, using explanations as an active tool to identify and mitigate algorithmic bias.

5. Conclusion

This paper presented a systematic survey of Explainable AI in the e-governance sector, addressing the critical problem of opaque AI in public administration by structuring the current research landscape. Our primary contribution is a two-dimensional taxonomy that classifies applications by governance domain and XAI technique. Our findings reveal a strong reliance on post-hoc methods and highlight persistent challenges related to explanation fidelity, stakeholder-specific needs, and meaningful evaluation. While significant technical progress has been made, the journey from black-box systems to genuinely transparent and accountable "glass-box" governance is far from complete. The future of trustworthy AI in the public sector will depend on a multidisciplinary effort to create explanations that are not only technically sound but are also human-centered, legally robust, and democratically accountable.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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