СЕКЦІЯ 7. ПУБЛІЧНЕ УПРАВЛІННЯ ТА АДМІНІСТРУВАННЯ
SECTION 7. PUBLIC MANAGEMENT AND ADMINISTRATION

УДК 005.8:004.8(477)
JEL Classification: H83, O33
DOI: https://doi.org/10.64076/eecsr250708.21

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MODERN METHODOLOGIES FOR EVALUATING ARTIFICIAL INTELLIGENCE EFFECTIVENESS IN PUBLIC ADMINISTRATION: A FOCUS ON TRANSPARENCY AND MULTICRITERION DECISION ANALYSIS

The implementation of Artificial Intelligence (AI) in public administration is increasingly recognized as a means of enhancing service delivery efficiency, transparency, and responsiveness. Nevertheless, concerns surrounding explainability, accountability, and societal impact necessitate the adoption of comprehensive evaluation methodologies. This study aims to systematize and critically assess the applicability of two promising approaches: Explainability Evaluation (XAI) and Multi-Criteria Decision Analysis (MCDA), focusing on their adaptability to crisis-prone and resource-constrained environments such as Ukraine.

The objective of this study is to develop a methodological framework that combines explainability and multicriteria evaluation, thereby enabling public authorities to assess not only the performance but also the legitimacy and societal acceptability of AI-driven services. Recent literature emphasizes the growing significance of explainability in AI governance [2, 3, 4], particularly in high-stakes sectors such as healthcare and welfare. Concurrently, public governance increasingly integrates MCDA tools [1, 6] to address multifaceted decision-making needs. While XAI enhances transparency and trust, MCDA supports rational prioritization in complex settings. Both methodologies are endorsed by international governance bodies such as the OECD and G7 [5, 7].

Explainability Evaluation (XAI) focuses on the ability of AI systems to generate intelligible rationales for decisions. This is essential for democratic legitimacy, mainly when decisions affect citizens’ rights. In practice, XAI involves using interpretable models (e.g., decision trees, SHAP, LIME) and user-centered design of explanations. Its application is evident in initiatives such as Canada’s AI audits and Estonia’s KrattAI framework.

MCDA provides a structured comparison of AI systems based on performance, equity, cost, and ethical criteria. It promotes stakeholder engagement and trade-off transparency, which are critical in settings with limited resources and competing objectives.

Table 1

Comparative characteristics of XAI and MCDA in public sector AI evaluation

Criterion	Explainability Evaluation (XAI)	Multi-Criteria Decision Analysis (MCDA)
Transparency	High – user-friendly explanations	Medium – formalized criteria may be complex
Accountability	Strong – supports traceable decisions	Medium – focuses on comparative choices
Adaptability	High – usable in sensitive sectors	High – applicable in diverse contexts
Quantifiability	Low – mostly qualitative reasoning	High – numeric weighting of alternatives
Ethical Alignment	Strong – based on AI ethics standards	Variable – depends on criteria design
Stakeholder Inclusion	Medium – centered on end-user	High – integrates multi-stakeholder views

Source: Compiled by the author based on [1–7].

Both approaches are well-suited to the current challenges facing public governance in Ukraine. XAI upholds human rights and procedural fairness, while MCDA facilitates rational resource allocation under conditions of uncertainty. Their integrated use supports the evaluation of existing systems and guides the design of future AI initiatives with built-in accountability mechanisms.

Conclusions. The combined application of Explainability Evaluation and Multi-Criteria Decision Analysis offers a robust methodological toolkit for public sector AI governance. Applied together, these methodologies ensure that AI systems are both technically efficient and socially legitimate. Their integration into Ukraine's digital governance framework can enhance transparency, reduce algorithmic risks, and build public trust.

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