

Large Language Models in Open Government Data Analysis: A Systematic Mapping Study

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Abstract: **Background:** The convergence of Large Language Models (LLMs) and open government data presents transformative potential for public administration, yet there exists a significant gap in understanding adoption patterns in this emerging domain. **Aim:** This study analyzes adoption patterns of Large Language Models in open government data analysis, characterizing researchers' perceptions about benefits, limitations, and methodological implications. **Method:** We conducted a systematic mapping study following Petersen et al. (2008) guidelines, searching six academic databases. After screening, 24 primary studies were analyzed covering contribution types, validation methods, government domains, and LLM models. **Results:** Analysis revealed GPT model family predominance, with health as priority domain (4 studies), followed by security and justice (3 studies each). Conversational interfaces and information extraction were dominant functions (9 studies each). **Conclusions:** The field demonstrates evolution toward hybrid solutions integrating LLMs with structured knowledge resources. Consistent challenges across technologies—ethical issues, privacy concerns, and data quality—indicate the need for unified frameworks. Future research should focus on developing practical solutions to achieve technical maturity comparable to established software engineering fields.

1 INTRODUCTION

The digital era has transformed government-citizen relationships through Open Government Data (OGD) - information produced by government entities for unrestricted access (Wang et al., 2024). Simultaneously, Large Language Models (LLMs) emerge as promising AI technology with remarkable natural language processing capabilities (Cabral et al., 2024).

The convergence between LLMs and OGD

presents unexplored transformative potential. While governments digitize public information, much remains in unstructured formats, which limits its practical use (Siciliani et al., 2024). LLMs can transform this data into actionable information, enhancing transparency and innovation.

However, a significant gap exists in understanding how LLMs are effectively applied in OGD analysis. The urgency is justified by the rapid advancement of LLMs and their potential for a disruptive impact on public sector transformation (Androutsopoulou et al., 2024). Models like GPT-4, Claude and Gemini present unprecedented capabilities, while ethical and governance issues emerge as fundamental considerations (Mureddu et al., 2025; Dua et al., 2025).

This research addresses this gap through systematic analysis of LLM adoption patterns in OGD contexts, characterizing researchers' perceptions about benefits, limitations, and methodological implications to inform strategic technology investment decisions and data

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policy implementation in the public sector.

The article is organized as follows: Section 2 presents the theoretical background; Section 3 details the methodology; Section 4 presents results; Section 5 discusses implications; and Section 6 concludes with future directions.

2 BACKGROUND

This section provides a theoretical foundation structured in three parts: Large Language Models fundamentals, open government data concepts, and their intersection in public administration applications.

2.1 Large Language Models: Fundamentals and Evolution

Large Language Models represent significant advances in natural language processing, demonstrating capabilities in text analysis, content generation, and information extraction (Bronzini et al., 2024). These technologies have particular relevance for governmental applications where automated processing of public information becomes critical (Alexopoulos et al., 2024). Contemporary LLM implementations have opened possibilities for enhancing public sector efficiency through intelligent data processing and natural language interfaces (Siciliani et al., 2024).

LLM evolution has been marked by advances in parameter scale, training data quality, and model architectures (Donner et al., 2024), enabling sophisticated applications while questions about reliability and transparency remain crucial (Germani et al., 2024).

2.2 Open Government Data: Concepts and Challenges

Open Government Data constitutes a fundamental pillar of transparency and innovation in the public sector (Nikiforova et al., 2024), presenting challenges in quality, interoperability, and usability (Alexopoulos et al., 2024). Public data ecosystem evolution has been driven by standardization and demand for efficient processing tools (Mureddu et al., 2025), with recent initiatives focusing on integrating advanced technologies to improve data accessibility and utility (Siciliani et al., 2024).

2.3 LLMs in Public Administration

LLM application in governmental contexts has expanded rapidly, covering public policy analysis, citizen

services, and document processing (Androutsopoulou et al., 2024), demonstrating transformative potential in modernizing public administration (Sandoval-Almazan et al., 2024). Practical implementations encompass automated document classification systems (Kliimask and Nikiforova, 2024), conversational interfaces for public services (Cortés-Cediel et al., 2023), and analysis tools for government reports (Pesqueira et al., 2024), though ethical and legal considerations remain central to adoption debates (Dua et al., 2025). Integration with government data shows particular potential in public health trend analysis (Tornimbene et al., 2025), regulatory document processing (Rizun et al., 2025), and sustainable development goals monitoring (Benjira et al., 2025).

3 RESEARCH METHOD

This study adopts the Systematic Mapping Study (SMS) approach (Petersen et al., 2008) to organize and analyze scientific production about LLM applications in government open data, allowing identification of trends, gaps, and categorization of contributions.

The methodological structure follows the **GQM (Goal-Question-Metric)** model with the objective: *Analyze the adoption of LLMs to characterize their application from researchers' perspectives in the context of government open data analysis.*

The mapping process followed five main steps (Petersen et al., 2008): (1) research questions definition, (2) search conduction, (3) screening and selection, (4) classification scheme construction, and (5) data extraction and mapping, as illustrated in Figure 1.

3.1 Research Questions

Seven exploratory research questions were formulated (Petersen et al., 2008):

- **RQ1 - What types of research contributions were produced?** This question investigates the nature of contributions according to established taxonomies (Shaw, 2003), examining whether studies focused on theoretical frameworks, empirical models, practical solutions, or procedural methodologies.
- **RQ2 - What validation approaches were employed in the articles?** This question analyzes the methodological strategies used to validate research findings, including evaluation-based assessments, example-driven demonstrations, experiential evidence, persuasive arguments, and analytical frameworks.

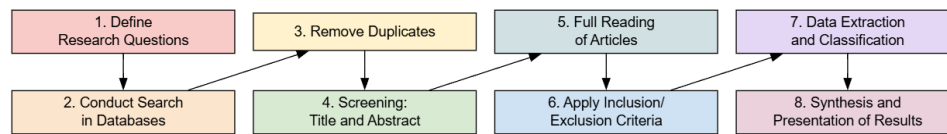


Figure 1: Mapping process, adapted from (Petersen et al., 2008).

- **RQ3 - Which governmental domains were investigated in the research?** This question examines the specific public sector areas and governmental functions where Large Language Model applications were studied, identifying the scope and focus of implementation contexts.
- **RQ4 - Which Large Language Model architectures were utilized?** This question identifies the specific LLM technologies, frameworks, and architectural approaches employed in the studies, examining both proprietary and open-source solutions.
- **RQ5 - What functional roles did LLMs serve in the research?** This question investigates the primary purposes and applications of LLMs within governmental contexts, examining their roles in data processing, analysis, generation, and decision support systems.
- **RQ6 - Which technical tools and methodologies were employed?** This question analyzes the complementary technologies, platforms, and methodological frameworks used alongside LLMs to implement solutions in open government data contexts.
- **RQ7 - What types of public datasets were utilized?** This question examines the characteristics, formats, and domains of governmental open data employed in the studies, investigating data sources and their structural properties.

3.2 Search Strategy

The search strategy used the **PIC** model (Kitchenham et al., 2007): **P** (Population): Public Data; **I** (Intervention): LLMs; **C** (Context): Government. The search string was:

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("Public Data" OR "Open data" OR
"Open information" OR "Transparent
data" OR "Transparent information")
AND ("LLM" OR "Generative AI") AND
("Government" OR "Administration"
OR "Governance" OR "Public
Administration" OR "Public sector"
OR "State")
  
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Searches were conducted in six databases: ACM Digital Library (559), IEEE Xplore (8), Web of

Science (8), ScienceDirect (317), Scopus (17), and Springer Link (459). After removing duplicates (n=34), 1,334 unique articles were screened.

The search of the databases occurred between March and April 2025.

3.3 Selection Process

Three sequential screening stages were conducted: **1st Reading** (title, abstract, keywords) resulted in 86 studies; **2nd Reading** (introduction, objectives, results, conclusions) yielded 43 articles; **3rd Reading** (complete analysis) included 24 final studies. Table 1 presents inclusion/exclusion criteria, and Table 2 shows selection evolution.

Table 1: Inclusion and Exclusion Criteria.

Inclusion Criteria	Exclusion Criteria
Articles published between 2017 and 2025.	Duplicate articles identified across databases.
Peer-reviewed studies with full text available.	Works not written in English.
Studies addressing the application of LLMs to open government data.	Partial publications such as extended abstracts, posters, or abstracts without complete articles.
Studies that answer, even partially, one of the defined research questions.	Studies dealing exclusively with private data or non-governmental use of LLMs.
	Secondary and tertiary studies (literature reviews).

Table 2: Evolution of Study Selection.

Stage	Excluded Articles	Retained Articles
1st Reading (exploratory)	1,282	86
2nd Reading (cross-sectional)	43	43
3rd Reading (analytical)	19	24
Initial Total	1,344	24 final articles

Cross-validation between researchers was applied with complete traceability via **Parsifal** tool, ensuring reliability and replicability.

3.4 Data Extraction and Mapping

Categorization used keywording technique (Petersen et al., 2008) with three facets: Type of Contribution (Shaw, 2003) (Table 3), Type of Validation (Table 4), and Application Domain (Table 5). Frequency analysis generated visualizations of contribution types, temporal distribution, technologies, and government areas.

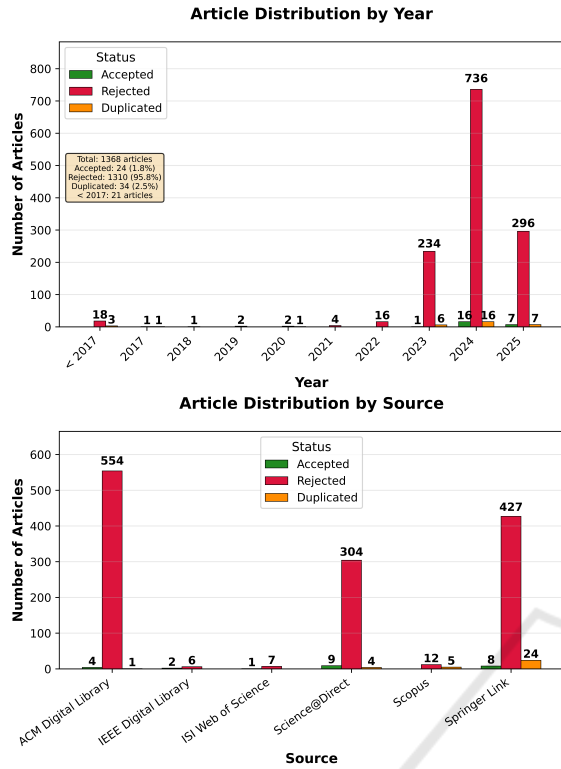


Figure 2: Article Distribution by Year, Source and Status.

This study followed validity recommendations (Petersen et al., 2008) through cross-validation, explicit criteria, complete traceability via Parsifal, ensuring transparency and replicability. Data and protocols are available at: https://github.com/AlbertoBastosMe/mapping_llm_ogd.

4 RESULTS

This section presents systematic mapping results across five dimensions: study characteristics, methodological approaches, application domains, LLM models, and technological ecosystem.

4.1 Study Selection and Characteristics

The systematic mapping identified 24 primary studies meeting the inclusion criteria. Temporal distribution shows increasing research interest (Figure 2), with significant growth from 2023 onwards, coinciding with ChatGPT's widespread adoption.

4.2 Methodological Approaches

Shaw's taxonomy (Shaw, 2003) reveals qualitative/descriptive models predominance (50.00%, n=12), as

shown in Table 3. Empirical models and procedures/techniques present equivalent representation (16.67% each, n=4). Specific solutions constitute 8.33% (n=2), while tools/notations and reports show the lowest representation (4.17% each, n=1).

Table 3: Distribution of Research Result Types (RQ1).

Result Type	Freq.	%	Articles
Qualitative or descriptive model	12	50.00%	P4; P5; P8; P9; P10; P15; P18; P19; P20; P22; P23; P24
Empirical model	4	16.67%	P2; P3; P6; P12
Procedure or technique	4	16.67%	P14; P16; P17; P21
Specific solution/prototype	2	8.33%	P7; P11
Tool or notation	1	4.17%	P1
Report	1	4.17%	P13

Validation approaches (Table 4) show evaluation as most prevalent (45.8%, n=11), followed by example-based validation (25.0%, n=6). Experience and persuasion present equivalent representation (12.5% each, n=3), while analysis represents the least frequent type (4.2%, n=1).

Table 4: Validation Types by Article (RQ2).

Response Type	Freq.	%	Articles
Evaluation	11	45.8%	P6; P16; P14; P15; P1; P12; P17; P11; P2; P7; P20
Example	6	25.0%	P5; P21; P18; P24; P8; P22
Experience	3	12.5%	P10; P3; P13
Persuasion	3	12.5%	P19; P4; P9
Analysis	1	4.2%	P23

4.3 Application Domains

Analysis reveals concentrated adoption across key governmental domains (Table 5). Open data management dominates (n=5), followed by Health (n=4), and Security, Justice, e-Government (n=3 each). This distribution reflects growing maturity in transparency initiatives and diversification across critical public administration sectors.

Table 5: Distribution of primary studies by government domain (RQ3).

Government Domain	Frequency	Studies
Health	4	P3, P4, P13, P20
Security	3	P18, P19, P21
Justice	3	P9, P17, P22
Budget	2	P5, P14
Procurement	1	P7
Open data management	5	P6, P11, P16, P23, P24
e-Government	3	P2, P10, P15
AI public policies	1	P12
Citizen participation	1	P8
Disinformation	1	P1
Total	24	

Data types analysis (Table 6) shows Statistical Data and Metrics, and Transparency and Accountability

Data as most prevalent (n=11 each), evidencing orientation toward government transparency. High frequency of Norms and Legislation (n=10) indicates an important trend in regulatory text processing.

Table 6: Types of Data Used in Studies (RQ7).

Data Types	Frequency	Articles
Statistical Data and Metrics	11	P1; P2; P5; P6; P13; P14; P16; P19; P22; P23; P24
Transparency and Accountability Data	11	P5; P6; P7; P8; P9; P10; P11; P14; P15; P16; P24
Norms and Legislation	10	P3; P4; P9; P14; P17; P18; P19; P21; P22; P24
Textual Data and Documents	4	P1; P12; P8; P15
AI and Machine Learning Data	5	P1; P4; P17; P18; P22
Research and Methodology Data	2	P3; P20
Health and Surveillance Data	3	P5; P13; P21
Social Media and Participation Data	3	P8; P15; P13
Metadata and Knowledge Graphs	4	P6; P11; P14; P17
Structured and Semantic Data	3	P7; P12; P16
Geospatial and IoT Data	2	P10; P23
Personal Data and Privacy	3	P9; P13; P21
Multimodal and Emerging Data	3	P18; P10; P13

4.4 LLM Models and Technological Ecosystem

Clear GPT family predominance emerges (Table 7), establishing it as the primary governmental choice. Alternative models like Claude, Llama, and Gemini appear concentrated in comparative studies (Hannah et al., 2025).

Table 7: Large Language Models identified in studies (RQ4).

LLM	Frequency	Studies
ChatGPT	8	P2; P8; P12; P1; P24; P19; P4; P13
BERT	6	P1; P16; P14
GPT-4	4	P19; P11; P4; P14
GPT-3.5	2	P19; P11
Gpt	2	P16; P14
GPT-3	1	P4
Ibm Watson Health	1	P5
Rebel	1	P7
Large Language Models	1	P10
Text-Davinci-003	1	P11
Claude	1	P11
T5	1	P11
PaLM	1	P11
Wizardlm	1	P14
Ada	1	P16
Gpt4 Vision	1	P18
Gemini	1	P18
Phi3	1	P18
Sora	1	P19
Bard	1	P24

Functional analysis (Table 8) reveals diverse applications with information extraction and conversational interfaces predominating (9 studies each), indicating a focus on data accessibility and citizen interaction.

Technological ecosystem analysis (Table 9) shows ChatGPT predominance (3 occurrences), followed by Hugging Face, BERT, and GPT-4. Five custom tools were identified, including TAGIFY (Kliimask and Nikiforova, 2024), OIE4PA (Siciliani et al., 2024), and SATIKAS (Sandoval-Almazan et al., 2024), demon-

Table 8: Large Language Model Functions (RQ5).

LLM Function	Frequency	Studies
Information extraction	9	P5; P11; P1; P14; P19; P7; P13; P3; P16
Conversational interface	9	P5; P1; P12; P17; P2; P18; P24; P8; P20
Content generation	7	P22; P19; P21; P17; P2; P18; P4
Classification	5	P11; P1; P19; P7; P8
Data analysis	4	P5; P3; P17; P6
Summarization	3	P12; P8; P13
NLP	3	P22; P10; P15
Fact-Checking	1	P4
Sentiment analysis	1	P8
NLP in medical records	1	P13
Semantic understanding	1	P14
Structured knowledge generation	1	P14
Information search and retrieval	1	P15
Schema Mapping	1	P16
Multimodal processing	1	P18
Automatic text analysis	1	P20
Analysis support	1	P24
Community facilitator	1	P24

Table 9: Tools and frameworks used in studies with LLMs (RQ6).

Tool/Framework	Frequency	Studies
ChatGPT	3	P4; P19; P8
Hugging Face	3	P18; P1; P14
BERT	3	P16; P1; P14
GPT-4	3	P19; P4; P11
Gemini	2	P17; P18
RoBERTa	1	P1
DistilBERT	1	P1
TrustServista API	1	P1
SATIKAS	1	P2
GPT-3	1	P4
IBM Watson Health	1	P5
Python	1	P6
math	1	P6
Pandas	1	P6
regular expressions	1	P6

strating emerging specialization for governmental demands.

5 DISCUSSION

This systematic mapping study provides a comprehensive analysis of Large Language Models applications in open government data contexts, revealing both significant opportunities and critical challenges that define the current state of this emerging field. The investigation demonstrates that while LLMs possess considerable potential for transforming government data analysis and citizen services, their effective implementation requires careful consideration of technical, ethical, and governance factors that span multiple interconnected dimensions of public administration.

5.1 Technological Landscape and Model Adoption Patterns

The analysis reveals a clear predominance of proprietary models in governmental applications, with GPT family models dominating the landscape (ChatGPT appearing in 8 studies, GPT-4 in 4 studies, as shown in Table 7). This concentration reflects both accessibility considerations and proven capabilities, but raises important concerns for public sector implementations. The reliance on proprietary models creates potential risks regarding data privacy, vendor lock-in, and long-term sustainability of governmental AI initiatives. There exists a significant opportunity for research exploring open-source alternatives such as Llama, which appeared only in comparative studies by (Hannah et al., 2025), despite potential advantages for government use, including enhanced data control, reduced costs, and greater transparency.

The temporal distribution evidences that research activity intensified markedly from 2023 onwards, coinciding with the public release and widespread adoption of ChatGPT, as shown in Figure 2. This pattern suggests that the field's development has been largely reactive to commercial technology availability rather than proactive in addressing specific governmental requirements.

5.2 Application Domains and Research Gaps

The domain analysis reveals significant imbalances in research focus that highlight both established strengths and critical gaps. Health applications represent the most mature area (4 studies), followed by security and justice domains (3 studies each), as detailed in Table 5. However, fundamental governmental areas remain severely underexplored, particularly education, which is essential for public service delivery but received minimal attention in the analyzed corpus.

The concentration in open data management (5 studies) demonstrates growing recognition of LLMs' potential for enhancing government transparency initiatives. Yet, the limited exploration of geospatial data applications represents a substantial missed opportunity, given the importance of location-based services and spatial analysis in urban planning, emergency response, and infrastructure management.

Furthermore, the geographic and linguistic limitations of current research constrain its global applicability. The predominance of English-language studies and Western legal frameworks limits the generalizability of findings to diverse governmental contexts, particularly those operating in different languages or

legal traditions. This represents a critical gap, as linguistic and cultural particularities significantly impact LLM performance in governmental applications.

5.3 Methodological Maturity and Validation Approaches

The distribution of research types according to Shaw's taxonomy reveals that 50% of studies employ qualitative or descriptive models (Table 3), indicating the field remains in a theoretical consolidation phase rather than operational maturity. The limited presence of empirical models (16.67%) and experimental approaches suggests a critical need for rigorous validation methodologies that can establish definitive performance benchmarks for governmental applications.

The predominance of evaluation-based validation (45.8% of studies, Table 4) demonstrates methodological awareness, yet the scarcity of longitudinal studies limits understanding of long-term impacts on government efficiency and citizen satisfaction. This gap becomes particularly problematic when considering the substantial investments required for governmental AI implementations and the need for evidence-based decision-making in public sector technology adoption.

5.4 Data Types and Processing Challenges

The analysis of utilized data types (Table 6) reveals that Statistical Data and Metrics, along with Transparency and Accountability Data, dominate applications (11 studies each). While this focus aligns with core governmental transparency objectives, it also highlights the underutilization of LLMs for processing more complex data types such as multimedia content, citizen feedback, and real-time sensor data that could enhance smart city initiatives.

The significant representation of Norms and Legislation (10 studies) underscores both the promise and complexity of applying LLMs to regulatory texts. However, the concentration on English-language legal frameworks limits practical applicability to diverse legal systems, particularly those operating under civil law traditions or incorporating customary legal practices.

5.5 Research Agenda and Future Directions

The identified gaps collectively point toward several critical research priorities that could advance the field toward operational maturity. First, there is an urgent

need for comprehensive comparative studies examining open-source versus proprietary model performance in governmental contexts, particularly addressing privacy, security, and cost considerations that are paramount for public sector implementations.

Second, the development of domain-specific evaluation frameworks for governmental AI applications represents a fundamental requirement. Unlike general-purpose AI applications, governmental implementations must address unique requirements, including transparency, accountability, fairness, and legal compliance that are not adequately captured by existing benchmarks.

Third, the expansion of research to underexplored domains such as education, environmental monitoring, and citizen engagement platforms could significantly broaden the impact of LLM applications in public administration. These areas present substantial opportunities for enhancing service delivery while addressing critical societal challenges.

Fourth, multilingual and cross-cultural studies are essential for developing globally applicable governmental AI solutions. Research examining LLM performance across different languages, legal systems, and cultural contexts would provide crucial insights for international cooperation and technology transfer initiatives.

Finally, longitudinal studies examining the sustained impact of LLM implementations on governmental efficiency, citizen satisfaction, and democratic participation represent critical knowledge gaps that must be addressed to inform strategic technology adoption decisions in the public sector.

The research landscape demonstrates that while significant progress has been made in exploring LLM applications for open government data, achieving technical maturity comparable to established software engineering fields requires coordinated efforts to address methodological limitations, develop empirical validation frameworks, and establish ethical governance standards that can guide responsible innovation in public sector AI implementations.

6 CONCLUSIONS

This systematic mapping study analyzed LLM adoption patterns in open government data analysis through a comprehensive examination of 24 primary studies, providing a consolidated overview of current applications in governmental contexts and characterizing researchers' perceptions about benefits, limitations, and methodological implications.

Key findings reveal proprietary model predomi-

nance, particularly GPT family, indicating commercial solution accessibility while highlighting underexploration of open-source alternatives better serving governmental transparency and data sovereignty requirements. Research concentration in health, security, and open data management demonstrates established applications, yet significant gaps remain in fundamental services like education and geospatial data processing.

Methodologically, the field exhibits theoretical consolidation characteristics rather than operational maturity, with 50% employing qualitative/descriptive approaches, suggesting substantial opportunities for advancing toward empirical validation and experimental methodologies establishing definitive performance benchmarks.

Despite contributions, several limitations constrain generalizability. Temporal coverage (2023-2025), 2, reflects the nascent stage but limits the longitudinal perspective on technological evolution. English-language study predominance and Western legal framework focus constrains applicability to diverse governmental contexts.

Future research directions emerge from identified gaps. Developing standardized evaluation metrics for LLM performance in government applications represents a fundamental requirement for evidence-based practices. Longitudinal studies examining long-term impacts on transparency, efficiency, and citizen engagement constitute critical priorities, while comparative analyses of open-source versus proprietary models offer substantial opportunities for advancing public sector AI governance.

Expanding research to underexplored domains such as education, environmental monitoring, and multilingual applications could significantly broaden the transformative potential. Developing domain-specific solutions addressing unique governmental requirements, including transparency, accountability, and legal compliance, represents an essential pathway toward technical maturity.

While LLM application in open government data analysis represents a rapidly evolving field with transformative potential, achieving operational maturity requires coordinated efforts addressing methodological limitations, developing empirical validation frameworks, and establishing ethical governance standards. The comprehensive framework established serves as a valuable reference for researchers, practitioners, and policymakers seeking to understand and contribute to this emerging interdisciplinary domain at the intersection of artificial intelligence and digital government.

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