ISSN 2007-9737

Impact of the Intelligent Assistants with RAG on Information Access and Consultations in Local Governments: a Systematic Review

Jhair Collado[1], Kevin Tupac-Agüero[1], Javier Gamboa-Cruzado[1], Grover Mejia Osorio[1], Javier Rojas Villanueva[1], Natalia Escate Donayre[1], Martín Gamboa-Cruzado[2], Blanca Cecilia López-Ramírez[3,*]

[1] Universidad Nacional Mayor de San Marcos, Lima, Peru

[2] Universidad Nacional de Trujillo, Trujillo, Peru

[3] Tecnológico Nacional de México/IT Roque, Celaya, Mexico

jhair.collado@unmsm.edu.pe, kevin.tupac@unmsm.edu.pe, jgamboac@unmsm.edu.pe, amejiao@unmsm.edu.pe, erojasv@unmsm.edu.pe, docente178.fca@unmsm.edu.pe, martingamboac@gmail.com, bllopez@itroque.edu.mx

Abstract. The need to ensure clear, timely, and equitable citizen access to public information has driven local governments to modernize their service processes. Within this framework, Intelligent Assistants with Retrieval-Augmented Generation (RAG) are emerging as a promising solution, although scientific evidence regarding their impact remains scattered and requires critical systematization. This paper aims to determine the impact of RAG-based intelligent assistants on query resolution and information access in local governments. A systematic literature review was conducted following the PRISMA methodology, analyzing 80 open-access papers published between 2020 and 2025 in IEEE Xplore, Scopus, ScienceDirect, ACM Digital Library, Wiley Online Library, and Taylor & Francis Online. The findings indicate that the most frequently used algorithms in e-commerce are Random Forest, SVM, and neural networks; that Python predominates as the development language, followed by Scala and Matlab; that most studies are published in Q1 journals with high academic rigor; and that the most recurrent keywords emphasize classification, prediction, and user experience. This paper provides a solid foundation for future research, guiding the development of more diverse and methodological approaches in the use of intelligent assistants with RAG in local governments.

Keywords. Revisión sistemática, retrieval-augmented generation (RAG), gobierno local, acceso a la información, consultas ciudadanas, modelos de lenguaje extensos (LLM).

1 Introduction

In recent years, local governments have begun adopting artificial intelligence technologies with the purpose of strengthening citizen services and optimizing the management of public resources. Among the most prominent innovations is the application of Intelligent Assistants with Retrieval-Augmented Generation (RAG), which integrate information retrieval with natural language generation. These tools not only facilitate data access and query resolution but also enhance the operational efficiency of local governments, driving them toward more agile, modern, and citizen-centered models.

An initial group of studies highlights the strategic role of artificial intelligence in sustainable digital transformation, emphasizing that factors such as positive attitudes and prior experience foster adoption [1, 22, 25].

In this regard, it has also been observed that citizen acceptance depends on the context, with greater openness in general and technological services, while human intervention is preferred in sensitive or ideological domains [22, 25]. Furthermore, electronic governance has been positioned as a driver of efficiency in public

ISSN 2007-9737

services, requiring reference models that address technological barriers and ensure privacy, while simultaneously promoting citizen participation through AI and IoT [2, 98]. Indeed, the combination of these technologies holds transformative potential to strengthen transparency and citizen orientation, provided that regulatory and ethical challenges are addressed [93, 98].

In the field of intelligent assistants, several proposals have validated chatbot-based platforms to improve government–citizen communication through NLP, machine learning, and data mining, achieving more expressive and effective interactions than traditional channels [4, 13, 15]. Complementarily, studies conducted in Norwegian municipalities have shown that message design—especially concise and utilitarian ones—improves the relevance of responses, illustrating how interaction aspects influence citizen perception [20]. In addition, research focused on specific sectors has proposed the use of energy chatbots with RAG and LLMs to support SMEs in sustainable decision-making toward carbon-neutral goals [6, 26], while other applications in environmental management, such as MyEcoReporter, demonstrate the utility of AI in reporting incidents to authorities through natural interaction [13, 16]. Similarly, studies on local policy highlight the need for evaluation metrics beyond immediate efficiency, as well as reference frameworks that ensure responsible innovation and adaptability [15, 16].

The literature also emphasizes that the integration of RAG with LLMs improves accuracy in domain-specific contexts, reduces training costs, and broadens the range of tasks, although its application in local governments remains at an early stage [7, 18]. Related findings show that the use of machine learning in the public sector increases operational efficiency, yet tensions persist between political and technical objectives, requiring methodological adjustments and more sophisticated metrics [18, 15]. On the other hand, applied cases highlight the versatility of AI in urban and social domains: the TeachVQA framework in smart cities enhances education by overcoming the limitations of previous models through NLP [21]; tourist forecasting with ARIMA and BERT in Torrevieja demonstrates its contribution to sustainable tourism management [23]; and the application of AI in Chinese mega-hospitals evidences improvements in urban health efficiency, though accompanied by ethical and privacy challenges [24]. These examples reveal how AI applications extend beyond government, reaching education, tourism, and healthcare sectors.

From a broader perspective, studies indicate that AI and associated technologies such as blockchain are transforming smart cities, fostering sustainability, efficiency, and connectivity, although their implementation must be responsible, inclusive, and adapted to each domain [82, 84, 96]. This perspective also reflects that the diffusion of AI in public administration is conditioned by tensions in data governance and regulatory challenges [91, 95], and it tends to focus on issues such as public services, economic affairs, and environmental protection [94]. Finally, evidence shows that the adoption of chatbots and AI in local governments and smart cities mirrors trends observed in other sectors, such as education, e-commerce, banking, and healthcare, where these technologies enhance query automation, learning improvement, customer experience, as well as medical guidance and patient monitoring [83, 87, 93, 99].

Given the rapid advancement of artificial intelligence technologies in public management, it becomes essential to examine in detail how Intelligent Assistants with Retrieval-Augmented Generation (RAG) can transform information access and query resolution in local governments. Despite their potential, the available scientific evidence remains fragmented, with limited critical systematization regarding evaluation metrics, functional components of implementation, and methodological quality levels in existing studies. Additionally, there is a restricted geographic and thematic diversity in the literature, limiting the understanding of their implications in distinct social, economic, and cultural contexts. In this scenario, a Systematic Literature Review (SLR) is necessary to identify trends, research gaps, and application opportunities, offering a comprehensive perspective that contributes to both governmental practice and academic research. The objective of this paper is to systematically analyze the impact of Retrieval-Augmented Generation (RAG)-based intelligent assistants on information access and query resolution in local governments, considering their potential to strengthen operational efficiency, improve response accuracy, and expand the availability of citizen-oriented public services. This review is structured as follows: Section 2 presents the background contextualizing the use of RAG-based intelligent assistants in local governments. Section 3 describes the methodology employed for the search, selection, and analysis of the reviewed studies. Section 4 discusses the main results and provides a critical analysis of the findings. Finally, Section 5 formulates the conclusions and proposes future research directions.

2 Background

To support the research and develop the analyses related to Intelligent Assistants based on Retrieval-Augmented Generation (RAG) and their impact on local governments, it is essential to establish a clear conceptual framework.

2.1 Intelligent Assistants with RAG

An intelligent assistant, also referred to as a chatbot, is defined as an artificial intelligence system designed to simulate conversations with human users, commonly employed to automate tasks and provide real-time information [32]. Retrieval-Augmented Generation (RAG) enhances the performance of these systems by enabling them to access and integrate external information relevant and specific to their domain, thereby increasing both factual accuracy and contextual relevance in their responses [6]. This process relies on advanced natural language processing models, including transformer-based architectures such as BERT, which facilitate semantic understanding and response generation across diverse contexts [56]. In the field of public services, chatbots operate as conversational agents that provide immediate support and escalate more complex requests to human personnel when necessary [69]. Moreover, since these systems are designed to simulate conversational interactions, they allow users to request information or perform specific actions, optimizing processes and delivering faster, more efficient responses [92]. However, despite their benefits, a gap persists between citizen expectations and current technological capabilities, which at times generates frustration and limits their acceptance [64].

2.2 Information Access and Queries in Local Governments

Citizen service encompasses the mechanisms through which local governments provide public services aimed at efficiently and effectively meeting population needs. To achieve this, various service channels are used, ranging from face-to-face interactions to digital platforms and AI-based tools, ensuring accessible and timely assistance [93]. In this context, digital society tools and governmental platforms contribute to building a more empowered and informed citizenry by expanding opportunities for access to public services [96]. Likewise, citizen service is grounded in values such as efficiency, equity, and political feasibility, which are essential to strengthening the legitimacy of public administration [85]. In particular, citizen access to information materializes through digital means that allow individuals to retrieve governmental data and documents based on their specific needs [15]. Within this framework, chatbots stand out for their ability to automate responses to citizen queries, supporting diverse population groups and ensuring the timely provision of services [69]. Ultimately, effective information access not only provides reliable data-driven assistance but also empowers multiple social actors by promoting informed decision-making processes [53].

2.3 Innovative ICT Tools

The management and organization of the selected research papers were carried out using Mendeley software, a widely recognized tool for managing bibliographic references and systematizing scientific literature. Additionally, for the creation of visualizations and the processing of significant statistics, the RAj (Research Assistant j) software—developed by Dr. Javier Gamboa Cruzado—was employed. This innovation is oriented toward optimizing analysis processes in systematic reviews and bibliometric studies.

Table 1. Research questions and objectives

Research Question (RQ)	Objective (OE)
RQ1: What indicators are used to evaluate the quality of service and query resolution through Intelligent Assistants with RAG?	**OE1**: Identify the indicators employed to measure the quality of service and query resolution through Intelligent Assistants with RAG.
RQ2: What functional components constitute the implementation of Intelligent Assistants with RAG?	**OE2**: Determine the functional components used in the implementation of Intelligent Assistants with RAG.
RQ3: What are the quartile levels of the journals where research on the effect of Intelligent Assistants with RAG on Information Access and Queries in Local Governments has been published?	**OE3**: Establish the quartile levels of the journals where research on the effect of Intelligent Assistants with RAG on Information Access and Queries in Local Governments has been published.
RQ4: Which keywords tend to show higher co-occurrence in studies analyzing Intelligent Assistants with RAG and their influence on Information Access and Queries in Local Governments?	**OE4**: Gather the keywords that frequently co-occur in research on Intelligent Assistants with RAG and their influence on Information Access and Queries in Local Governments.
RQ5: What thematic categories are identified in research on Intelligent Assistants with RAG and their influence on Information Access and Queries in Local Governments?	**OE5**: Classify the thematic categories presented in research on Intelligent Assistants with RAG and their influence on Information Access and Queries in Local Governments.

3 Methodology

The research was developed through an adapted methodology that integrates the PRISMA approach with the methodological framework proposed by Kitchenham [81], widely applied in systematic literature reviews in the fields of engineering and computational sciences. First, the study topic and title were formulated, identifying the dependent and independent variables. Based on this, the research questions and objectives that guided the entire process were defined. As noted by Andrade-Mogollon and colleagues [87] in their study on precision agriculture, the use of PRISMA diagrams and specific quality criteria makes it possible to narrow the selection to a set of studies that met the requirements for subsequent quality assessment, ensuring that the findings are not only relevant but also methodologically sound.

3.1 Research Problems and Objectives

The research approach requires breaking down the study analytically into a set of research questions, which allow for structuring, guiding, and directing methodological development. Each of these questions is linked to a specific objective, thereby ensuring coherence between what is proposed and what is achieved throughout the investigative process.

Table 1 presents the research questions along with the corresponding objectives that will be addressed in this study.

3.2 Sources of Information and Search Strategies

The research requires a rigorous selection of scientific information from repositories specialized in the fields of technology and public management.

For this purpose, the following databases of recognized academic prestige were defined as sources of consultation: Scopus, IEEE Xplore, ScienceDirect, ACM Digital Library, Wiley Online Library, and Taylor & Francis Online.

These platforms were selected for their broad coverage of relevant scientific literature and for ensuring access to high-quality publications that allow the research problem to be addressed in a well-founded manner.

ISSN 2007-9737

Table 2. Search Descriptors and Synonyms

Descriptor	Description
intelligent assistant / intelligent agent / chatbot / artificial intelligence / AI / intelligent bot / conversational bot / conversational system / conversational interface / RAG / retrieval-augmented generation / LLM / large language model / ChatGPT / digital assistant / conversational agent / fine-tuned	Intelligent Assistant with RAG (A)
information access / information retrieval / information seeking / citizen inquiries / public inquiries / FAQ / frequently asked questions / information services / citizen service / query answering / information support + public service / state government / state level / government / county / municipality / city / town / public administration / citizen engagement / public sector	Information Access and Queries in Local Governments (B)

3.2.1 Descriptors and Alternative Terms

The information retrieval process was carried out strategically with the aim of identifying studies that addressed the research variables directly or indirectly. To this end, a scheme of keywords and synonyms was designed to broaden the scope of the search and ensure the retrieval of relevant literature. Table 2 presents the synonyms selected for each variable, as well as the search terms employed to precisely identify the scientific papers linked to this research.

3.2.2 Search Equations

The advanced search was structured based on a general research equation that integrates the main variables of the study. This equation was adapted to each database through the use of Boolean operators, synonyms, and relevance filters.

General equation:

("intelligent assistant" OR "intelligent agent" OR chatbot OR "artificial intelligence" OR ai OR "intelligent bot" OR "conversational bot" OR "conversational system" OR "conversational interface" OR rag OR "retrieval augmented generation" OR llm OR "large language model" OR chatgpt OR "digital assistant" OR "conversational agent" OR "fine tuned") AND ("information access" OR "information retrieval" OR "information seeking" OR "citizen inquiries" OR "public inquiries" OR “faq” OR "frequently asked questions" OR "information services" OR "citizen service" OR "query answering" OR "information support") AND ("public service" OR "state government" OR "state level" OR government OR county OR municipality OR city OR town OR "public administration" OR "citizen engagement" OR "public sector")

3.3 Identified Studies

The application of the search equations across the different sources of information allowed for the identification of a considerable number of papers related to the research topic. Figure 1 presents the breakdown of the results obtained from each database consulted.

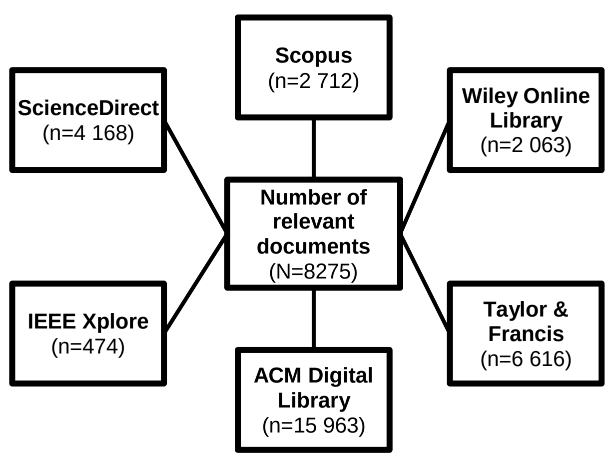


Fig. 1. Number of documents by Source

ISSN 2007-9737

3.4 Study Selection

To refine the identified literature and ensure the methodological consistency of the review, exclusion criteria (EC) were established and applied sequentially.

These criteria considered aspects of timeliness (papers older than seven years were discarded), accessibility (papers without full text or written in a language other than English), scientific quality (works without peer review or with methodological deficiencies), and thematic relevance (studies that did not directly or indirectly address the use of Intelligent Assistants with RAG in local governments).

The filtering process was carried out under the PRISMA methodological framework, which ensured transparency in the selection process. Figure 2 graphically summarizes the stages of identification, screening, and final selection of the papers included in the review.

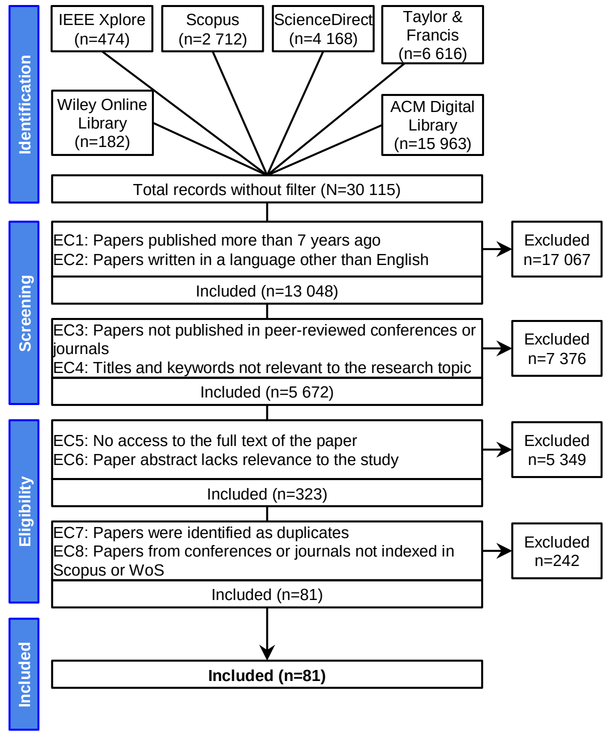


Fig. 2. PRISMA flow diagram

3.5 Quality Assessment

Once the selection process was completed using the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), it was necessary to conduct a critical assessment of the resulting papers.

For this purpose, a set of quality assessment criteria (QA) was defined to ensure the validity, consistency, and relevance of the selected studies with respect to the research question.

These criteria constituted the final filter to determine the papers that would form the analytical basis of this review. The applied QA criteria were as follows:

QA1: Are the objectives of the research clearly formulated and explicitly linked to the impact of Intelligent Assistants with RAG on information access and inquiries in local governments?

QA2: Is the methodological design appropriate to address the objectives related to Intelligent Assistants with RAG and their implementation in local governments?

QA3: Is the description of the population or sample precise and adequate to represent the context of local governments or municipal service users?

QA4: Are the data collection procedures appropriate, valid, and reliable for the analysis of Intelligent Assistants with RAG?

QA5: Are the data analysis techniques suitable and correctly applied to interpret the findings related to Intelligent Assistants with RAG?

QA6: Are the reported results presented clearly and coherently, supporting the conclusions about the effect of Intelligent Assistants with RAG in local governments?

QA7: Was the study peer-reviewed or published in a refereed journal with a significant quartile ranking within the field of Computer Science or Software Engineering?

ISSN 2007-9737

Table 3. Quality Assessment Criteria

Ref	Type	QA1	QA2	QA3	QA4	QA5	QA6	QA7	Score
[1]	Journal	3	3	1	3	3	2	3	18
[2]	Journal	2	3	2	3	3	2	3	18
[3]	Journal	3	3	2	2	2	2	3	17
[4]	Journal	2	2	2	3	3	2	3	17
[5]	Journal	2	1	2	1	2	3	3	14
[6]	Journal	3	3	2	2	2	2	2	16
[7]	Journal	3	1	3	2	3	2	3	17
[8]	Journal	2	1	2	2	2	2	3	14
[9]	Journal	3	1	3	2	2	1	3	15
[10]	Journal	2	3	2	2	2	2	3	16
[11]	Journal	2	2	2	2	2	2	3	15
[12]	Journal	3	3	2	2	3	3	3	19
[13]	Journal	2	2	2	3	3	2	3	17
[14]	Journal	2	3	2	2	3	3	3	18
[15]	Journal	2	3	2	2	3	2	3	17
[16]	Journal	2	3	2	3	3	2	3	18
[17]	Journal	2	3	2	2	3	2	3	17
[18]	Journal	3	2	2	2	2	2	3	16
[19]	Journal	2	3	2	2	3	2	1	15
[20]	Journal	3	1	2	2	3	3	2	16
[21]	Journal	3	1	3	2	3	3	2	17
[22]	Journal	2	3	2	2	3	3	1	16
[23]	Journal	2	2	2	2	3	3	2	16
[24]	Journal	3	3	2	2	3	3	2	18
[25]	Journal	2	1	2	2	3	3	2	15
[26]	Journal	3	1	1	2	3	3	2	15
[27]	Journal	3	3	2	2	2	2	3	17
[28]	Journal	2	3	1	1	3	3	2	15
[29]	Journal	2	3	3	1	2	3	3	17
[30]	Journal	3	1	1	3	3	3	3	17
[31]	Journal	3	1	1	2	3	3	2	15
[32]	Journal	2	1	2	2	2	3	2	14
[33]	Journal	2	2	2	2	3	3	2	16
[34]	Journal	3	3	2	1	2	3	2	16
[35]	Journal	2	1	2	2	2	3	2	14
[36]	Journal	2	1	2	2	2	3	2	14
[37]	Journal	3	2	2	1	3	3	2	16
[38]	Journal	2	1	3	2	3	3	2	16
[39]	Journal	2	3	2	2	2	3	2	16
[40]	Journal	2	3	2	2	3	3	2	17
[41]	Journal	2	3	2	3	2	3	3	18
[42]	Journal	2	1	2	1	3	3	2	14
[43]	Journal	2	3	1	2	3	3	2	16
[44]	Journal	3	3	2	2	3	2	3	18

For the final quality filtering process, a scoring scale was applied assigning 1 (Poor), 2 (Fair), and 4 (Excellent), with a minimum threshold of 17 out of 28 points to ensure the quality, adequacy, and relevance of the papers. After applying this procedure, it was found that only one of the 81

Table 3 (cont). Quality Assessment Criteria (cont.)

Ref	Type	QA1	QA2	QA3	QA4	QA5	QA6	QA7	S
[45]	Journal	3	3	1	2	2	3	1	
[46]	Journal	2	3	2	2	3	3	2	
[47]	Journal	3	1	2	2	3	3	3	
[48]	Journal	1	1	2	3	1	1	1	
[49]	Journal	3	1	2	2	3	3	2	
[50]	Journal	3	1	2	2	2	3	2	
[51]	Journal	3	1	2	2	2	2	2	
[52]	Journal	3	2	3	2	2	3	2	
[53]	Journal	2	1	3	1	3	3	1	
[54]	Journal	3	3	2	2	2	3	3	
[55]	Journal	2	2	2	2	3	3	2	
[56]	Journal	3	3	2	2	2	3	2	
[57]	Journal	2	3	2	2	3	2	2	
[58]	Journal	2	1	2	2	3	3	2	
[59]	Journal	2	3	2	3	3	3	3	
[60]	Journal	2	3	2	2	3	3	3	
[61]	Journal	2	3	2	2	3	3	2	
[62]	Journal	3	2	2	2	2	3	1	
[63]	Journal	3	3	2	2	3	2	2	
[64]	Journal	3	1	3	3	1	3	2	
[65]	Journal	3	3	2	2	2	2	2	
[66]	Journal	3	1	2	2	2	2	2	
[67]	Journal	2	3	3	2	2	3	2	
[68]	Journal	2	3	1	2	2	3	1	
[69]	Journal	3	3	2	2	2	3	1	
[70]	Journal	3	2	2	3	3	3	2	
[71]	Journal	2	3	2	2	1	3	3	
[72]	Journal	2	3	3	2	3	3	1	
[73]	Journal	2	1	2	2	2	3	2	
[74]	Journal	2	3	2	1	3	3	2	
[75]	Journal	3	3	1	2	3	3	3	
[76]	Journal	2	1	2	2	3	3	3	
[77]	Journal	3	1	2	2	3	3	3	
[78]	Journal	3	3	2	2	3	3	2	
[79]	Journal	2	3	2	2	2	2	2	
[80]	Journal	3	3	2	2	3	3	1	
[81]	Journal	3	3	2	3	2	3	2	

papers did not reach the required score, while the remaining 80 surpassed the minimum level, confirming their pertinence for the research. Table 3 presents the qualitative assessment of the results obtained from this analysis.

3.6 Data Extraction Strategies

The selected papers were managed in the bibliographic system Mendeley, which allowed the organization and recording of relevant metadata for each publication. During the data extraction process, a detailed reading was conducted, noting key elements such as authors, country of origin, institutional affiliation, abstracts, main findings, and conclusions. This information was integrated with the data from Mendeley to consolidate a unified record that included both metadata and conceptual aspects. Finally, the collected inputs were systematized in an analysis sheet, which facilitated the identification of associations, overlaps, and discrepancies among the studies, as shown in Figure 3.

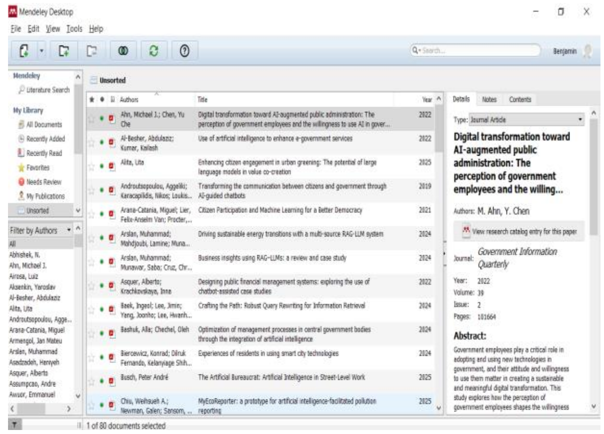


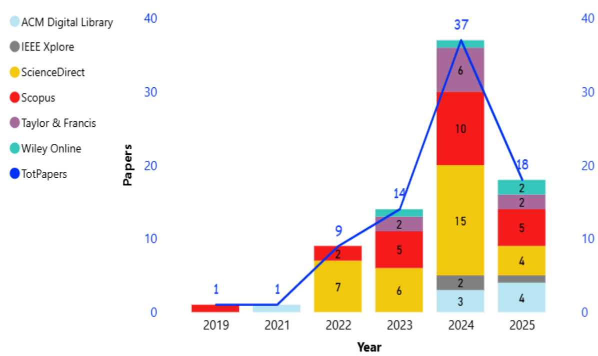
Fig. 3. Document management with Mendeley

3.7 Synthesis of Findings

The core of this research lies in the synthesis of the findings obtained from the selected papers. At this stage, the extracted data were organized, transformed, and systematized for analysis, using statistical graphs, tables, and analytical notes that constitute the essential inputs for presenting the results and for the subsequent discussion of the study.

4 Results and Discussion

This section presents the findings obtained through the systematic review, organized according to the research questions. First, the temporal, geographical, and source distribution of the selected studies is described in general terms; then, specific answers to each RQ are provided. This approach makes it possible to synthesize current trends while also identifying conceptual and practical gaps in the adoption of Intelligent Assistants with RAG in local governments.



Kendall Trend

Trend	p-value	Ecuation	R²
Increasing	0,035	y= 9226052136.474268 -13688194.144234924X +6769.471017218824X² -1.1159420294352458X³	0,82

Fig. 4. Papers by Year and Source

4.1. General Overview of the Studies

The selected studies are concentrated in the period 2019–2025, reflecting the recent incorporation of Intelligent Assistants with RAG into public management and allowing the capture of current trends in local governments.

Figure 4 shows the evolution of the papers published between 2019 and August 2025, distributed by scientific database, while the Kendall trend analysis confirms a statistically significant growth pattern.

First, an incipient beginning is observed in 2019 and 2021, followed by sustained growth from 2022 onward, which coincides with the maturation of Intelligent Assistants with RAG. The year 2024 records a peak with 37 publications, evidencing the moment of greatest interest and consolidation of the topic. In 2025, a relevant volume is maintained (18 studies), suggesting continuity of research beyond the observed peak.

The Kendall test ($p = 0.035$; $R^2 = 0.82$) confirms an upward trend, with a strong correlation between time and the increase in publications. The diversity of sources—particularly Scopus, IEEE Xplore, and ScienceDirect—demonstrates that the field has captured the attention of high-impact repositories.

ISSN 2007-9737

Table 4. Number of Publications by Affiliation and their Impact

Affiliation	No. of Papers	Total Citations	Sum H-Index	Citations/ Paper
Queensland University of Technology	6	202	721	34
Hong Kong Shue Yan University	3	88	345	29
Huazhong University of Science and Technology	3	31	694	10
Norwegian University of Science and Technology	3	100	361	33
Tsinghua University	3	31	694	10
Arizona State University	2	24	201	12
Beijing Institute of Technology	2	4	88	2
City University of Hong Kong	2	0	82	0
Institute of Political Science	2	4	288	2
International Hellenic University	2	2	189	1
Ionian University	2	2	189	1
Macquarie University	2	5	36	3
National University of Computer and Emerging Sciences (NUCES)	2	8	283	4
San Francisco	2	0	428	0
SINTEF Digital	2	120	288	60
Universidad Autónoma de Madrid	2	43	247	22
…	…	…	…	…

Scientific production shows sustained growth since 2019 [82]. In particular, 2022 stands out as a turning point in the trend [84], accompanied by an increase in quantitative papers from that year [93] and reinforced by the notable peak reached in 2023 [88]. Finally, since 2021, a more moderate yet steady growth trajectory has been observed [96].

These results suggest that Intelligent Assistants with RAG are consolidating as an emerging field with transferable applications to other sectors, such as healthcare and education. Furthermore, the continuity of publications in 2025 allows projecting their adoption into new geographic regions and governments with lower levels of digital maturity. Finally, the temporal analysis indicates that this line of research may extend into future decades, adapting to regulatory, technological, and social changes.

Figure 5 shows the geographic distribution of studies on Intelligent Assistants with RAG in local governments, highlighting leading countries and regional gaps.

China leads production with 14 publications, followed by the United States (10) and Australia (9), confirming their role as hubs of innovation in digital administration. Europe shows a balanced contribution, with Italy, the Netherlands, and Greece recording 5 studies each, consolidating a secondary block of influence. In Asia, South Korea, Hong Kong, and Saudi Arabia stand out with 3 publications each, evidencing expansion in countries with strong technological capacity. In contrast, the scarce presence in Latin America and Africa reveals significant gaps that limit the generalization of results to global contexts.

In the study by [85], the United States and China were identified as the countries with the highest proportion of production.

Similarly, [93] reported a greater predominance of papers with implementations in the United States, the United Kingdom, and European countries, with the absence of Asian nations. In contrast, [82] pointed to China as the main contributor of studies, followed by India and South Korea. Finally, [88] highlighted the United States as the major source of research, while [100] ranked China, followed by India and Canada, as the leading contributors of scientific papers.

The findings highlight the urgency of promoting research in underrepresented regions, where Intelligent Assistants with RAG could have a greater impact on government efficiency. They also suggest the possibility of transferring these solutions to business sectors such as education, healthcare, and banking. Finally, future analyses in other periods and geographic areas will make it

ISSN 2007-9737

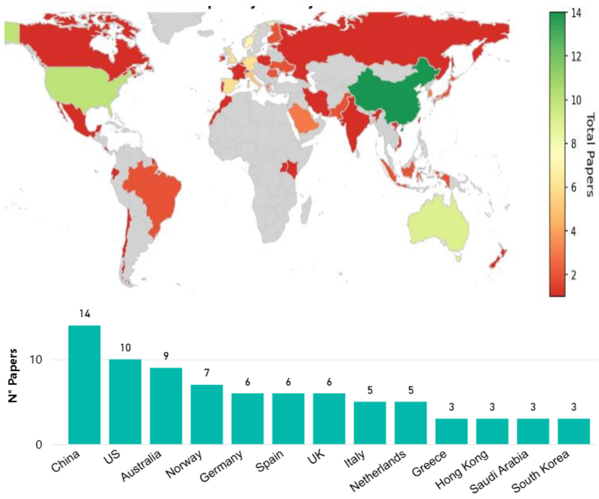


Fig. 5. Geographic distribution of Papers

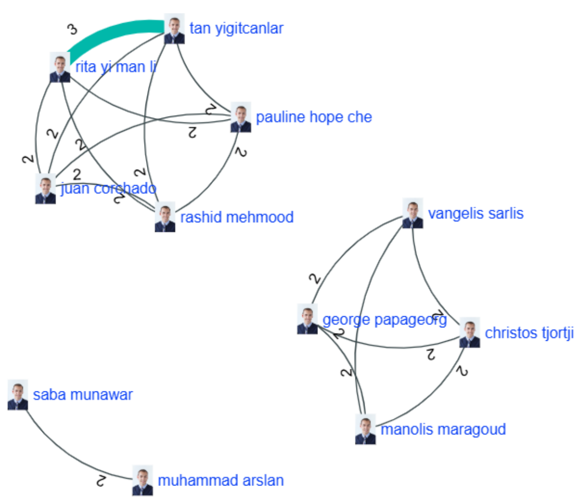


Fig. 6. Bibliometric Network of Associated Authors

possible to assess sustainability and technological adaptation across different contexts.

Table 4 shows the institutions with the highest scientific output and the level of influence measured through citations and H-indexes, allowing the identification not only of volume but also of quality and impact in research on Intelligent Assistants with RAG in local governments.

The Queensland University of Technology leads in production with six papers and 202 citations, achieving an average of 34 citations per paper, which reflects strong recognition in the scientific community. Universities such as Hong Kong Shue Yan and Huazhong University of Science and Technology stand out with three publications each, recording averages of 29 and 33 citations per paper, respectively, demonstrating their influence in the field. Institutions such as the Norwegian University of Science and Technology and Tsinghua University reinforce the relevance of Asia and Europe in the domain, with a notable impact in citations per paper. However, several universities—such as the City University of Hong Kong and the International Hellenic University—show production with low citation counts, suggesting limited impact or emerging studies. Overall, the table reflects a pattern concentrated in a few high-prestige institutions, indicating the existence of research excellence hubs.

These findings highlight the need to foster international cooperation with leading centers to disseminate best practices. Moreover, the knowledge generated can be transferred to sectors such as healthcare, education, and digital banking, where RAG holds high potential. Finally, monitoring in future periods will allow for the evaluation of the sustainability of these contributions across different regions.

Figure 6, together with Tables 5 and 6, illustrates the main academic collaborations and the level of scientific impact in the field of Intelligent Assistants with RAG applied to local governments.

Rita Yi Man Li and Tan Yigitcanlar stand out as the most influential authors, with three publications each, 88 citations, and an average of 29 citations per paper, consolidating a shared leadership. The co-authorship network shows strong associations, particularly between Li and Yigitcanlar (weight 3), as well as the participation of Juan Corchado in multiple international collaborations. Authors such as Christos Tjortjis, George Papageorgiou, and Manolis Maragoudakis form a solid subgroup with recurrent interactions, reflecting research cohesion within specific nodes. Kevin C. Desouza, with two publications and 28 citations per paper, demonstrates a notable impact despite a moderate production volume. In contrast, some authors show low citation counts, evidencing disparities in academic visibility within the field.

In this study, Tan Yigitcanlar emerges as an influential author, with a particularly strong co-authorship link. These findings are consistent with

ISSN 2007-9737

Table 5. Co-authors by Association Weight

Author1	Author2	Weight
rita yi man li	tan yigitcanlar	3
christos tjortjis	george papageorgiou	2
christos tjortjis	manolis maragoudakis	2
christos tjortjis	vangelis sarlis	2
george papageorgiou	manolis maragoudakis	2
george papageorgiou	vangelis sarlis	2
juan corchado	pauline hope cheong	2
juan corchado	rashid mehmood	2
juan corchado	rita yi man li	2
juan corchado	tan yigitcanlar	2
manolis maragoudakis	vangelis sarlis	2
muhammad arslan	saba munawar	2
pauline hope cheong	rashid mehmood	2
pauline hope cheong	rita yi man li	2
pauline hope cheong	tan yigitcanlar	2
…	…	…
Total		**35**

Table 6. Authors' Impact

Author	No. of Papers	Total Citations	Citations/ Paper	Sum H-Index
Tan Yigitcanlar	3	88	29	345
Rita Yi Man Li	3	88	29	345
Asbjørn Følstad	2	29	15	244
Christos Tjortjis	2	2	1	189
Papageorgiou	2	2	1	189
Juan Corchado	2	24	12	201
Kevin C. Desouza	2	56	28	189

the review by Szpilko and colleagues [95], which identifies T. Yigitcanlar as the most prolific author in artificial intelligence for smart cities. Regarding collaboration, the analyzed network reveals associations concentrated in specific cores, while the study by Alaeddini and colleagues [82] describes a broader mesh with 888 co-authorship links across 589 papers. Complementarily, Lubis and colleagues [90] emphasize the relevance of international and multidisciplinary collaborations, a pattern equally visible in the associations identified in our analysis.

The results demonstrate that strengthening collaboration networks between consolidated and emerging groups can enhance knowledge dissemination. Furthermore, the methodology applied in this domain can be transferred to sectors such as healthcare, banking, and education to improve the efficiency of intelligent assistants with RAG. Finally, the longitudinal analysis of these networks will allow for the evaluation of how associations evolve and their impact across different regions and business contexts.

4.2. Responses to the Research Questions

The research questions were designed with the purpose of breaking down a complex problem into specific components, allowing for the analysis of its guidelines and providing solid scientific answers to the general question of the study. Below are the responses to the five RQs, grounded in qualitative and quantitative data that comprehensively reflect the different aspects of the reality addressed.

RQ1: What indicators are used to evaluate the quality of service and the resolution of inquiries through Intelligent Assistants with RAG?

Table 7 and Figure 7 identify the main criteria employed in the literature to evaluate the effectiveness of Intelligent Assistants with RAG in local governments.

The results show that technical performance (22.2%) is the most valued metric, reflecting the need to ensure stable and efficient systems. Accuracy and truthfulness (18.9%), along with communication effectiveness (18.9%), stand out as central indicators for ensuring reliable and understandable responses.

User experience (17.8%) holds a relevant position, underlining the importance of smooth interaction in public service contexts. Aspects such as ethics and information reliability (12.2%) highlight concerns regarding data integrity and transparency. Finally, engagement and adaptability (10%) appear less frequently, revealing an area that remains underdeveloped in this field.

Author [93] proposes five specific metrics—usability, accuracy, effectiveness, coverage, and ease of use—to assess chatbot performance from the perspective of user experience.

ISSN 2007-9737

Table 7. Metrics for Measuring Service Quality and Inquiry Resolution

Criterion	Reference	Qty. (%)
Accuracy and Truthfulness	[6], [7], [17], [24], [26], [30], [31], [35], [37], [43], [44], [71], [73], [74], [76], [77], [78]	17 (19)
Engagement and Adaptability	[3], [16], [27], [28], [42], [45], [58], [59], [76]	9 (10)
Ethical and Information Reliability(Data integrity)	[16], [37], [42], [44], [50], [60], [65], [66], [70], [73], [79]	11 (13)
Technical Performance	[6], [7], [15], [21], [26], [30], [32], [35], [36], [40], [42], [49], [52], [53], [54], [55], [65], [71], [74], [76]	20 (23)
User Experience	[13], [20], [27], [29], [32], [39], [40], [42], [45], [49], [53], [63], [65], [66], [68], [75]	16 (17)
Communication Effectiveness	[10], [13], [15], [20], [26], [34], [38], [44], [45], [47], [52], [56], [64], [65], [68], [71], [76]	17 (18)

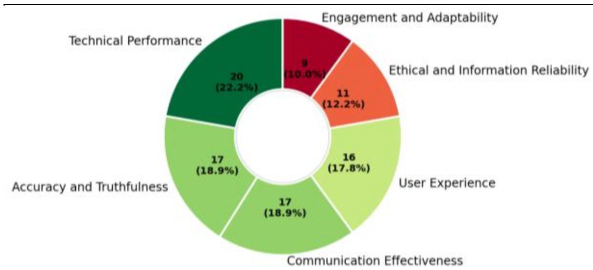


Fig. 7. Criteria for Measuring Service Quality and Inquiry Resolution

The emphasis on technical and accuracy-based metrics indicates that future applications in sectors such as healthcare, banking, and education should prioritize reliability and performance.

The low presence of indicators related to adaptability and ethics suggests the need for more inclusive and contextualized approaches in other geographic regions. Furthermore, strengthening these metrics in future timeframes will allow for greater social acceptance and sustainability of RAG systems.

RQ2: What functional components make up the implementation of Intelligent Assistants with RAG?

Table 8 and Figure 8 show the distribution of the most commonly used components in the implementation of Intelligent Assistants with RAG, reflecting the current technological priorities in this field.

The Answer Generator (43.1%) is the predominant component, confirming that the ability to produce coherent and contextualized information constitutes the functional core of RAG systems. It is followed by the Embedding Generator (27.5%), which is crucial for representing semantic information and improving retrieval accuracy. The Context Retriever (11.8%), although less frequent, is essential to ensure that responses are grounded in specific and up-to-date information. This hierarchy reflects a clear orientation toward content generation rather than optimization of retrieval.

The predominance of the Answer Generator suggests that, in sectors such as healthcare, justice, or education, assistants should prioritize the generation of reliable and adaptive content. However, in regions with limited digital infrastructure, strengthening retrieval and data organization modules would be strategic. Looking ahead, balancing the four components will enable broader applicability of RAG systems across different business and geographic contexts.

RQ3: What distribution of quartile levels is presented by the journals that publish research on the effect of Intelligent Assistants with RAG on Information Access and Consultations in Local Governments?

Figure 9 represents the relationship between the quartile levels of journals, the publication databases, and the temporal evolution of papers on Intelligent Assistants with RAG in local governments, allowing observation of both the quality and the distribution of scientific production.

The results show that the largest proportion of papers is concentrated in Q1 journals (50), highlighting the preference for publishing in high-impact academic outlets. In contrast, publications in Q4 (1) are marginal, suggesting low positioning in lower-prestige journals. The main associated

Table 8. Functional Components in the Papers

Component	Reference	Qty. (%)
Text Embedding Generator	[6], [9], [10], [21], [26], [31], [32], [35], [38], [56], [71], [73], [74], [77]	14 (27)
Semantic Index	[5], [6], [26], [35], [46], [53], [54], [71], [76]	9 (18)
Context Retriever	[6], [9], [26], [54], [71], [76]	6 (12)
Answer Generator	[6], [7], [9], [13], [17], [19], [26], [35], [37], [38], [40], [46], [53], [54], [55], [60], [65-67], [71], [76], [77]	22 (43)

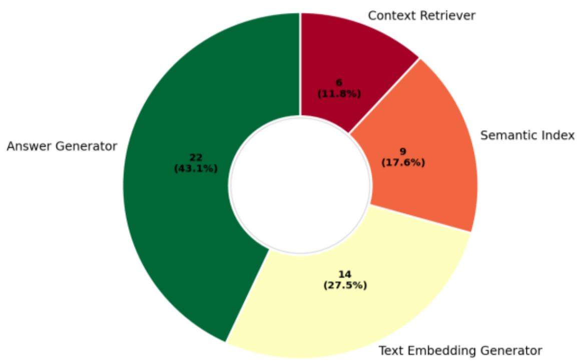


Fig. 8. Distribution of System Components

databases are ScienceDirect (32) and Scopus (23), followed by Taylor & Francis (10) and ACM Digital Library (8). Temporally, the highest publication peak is recorded in 2024 (37 papers), indicating a recent surge in the topic.

The predominance of Q1 suggests that this field is already consolidated in high-quality journals, which can strengthen its recognition in other sectors such as healthcare, banking, and education. The concentration in certain databases opens the opportunity to diversify toward regional repositories in order to expand geographic coverage. In future periods, an expansion toward interdisciplinary journals is expected, reinforcing the applicability of RAG in diverse governmental and business contexts.

Figure 10 together with Table 9 illustrate the distribution of scientific production and its impact in terms of citations, differentiating publication sources and their positioning across quartile levels.

The dendrogram shows that the largest and most vividly colored nodes correspond to Q1, underscoring its central role in the research; this finding is corroborated by the table, where Q1 accounts for 50 papers and 1,499 citations, representing the core of impact. ScienceDirect emerges as the most influential source (32 papers and 734 citations), followed by Scopus (23 papers and 530 citations), confirming that these databases concentrate academic leadership. In contrast, the dendrogram highlights smaller, paler nodes in Q3 and Q4, consistent with the table data (only 5 papers and 14 citations combined), revealing low production and limited impact in those quartiles. Likewise, Taylor & Francis and Wiley Online present an intermediate role: with lower publication volumes but contributing in Q1 and Q2, thereby adding diversity to the literature. Finally, the NQ papers appear in the dendrogram as secondary nodes with low citation intensity, in line with the table figures (16 papers and only 29 citations).

The combined analysis confirms that research on Intelligent Assistants with RAG is consolidated in high-impact journals (Q1), reinforcing its academic legitimacy and applicability in strategic sectors such as healthcare, education, and finance. However, the low presence in Q3 and Q4 indicates limited diversity in publication channels, restricting dissemination to regional or emerging contexts. Looking ahead, diversifying sources and expanding publications beyond Q1 could foster the transfer of knowledge to other business areas, different geographic regions, and broader periods of application.

RQ4: Which keywords tend to show greater co-occurrence in studies that analyze Intelligent Assistants with RAG and their influence on Information Access and Citizen Inquiries in Local Governments?

Figure 11 displays the most frequent terms and conceptual associations in studies on Intelligent Assistants with RAG applied to local governments, revealing semantic patterns that guide the research agenda.

To calculate the association strength between keywords and determine their co-occurrence, the

Table 9. Number of Papers and Citations by Source and Quartile

Quartile	NQ		Q1		Q2		Q3		Q4		Total	
Source	**Paper**	**Cit.**	**Paper**	**Cit.**	**Paper**	**Cit.**	**Paper**	**Cit.**	**Paper**	**Cit.**	**Paper**	**Citations**
ScienceDirect	4	23	26	678	2	33	0	0	0	0	**32**	**734**
Scopus	3	0	10	466	5	50	4	8	1	6	**23**	**530**
Taylor & Francis	0	0	7	77	2	2	1	0	0	0	**10**	**79**
ACM Digital Library	8	6	0	0	0	0	0	0	0	0	**8**	**6**
Wiley Online	0	0	4	278	0	0	0	0	0	0	**4**	**278**
IEEE Xplore	1	0	2	0	0	0	0	0	0	0	**3**	**0**
Total	**16**	**29**	**50**	**1499**	**9**	**85**	**4**	**8**	**1**	**6**	**80**	**1627**

cosine similarity measure was used. This metric quantifies the closeness between term vectors, with higher similarity values obtained as the angle between them decreases. With the following equation, we obtain the cosine measure between documents d_i and d_j, where d_{ik} is the weight of the semantic feature k in document d_i:

$$\mathrm{sim}\left(d_i, d_j\right) = \cos(a) = \frac{\sum_{k=1}^{m}(d_{ik} * d_{jk})}{\sqrt{(\sum_{k=1}^{m} d_{ik}^2) * (\sum_{k=1}^{m} d_{jk}^2)}}.$$

The central node is “AI”, strongly connected with “local government”, “large language models”, and “chatbot”, indicating that research is structured around artificial intelligence as the main axis. From there, connections emerge with “policy” and “public administration”, reflecting the interest in the regulatory and organizational framework. Other key terms such as “chatbot”, “NLP”, “user experience”, and “design” show that the technological dimension is complemented by interaction and usability approaches. The appearance of “retrieval-augmented” and “generative artificial” in peripheral nodes reveals emerging areas with lower density, which indicates opportunities for future exploration. Finally, the strength of the links suggests that studies prioritize the application of AI in public services with direct impact on citizens.

In this study, the terms “AI”, “local government”, and “large language models” emerge as the central core of the co-occurrence network, with particularly strong links among them. These findings are consistent with the review by [90], which identifies “artificial intelligence” as the most central keyword in governance applications. Regarding thematic structure, while our network shows a concentration on conversational artificial intelligence applied to local government, the study by [82] describes a broader configuration centered on “Internet of Things” and “smart city.” Complementarily, [89] highlights the relevance of basic co-occurrence pairs such as “deep learning–government” and “classification–document,” a pattern that our analysis shows has evolved toward more advanced concepts such as “RAG” and “large language models.”

The predominance of “AI” as the central node confirms that discussions are not limited to RAG but are embedded in a broader framework of artificial intelligence applied to public management. This opens possibilities for transferring the findings to other business sectors such as healthcare, energy, or transportation. Likewise, the low density of emerging terms indicates the need for further research to strengthen the connection between RAG and local services. Replicating these analyses across different regions and over time will allow assessing how the acceptance and effectiveness of AI evolve in diverse contexts.

RQ5: What thematic categories are identified in research on Intelligent Assistants with RAG and their influence on Information Access and Citizen Inquiries in Local Governments?

Figure 12 and Table 10 present the thematic clusters identified from the keyword co-occurrence analysis, where density reflects the degree of development of the topic and centrality indicates its structural relevance within the network.

The theme Conversational RAG is positioned as a Specialized Theme, with high density but medium centrality, indicating solid development

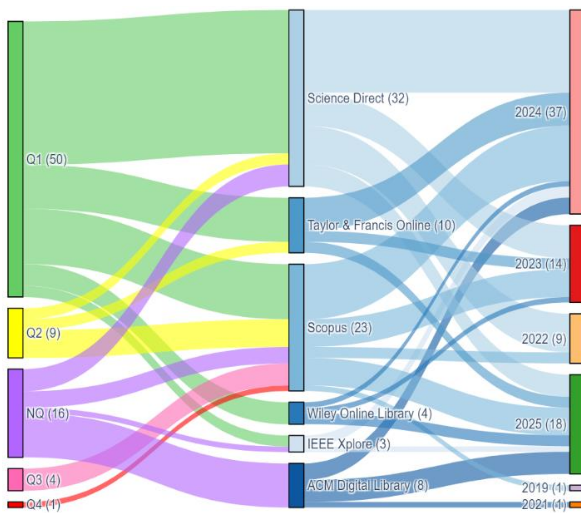


Fig. 9. Distribution of Papers by Quartile, Source, and Year

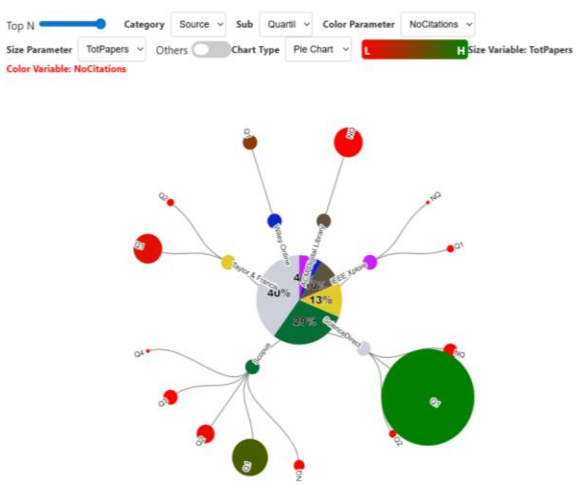


Fig. 10. Dendrogram with Total Papers and Citations by Quartile and Source

while still remaining peripheral in the research agenda. In contrast, Chatbot Design appears as a Basic Theme, with high centrality but low density, positioning it as an underdeveloped conceptual core. The clusters AI Chatbot Experience and Chatbot Services are classified as Marginal Themes, with high citation counts (358) but low density, revealing still fragmented academic interest. Other marginal nodes such as AI Innovation, AI Governance, and Chatbot NLP reflect incipient connections, with both low density and centrality, pointing to emerging fields. Finally, ChatGPT LLMs shows recent but limited density, representing a growing area that has not yet consolidated its centrality.

According to Lubis [90], artificial intelligence, with a centrality of 40.9% and an impact of 21.5%, is still under development, but when integrated with blockchain (85.7%) and sustainability (59.3%), it can provide key solutions for the challenges of smart cities.

These results suggest the need to strengthen research lines around chatbot design as a conceptual core and to expand the development of marginal themes toward more consolidated categories. Furthermore, the findings can be extrapolated to other sectors such as healthcare, education, and commerce, where Intelligent Assistants with RAG may generate strategic impact. Replicating this analysis in other geographic and temporal contexts will make it possible to anticipate how research priorities evolve at the intersection of AI, governance, and citizen services.

5 Conclusions and Future Research

The findings related to RQ1 show that the most frequently employed metrics are concentrated on technical performance, accuracy, and communicative effectiveness, reflecting the priority of ensuring robust, reliable systems with understandable interactions. This emphasis confirms that the literature privileges technological stability over ethical or adaptability aspects, although the latter emerge as critical but still underexplored dimensions. Consequently, the quality of service in Intelligent Assistants with RAG is directly linked to reliability and transparency, establishing the basis for their acceptance in local governments and related sectors. Regarding RQ2, the results show that the Answer Generator is the most recurrent functional component, followed by embeddings and contextual retrieval modules. This pattern indicates that research prioritizes the generation of coherent and contextualized content over the optimization of information organization. While this orientation has fostered notable

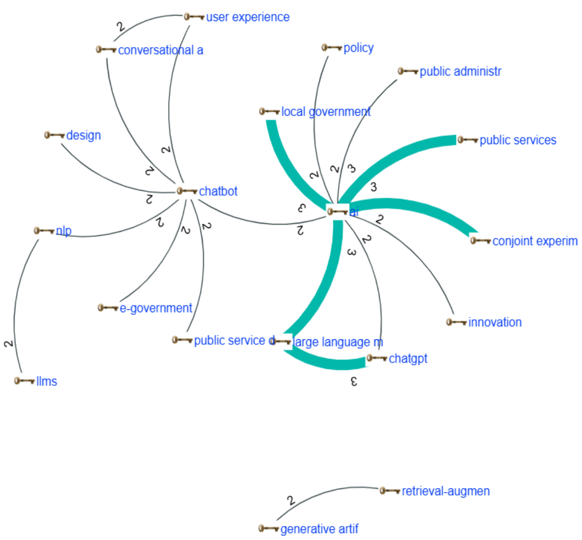


Fig. 11. Keyword Co-occurrence

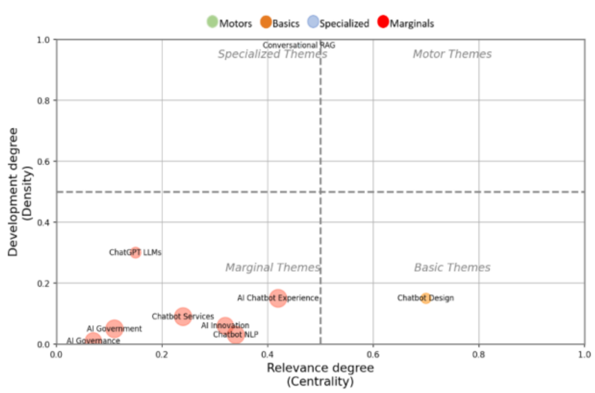


Fig. 12. Thematic Categories

Table 10. Description and Content of Thematic Clusters

Theme	Density	Centrality	Total Citations	Total Documents	Category
Conversational RAG	0,98	0,46	1	4	Specialized
ChatGPT LLMs	0,30	0,15	102	6	Marginal
AI Chatbot Experience	0,15	0,42	358	18	Marginal
Chatbot Design	0,15	0,70	75	8	Basic
Chatbot Services	0,09	0,24	358	17	Marginal
AI Innovation	0,06	0,32	319	12	Marginal
AI Government	0,05	0,11	358	17	Marginal
Chatbot NLP	0,03	0,34	344	17	Marginal
AI Governance	0,01	0,07	319	12	Marginal

advances, it also limits the potential of these systems in contexts with low digital maturity, where data retrieval and organization are key. Thus, a duality emerges between sophistication in text generation and structural gaps in knowledge management.

For RQ4, the keyword co-occurrence analysis reveals that "AI" acts as the central node connected with concepts such as local government, chatbot, and large language models, while other terms such as retrieval-augmented or generative artificial remain in peripheral positions. This finding confirms that the field is structured around artificial intelligence in general, not exclusively around RAG, broadening the discussion toward regulatory, normative, and user experience dimensions. The semantic structure of the network suggests that studies emphasize the application of AI to public services, although gaps remain concerning ethics, governance, and integration with public policies. In RQ5, the results show that the most consolidated themes include Chatbot Design as a basic core, while Conversational RAG is positioned as a specialized theme with solid development but still peripheral. In contrast, categories such as AI Governance, AI Innovation, or ChatGPT LLMs appear as marginal, reflecting emerging fields with relevant citation counts but low research density. This landscape indicates an academic agenda in transition, where the exploration of user experiences and complementary services still lacks sufficient maturity to become central themes.

Taken together, these conclusions show that the literature on Intelligent Assistants with RAG in local governments is in a stage of partial consolidation: the technical and quality foundations are well defined, but the social, ethical, and normative aspects remain fragmented. Likewise, the bibliometric analysis reveals that research is concentrated in technologically advanced regions, leaving significant gaps in Latin America and Africa, which limits the extrapolation of results. The emphasis on high-impact (Q1) academic production reinforces the legitimacy of the field but restricts its practical transfer to contexts with lower visibility. Overall, the systematic review demonstrates that Intelligent Assistants with RAG hold significant potential to transform public management, although their success will depend on the ability to integrate ethical metrics, balanced functional components, and inclusive design strategies. The thematic outlook confirms the need to promote interdisciplinary studies that combine AI, governance, and public policy.

Future research should explore how the integration of ethical and adaptability metrics affects the social acceptance of RAG in local governments. It is also recommended to strengthen research in emerging regions to reduce the detected geographical gaps. Finally, broadening the thematic coverage toward innovation and governance will help consolidate a more inclusive and sustainable research agenda over time.

References

1. **Ahn, M. J., Chen, Y. C. (2022).** Digital transformation toward AI-augmented public administration: the perception of government employees and the willingness to use AI in government. Government Information Quarterly, 39(2), 101664. doi: 10.1016/j.giq.2021.101664
2. **Al-Besher, A., Kumar, K. (2022).** Use of artificial intelligence to enhance e-government services. Measurement: Sensors, 24, 100484. doi: 10.1016/j.measen.2022.100484
3. **Alita, L. (2025).** Enhancing citizen engagement in urban greening: the potential of large language models in value co-creation. Technological Forecasting and Social Change, 216, 124134. doi: 10.1016/j.techfore.2025.124134
4. **Androutsopoulou, A., Karacapilidis, N., Loukis, E., Charalabidis, Y. (2019).** Transforming the communication between citizens and government through AI-guided chatbots. Government Information Quarterly, 36(2), 358-367. doi: 10.1016/j.giq.2018.10.001
5. **Arana-Catania, M., Lier, F.-A. V., Procter, R., Tkachenko, N., He, Y., Zubiaga, A., Liakata, M. (2021).** Citizen participation and machine learning for a better democracy. Digital Government: Research and Practice, 2(3), 1-22. doi: 10.1145/3452118
6. **Arslan, M., Mahdjoubi, L., Munawar, S. (2024).** Driving sustainable energy transitions with a multi-source RAG-LLM system. Energy and Buildings, 324, 114827. doi: 10.1016/j.enbuild.2024.114827
7. **Arslan, M., Munawar, S., Cruz, C. (2024).** Business insights using RAG-LLMs: a review and case study. Journal of Decision Systems, 1-30. doi: 10.1080/12460125.2024.2410040
8. **Asquer, A., Krachkovskaya, I. (2022).** Designing public financial management systems: exploring the use of chatbot-assisted case studies. Public Money and Management, 42(7), 551-557. doi: 10.1080/09540962.2022.2069412
9. **Baek, I., Lee, J., Yang, J., Lee, H. (2024).** Crafting the path: robust query rewriting for information retrieval. IEEE Access, 13, 24171-24180. doi: 10.1109/ACCESS.2025.3538665
10. **Bashuk, A., Chechel, O. (2024).** Optimization of management processes in central government bodies through the integration of artificial intelligence. Eastern-European Journal of Enterprise Technologies, 6(13 (132)), 98-105. doi: 10.15587/1729-4061.2024.318018
11. **Biercewicz, K., Fernando, K. S. D., Misiak-Kwit, S., Wiscicka-Fernando, M. (2024).** Experiences of residents in using smart city technologies. Procedia Computer Science, 246, 5074-5083. doi: 10.1016/j.procs.2024.09.592
12. **Busch, P. A. (2025).** The artificial bureaucrat: artificial intelligence in street-level work. Digital Government: Research and Practice. doi: 10.1145/3721138
13. **Chiu, W. A., Newman, G., Sansom, G., Ye, X., Rusyn, A., Wu, H., Winckelman, T., Rusyn, I. (2025).** MyEcoReporter: a prototype for artificial intelligence-facilitated pollution reporting. Journal of Exposure Science and Environmental Epidemiology. doi: 10.1038/s41370-025-00747-5

14. **Chou, Y.-H., Lin, C., Lee, S.-H., Lee, Y.-F., Cheng, L.-C. (2024).** User-friendly chatbot to mitigate the psychological stress of older adults during the COVID-19 pandemic: development and usability study. JMIR Formative Research, 8, e49462. doi: 10.2196/49462
15. **Cortés-Cediel, M. E., Segura-Tinoco, A., Cantador, I., Rodríguez Bolívar, M. P. (2023).** Trends and challenges of e-government chatbots: advances in exploring open government data and citizen participation content. Government Information Quarterly, 40(4), 101877. doi: 10.1016/j.giq.2023.101877
16. **David, A., Yigitcanlar, T., Desouza, K., Li, R. Y. M., Cheong, P. H., Mehmood, R., Corchado, J. (2024).** Understanding local government responsible AI strategy: an international municipal policy document analysis. Cities, 155, 105502. doi: 10.1016/j.cities.2024.105502
17. **De Nicola, A., Formica, A., Mele, I., Missikoff, M., Taglino, F. (2024).** A comparative study of LLMs and NLP approaches for supporting business process analysis. Enterprise Information Systems, 18(10). doi: 10.1080/17517575.2024.2415578
18. **Fischer-Abaigar, U., Kern, C., Barda, N., Kreuter, F. (2023).** Bridging the gap: towards an expanded toolkit for ML-supported decision-making in the public sector. Government Information Quarterly, 41(4), 101976. doi: 10.1016/j.giq.2024.101976
19. **Formosa, P., Kashyap, B., Sahebi, S. (2025).** Generative AI and the future of democratic citizenship. Digital Government: Research and Practice, 6(2), Article 31. doi: 10.1145/3674844
20. **Følstad, A., Bjerkreim-Hanssen, N. (2023).** User interactions with a municipality chatbot-lessons learnt from dialogue analysis. International Journal of Human-Computer Interaction, 40(18), 4973-4986. doi: 10.1080/10447318.2023.2238355
21. **Gao, T., Wang, G. (2024).** Integrating IoT and visual question answering in smart cities: enhancing educational outcomes. Alexandria Engineering Journal, 108, 878-888. doi: 10.1016/j.aej.2024.09.059
22. **Gesk, T. S., Leyer, M. (2022).** Artificial intelligence in public services: when and why citizens accept its usage. Government Information Quarterly, 39(3), 101704. doi: 10.1016/j.giq.2022.101704
23. **Giménez Manuel, J. G., Giner Pérez de Lucia, J., Celdrán Bernabeu, M. A., Mazón López, J. N., Cano Escribá, J. C., Cecilia Canales, J. M. (2024).** Advancing smart tourism destinations: a case study using bidirectional encoder representations from transformers-based occupancy predictions in torrevieja (Spain). IET Smart Cities, 6(4), 422-440. doi: 10.1049/smc2.12085
24. **Guo, Z., Cugurullo, F. (2025).** Smart urbanism through artificial intelligence (AI)-megaprojects: the case of China's healthcare services. Public Administration and Development, 1-17. doi: 10.1002/pad.2111
25. **Haesevoets, T., Verschuere, B., Van Severen, R., Roets, A. (2024).** How do citizens perceive the use of artificial intelligence in public sector decisions? Government Information Quarterly, 41(1), 101906. doi: 10.1016/j.giq.2023.101906
26. **Han, T., Cong, R. G., Yu, B., Tang, B., Wei, Y. M. (2024).** Integrating local knowledge with ChatGPT-like large-scale language models for enhanced societal comprehension of carbon neutrality. Energy and AI, 18, 100440. doi: 10.1016/j.egyai.2024.100440
27. **Hatami, A., Jeloudarlou, S. N., Asadzadeh, H. (2025).** Empowering smart cities: unlocking citizen participation through AI-driven personalization and perceived value. Sustainable Futures, 9, 100664. doi: 10.1016/j.sftr.2025.100664
28. **Heinisuo, E., Kuoppakangas, P., Stenvall, J. (2025).** Navigating AI implementation in local government: addressing dilemmas by fostering mutuality and meaningfulness. Information Systems Frontiers. doi: 10.1007/s10796-025-10599-x
29. **Hemesath, S., Tepe, M. (2024).** Public value positions and design preferences toward AI-based chatbots in e-government. Evidence from a conjoint experiment with citizens and municipal front desk officers. Government

Information Quarterly, 41(4), 101985. doi: 10.1016/j.giq.2024.101985

30. **Horvath, L., James, O., Banducci, S., Beduschi, A. (2023).** Citizens' acceptance of artificial intelligence in public services: evidence from a conjoint experiment about processing permit applications. Government Information Quarterly, 40(4), 101876. doi: 10.1016/j.giq.2023.101876
31. **Huang, A. H., Wang, H., Yang, Y. (2023).** FinBERT: a large language model for extracting information from financial text. Contemporary Accounting Research, 40(2), 806-841. doi: 10.1111/1911-3846.12832
32. **Husain, H., Afandi, R., Sensuse, D. I., Lusa, S., Safitri, N., Elisabeth, D. (2024).** Designing a knowledge-based chatbot to elevate business licensing services in Indonesia. Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi), 8(5), 681-689. doi: 10.29207/resti.v8i5.6069
33. **Jackson-Triche, M., Vetal, D., Turner, E.-M., Dahiya, P., Mangurian, C. (2023).** Meeting the behavioral health needs of health care workers during COVID-19 by leveraging chatbot technology: development and usability study. Journal of Medical Internet Research, 25, e40635. doi: 10.2196/40635
34. **Ju, J., Meng, Q., Sun, F., Liu, L., Singh, S. (2023).** Citizen preferences and government chatbot social characteristics: evidence from a discrete choice experiment. Government Information Quarterly, 40(3), 101785. doi: 10.1016/j.giq.2022.101785
35. **Kalyuzhnaya, A., Mityagin, S., Lutsenko, E., Getmanov, A., Aksenkin, Y., Fatkhiev, K., Fedorin, K., Nikitin, N. O., Chichkova, N., Vorona, V., Boukhanovsky, A. (2025).** LLM agents for smart city management: enhancing decision support through multi-agent AI systems. Smart Cities, 8(1), 19. doi: 10.3390/smartcities8010019
36. **Kano, E., Tsuda, K. (2024).** Extracting skills for promoting local government digital transformation (DX) using text generative AI. Procedia Computer Science, 246, 463-472. doi: 10.1016/j.procs.2024.09.426
37. **Kharitonova, K., Pérez-Fernández, D., Gutiérrez-Hernando, J., Gutiérrez-Fandiño, A., Callejas, Z., Griol, D. (2024).** Incorporating evidence into mental health Q&A: a novel method to use generative language models for validated clinical content extraction. Behaviour and Information Technology, 3001, 1-18. doi: 10.1080/0144929X.2024.2321959
38. **Kim, Y., Hwang, Y., Bae, H., Kang, T., Jung, K. (2024).** Flowlogue: a novel framework for synthetic dialogue generation with structured flow from text passages. IEEE Access, 12, 151920-151929. doi: 10.1109/ACCESS.2024.3409377
39. **Kiuchi, K., Otsu, K., Hayashi, Y. (2023).** Psychological insights into the research and practice of embodied conversational agents, chatbots and social assistive robots: a systematic meta-review. Behaviour and Information Technology, 43(15), 3696-3736. doi: 10.1080/0144929X.2023.2286528
40. **Kleiman, F., Barbosa, M. M. (2024).** Management and performance program chatbot: a use case of large language model in the federal public sector in Brazil. Digital Government: Research and Practice. doi: 10.1145/3700141
41. **Kruhlov, V., Bobos, O., Hnylianska, O., Rossikhin, V., Kolomiiets, Y. (2024).** The role of using artificial intelligence for improving the public service provision and fraud prevention. Pakistan Journal of Criminology, 16(2), 913-928. doi: 10.62271/pjc.16.2.913.928
42. **Kulal, A., Rahiman, H. U., Suvarna, H., Abhishek, N., Dinesh, S. (2024).** Enhancing public service delivery efficiency: exploring the impact of AI. Journal of Open Innovation: Technology, Market, and Complexity, 10(3), 100329. doi: 10.1016/j.joitmc.2024.100329
43. **Langgeng, Y. S. H. (2023).** Long short-term memory-based chatbot for vocational registration information services. Journal of Applied Data Sciences, 4(4), 414-430. doi: 10.47738/jads.v4i4.128
44. **Larsen, A. G., Følstad, A. (2024).** The impact of chatbots on public service provision: a

qualitative interview study with citizens and public service providers. Government Information Quarterly, 41(2), 101927. doi: 10.1016/j.giq.2024.101927

45. **Li, X., Wang, J. (2024).** Should government chatbots behave like civil servants? The effect of chatbot identity characteristics on citizen experience. Government Information Quarterly, 41(3), 101957. doi: 10.1016/j.giq.2024.101957

46. **Li, Z., Ning, H. (2023).** Autonomous GIS: the next-generation AI-powered GIS. International Journal of Digital Earth, 16(2), 4668-4686. doi: 10.1080/17538947.2023.2278895

47. **Makasi, T., Nili, A., Desouza, K. C., Tate, M. (2022).** A typology of chatbots in public service delivery. IEEE Software, 39(3), 58-66. doi: 10.1109/MS.2021.3073674

48. **Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., Gupta, M., Niehaves, B. (2022).** Enabling AI capabilities in government agencies: a study of determinants for European municipalities. Government Information Quarterly, 39(4), 101596. doi: 10.1016/j.giq.2021.101596

49. **Monteiro, M. de S., Batista, G. O. da S., Salgado, L. C. de C. (2023).** Investigating usability pitfalls in Brazilian and Foreign governmental chatbots. Journal on Interactive Systems, 14(1), 331-340. doi: 10.5753/jis.2023.3104

50. **Nagitta, P. O., Mugurusi, G., Obicci, P. A., Awuor, E. (2022).** Human-centered artificial intelligence for the public sector: the gate keeping role of the public procurement professional. Procedia Computer Science, 200, 1084-1092. doi: 10.1016/j.procs.2022.01.308

51. **Nasar, W., Gundersen, O. E., da Silva Torres, R., Karlsen, A. (2024).** Knowledge graphs to accumulate and convey knowledge from past experiences in search and rescue planning and resource allocation. Applied Artificial Intelligence, 38(1). doi: 10.1080/08839514.2024.2434296

52. **Popescu, R.-I., Sabie, O. M., Trușcă, M. I. (2023).** The contribution of artificial intelligence to stimulating the innovation of educational services and university programs in public administration. Transylvanian Review of Administrative Sciences, 2023(70 E), 85-108. doi: 10.24193/tras.70E.5

53. **Papageorgiou, G., Sarlis, V., Maragoudakis, M., Tjortjis, C. (2025).** A multimodal framework embedding retrieval-augmented generation with MLLMs for Eurobarometer data. AI, 6(3), 50. doi: 10.3390/ai6030050

54. **Papageorgiou, G., Sarlis, V., Maragoudakis, M., Tjortjis, C. (2024).** Enhancing E-Government services through state-of-the-art, modular, and reproducible architecture over large language models. Applied Sciences, 14(18), 8259. doi: 10.3390/app14188259

55. **Pereira, J., Assumpcao, A., Trecenti, J., Airosa, L., Lente, C., Cléto, J., Dobins, G., Nogueira, R., Mitchell, L., Lotufo, R. (2025).** INACIA: integrating large language models in Brazilian audit courts: opportunities and challenges. Digital Government: Research and Practice, 6(1), 1-20. doi: 10.1145/3652951

56. **Piizzi, A., Vavallo, D., Lazzo, G., Dimola, S., Zazzera, E. (2024).** A natural language processing model for the development of an Italian-language chatbot for public administration. International Journal of Advanced Computer Science and Applications, 15(9), 54-58. doi: 10.14569/IJACSA.2024.0150906

57. **Pini, B., Dolci, V., Gianatti, E., Petroni, A., Bigliardi, B., Barani, A. (2025).** Artificial intelligence as a facilitator for public administration procedures: a literature review. Procedia Computer Science, 253, 2537-2546. doi: 10.1016/j.procs.2025.01.313

58. **Pislaru, M., Vlad, C. S., Ivascu, L., Mircea, I. I. (2024).** Citizen-centric governance: enhancing citizen engagement through artificial intelligence tools. Sustainability, 16(7), 2686. doi: 10.3390/su16072686

59. **Relvas, H., Lopes, D., Armengol, J. M. (2025).** Empowering communities: advancements in air quality monitoring and citizen engagement. Urban Climate, 60, 102344. doi: 10.1016/J.UCLIM.2025.102344

60. **Rivadeneira, L., Bellido de Luna, D., Fernandez, C. (2024).** Exploring the role of ChatGPT in higher education institutions: where does Latin America stand? Digital Government: Research and Practice. doi: 10.1145/3689370

61. **Sandoval-Almazan, R., Millan-Vargas, A. O., Garcia-Contreras, R. (2024).** Examining public managers' competencies of artificial intelligence implementation in local government: a quantitative study. Government Information Quarterly, 41(4), 101986. doi: 10.1016/j.giq.2024.101986

62. **Saker, M., Mercea, D., Myers, C.-A. (2024).** "Wayfearing" and the city: exploring how experiential fear of crime frames the mobilities of women students at a city-based university using a bespoke chatbot app. Mobile Media & Communication, 12(1), 131-151. doi: 10.1177/20501579231203556

63. **Shan, Y., Ji, M., Xie, W., Zhang, X., Qian, X., Li, R., Hao, T. (2022).** Use of health care chatbots among young people in China during the Omicron wave of COVID-19: evaluation of the user experience of and satisfaction with the technology. JMIR Human Factors, 9(2), e36831. doi: 10.2196/36831

64. **Sievers, T., Russwinkel, N. (2024).** Project report: requirements for a social robot as an information provider in the public sector. KI - Kunstliche Intelligenz, 38(3), 145-149. doi: 10.1007/s13218-024-00840-1

65. **Sprenkamp, K., Eckhardt, S., Zavolokina, L., Schwabe, G. (2025).** From information-seeking to information-asking: designing RefuGPT, a chatbot for Ukrainian refugees in Switzerland. Digital Government: Research and Practice. doi: 10.1145/3735140

66. **Torkamaan, H., Steinert, S., Pera, M. S., Kudina, O., Freire, S. K., Verma, H., Kelly, S., Sekwenz, M. T., Yang, J., van Nunen, K., Warnier, M., Brazier, F., Oviedo-Trespalacios, O. (2024).** Challenges and future directions for integration of large language models into socio-technical systems. Behaviour and Information Technology, 3001, 1-20. doi: 10.1080/0144929X.2024.2431068

67. **Tuan, N. T., Moore, P., Thanh, D. H. V., Pham, H. V. (2024).** A generative artificial intelligence using multilingual large language models for ChatGPT applications. Applied Sciences, 14(7), 3036. doi: 10.3390/app14073036

68. **Urbanelli, A., Frisiello, A., Bruno, L., Rossi, C. (2024).** The ERMES chatbot: a conversational communication tool for improved emergency management and disaster risk reduction. International Journal of Disaster Risk Reduction, 112, 104792. doi: 10.1016/j.ijdrr.2024.104792

69. **Vassilakopoulou, P., Haug, A., Salvesen, L. M., Pappas, I. O. (2023).** Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government. European Journal of Information Systems, 32(1), 10-22. doi: 10.1080/0960085X.2022.2096490

70. **Virnandes, S. R., Shen, J., Vlahu-Gjorgievska, E. (2025).** Demystifying the relationship between digitalization of government services and public trust: a scoping review. Digital Government: Research and Practice. doi: 10.1145/3716172

71. **Wahidur, R. S. M., Kim, S., Choi, H., Bhatti, D. S., Lee, H.-N. (2025).** Legal Query RAG. IEEE Access, 13, 36978-36994. doi: 10.1109/ACCESS.2025.3542125

72. **Wang, S., Min, C., Liang, Z., Zhang, Y., Gao, Q. (2024).** The decision-making by citizens: evaluating the effects of rule-driven and learning-driven automated responders on citizen-initiated contact. Computers in Human Behavior, 161, 108413. doi: 10.1016/j.chb.2024.108413

73. **Wang, S., Li, R., Wu, H., Li, J., Shen, Y. (2025).** Fine-grained flood disaster information extraction incorporating multiple semantic features. International Journal of Digital Earth, 18(1), 1-32. doi: 10.1080/17538947.2024.2448221

74. **Wang, Y., Lian, D., Chen, E. (2024).** Event assignment based on KBQA for government service hotlines. Applied Artificial Intelligence, 38(1). doi: 10.1080/08839514.2024.2348162

75. **Yigitcanlar, T., Li, R. Y. M., Beeramoole, P. B., Paz, A. (2023).** Artificial intelligence in local government services: public perceptions from Australia and Hong Kong. Government Information Quarterly, 40(3), 101833. doi: 10.1016/j.giq.2023.101833
76. **Yun, L., Yun, S., Xue, H. (2024).** Improving citizen-government interactions with generative artificial intelligence: novel human-computer interaction strategies for policy understanding through large language models. PLoS ONE, 19(12), 1-18. doi: 10.1371/journal.pone.0311410
77. **Zaidani, H., Koulali, R., Maizate, A., Ouzzif, M. (2025).** Augmentation and classification of requests in Moroccan dialect to improve quality of public service: a comparative study of algorithms. Future Internet, 17(4), 176. doi: 10.3390/fi17040176
78. **Zhang, X., Lu, F. (2025).** Enhancing public health policy communication through government-citizen social media interactions: the impact of replying agents, inquiry tone, and institutional trust. Policy & Internet, 17(1). doi: 10.1002/poi3.70000
79. **van Noordt, C., Misuraca, G. (2022).** Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union. Government Information Quarterly, 39(3), 101714. doi: 10.1016/j.giq.2022.101714
80. **van Veggel, E., Liebrecht, C., Kamoen, N. (2025).** How life-like digital humans in voting advice applications can stimulate young voters to inform themselves about politics: the role of familiarity and expertise. International Journal of Human-Computer Interaction, 0(0), 1-15. doi: 10.1080/10447318.2025.2465859
81. **Kitchenham, B., Charters, S. (2007).** Guidelines for performing systematic literature reviews in software engineering. EBSE Technical Report, Version 2.3. Keele University and Durham University Joint Report. doi: 10.13140/2.1.1227.2086
82. **Alaeddini, M., Hajizadeh, M., Reaidy, P. (2023).** A bibliometric analysis of research on the convergence of artificial intelligence and blockchain in smart cities. Smart Cities, 6(2), 764-795. doi: 10.3390/smartcities6020037
83. **Gamboa-Cruzado, J., Carbajal-Jiménez, P., Romero-Villón, M., Mujica Ruiz, O. H., Coveñas Lalupú, J., Campos Miranda, M. (2022).** Chatbots for customer service: a comprehensive systematic literature review. Journal of Theoretical and Applied Information Technology, 100(19), 5587-5597.
84. **Alsabt, R., Adenle, Y. A., Alshuwaikhat, H. M. (2024).** Exploring the roles, future impacts, and strategic integration of artificial intelligence in the optimization of smart city-from systematic literature review to conceptual model. Sustainability, 16(8), 3389. doi: 10.3390/su16083389
85. **Babšek, M., Ravšelj, D., Umek, L., Aristovnik, A. (2025).** Artificial intelligence adoption in public administration: an overview of top-cited articles and practical applications. AI, 6(3), 44. doi: 10.3390/ai6030044
86. **Bibri, S. E., Huang, J., Jagatheesaperumal, S. K., Krogstie, J. (2024).** The synergistic interplay of artificial intelligence and digital twin in environmentally planning sustainable smart cities: a comprehensive systematic review. Environmental Science and Ecotechnology, 20, 100433. doi: 10.1016/j.ese.2024.100433
87. **Andrade-Mogollon, T., Gamboa-Cruzado, J., Amayo-Gamboa, F. (2025).** Systematic literature review of generative AI and IoT as key technologies for precision agriculture. Computación y Sistemas, 29(2), 857–882. https://doi.org/10.13053/CyS-29-2-5738
88. **Henk, A., Henk, O. (2025).** From antecedents to outcomes: a structured literature review on AI implementation in public sector organizations. Hawaii International Conference on System Sciences. doi: 10.24251/HICSS.2025.228
89. **Jiang, Y., Pang, P. C.-I., Wong, D., Kan, H. Y. (2023).** Natural language processing adoption in governments and future research directions: a systematic review. Applied Sciences, 13(22), 12346. doi: 10.3390/app132212346
90. **Lubis, S., Nurmandi, A., Ahmad, J., Purnomo, E. P., Purwaningsih, T., Jovita-Olvez, H. D. (2025).** Synergizing AI and

blockchain: a bibliometric analysis of their potential for transforming e-governance in smart cities. Frontiers in Sustainable Cities, 7, 1553816. doi: 10.3389/frsc.2025.1553816

91. **Madan, R., Ashok, M. (2023).** AI adoption and diffusion in public administration: a systematic literature review and future research agenda. Government Information Quarterly, 40(1), 101774. doi: 10.1016/j.giq.2022.101774
92. **Albites-Tapia, A., Gamboa-Cruzado, J., Almeyda-Otiz, J., Moreno-Lázaro, A. (2022).** Chatbots for the detection of Covid-19: a systematic review of the literature. International Journal of Advanced Computer Science and Applications, 13(4), 1-8. doi: 10.14569/IJACSA.2022.01304113
93. **Senadheera, S., Yigitcanlar, T., Desouza, K. C., Mossberger, K., Corchado, J., Mehmood, R., Li, R. Y. M., Cheong, P. H. (2024).** Understanding chatbot adoption in local governments: a review and framework. Journal of Urban Technology, 1-35. doi: 10.1080/10630732.2023.2297665
94. **Gomes de Sousa, W., Pereira de Melo, E. R., De Souza Bermejo, P. H., Sousa Farias, R. A., Oliveira Gomes, A. (2019).** How and where is artificial intelligence in the public sector going? A literature review and research agenda. Government Information Quarterly, 36(4), 101392. doi: 10.1016/j.giq.2019.07.004
95. **Szpilko, D., Naharro, F. J., Lăzăroiu, G., Nica, E., Gallegos, A. D. L. T. (2023).** Artificial intelligence in the smart city-a literature review. Engineering Management in Production and Services, 15(4), 53-75. doi: 10.2478/emj-2023-0028
96. **Wolniak, R., Stecuła, K. (2024).** Artificial intelligence in smart cities-applications, barriers, and future directions: a review. Smart Cities, 7(3), 1346-1389. doi: 10.3390/smartcities7030057
97. **Zuiderwijk, A., Chen, Y.-C., Salem, F. (2021).** Implications of the use of artificial intelligence in public governance: a systematic literature review and a research agenda. Government Information Quarterly, 38(3), 101577. doi: 10.1016/j.giq.2021.101577
98. **Al-Ansi, A. M., Garad, A., Jaboob, M., Al-Ansi, A. (2024).** Elevating e-government: unleashing the power of AI and IoT for enhanced public services. Heliyon, 10(23), e40591. doi: 10.1016/j.heliyon.2024.e40591
99. **Gamboa-Cruzado, J., Menendez-Morales, C., Del Carpio, C. F., López-Goycochea, J., Alva Arévalo, A., Ríos Vargas, C. (2023).** Use of chatbots in e-commerce: a comprehensive systematic review. Journal of Theoretical and Applied Information Technology, 101(4), 1172-1183.
100. **De Jesús Camacho, J., Aguirre, B., Ponce, P., Anthony, B., Molina, A. (2024).** Leveraging artificial intelligence to bolster the energy sector in smart cities: a literature review. Energies, 17(2), 353. doi: 10.3390/en17020353

Article received on 15/04/2025; accepted on 23/07/2025.
**Corresponding author is Blanca Cecilia López-Ramírez.*