Factors Influencing Generative AI-Enabled e-Government Services (GAIGS) Information Quality: A Systematic Literature Review

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***Abstract*—The integration of Generative Artificial Intelligence (GAI) into electronic government (e-Government) services has transformed the delivery of public information, raising critical questions about the quality of AI-generated content. This study presents a systematic literature review (SLR) to identify and categorise the key factors influencing information quality in GAI-enabled e-Government Services (GAIGS). Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and using the Population, Interest, and Context (PICo) framework, the review screened 664 articles from major databases, including Web of Science (WoS), Scopus, IEEE Xplore, and Wiley Online Library. A total of 33 high-quality studies published between 2021 and 2025 were selected for thematic analysis. The findings reveal 22 distinct information quality factors, which were synthesised into five overarching themes: trustworthiness and verifiability, security and ethics, content quality and structure, user perception and value, and adaptability and system behaviour. The themes indicate a holistic model that encompasses the multidimensional nature of issues and needs of measuring the quality of information in the AI-mediated delivery of public services. The research adds value to the scholarly knowledge of information quality in the changing digital governance environments. It offers workable lessons to policymakers and developers who want to design credible and citizen-centred GAI applications. This review provides a systematic overview of the existing body of knowledge, which can guide future research and model development in the context of GAIGS.**

Keywords*—Generative AI; e-government services; information quality; PRISMA; PICo

I. Introduction

The growing use of Generative Artificial Intelligence (GAI) in electronic government services is shifting the paradigm of how state information is created, shared, and used. Worldwide, governments are using Generative AI to enhance services and citizen engagement by streamlining administrative tasks through the use of intelligent chat interfaces, automated content generators, and large language models [1]. Such innovations open the possibilities of fast feedback, individualised information flow, and scalable digital communications [2]. Nevertheless, the transition to GAI-created information comes with severe issues regarding the quality of generated information [3]. The issue of information quality in the public sector cannot be reduced to a technical issue but is a part of efficient governance. The government-issued information guides the citizens to make sound decisions on healthcare, taxation, education, and legal issues. It is therefore imperative that the accuracy, completeness, relevance, and credibility of GAI-generated content are ensured to uphold public trust, reliability of service, and matters of policy are adhered to [4]. For this review, the authors operationalise information quality in the context of GAIGS as the degree to which AI-generated outputs are accurate, complete, timely, credible, transparent, and contextually appropriate for use in public service delivery. Drawing from the reviewed literature, this study further identifies that GAI introduces distinct quality challenges, including hallucination, algorithmic opacity, and dynamic content variability, that are absent from conventional manually curated or static e-government systems, and which existing frameworks do not fully address.

Though the concept of information quality has long been in the focus of the information systems community, most of the existing literature was formulated in a setting that does not include GAI-generated content [5]. Such previous frameworks were mostly created to fit into scenarios, like structured databases, static websites, or enterprise systems, including early e-Government offerings, where data was manually curated and the quality of information upheld by administrative procedures, organisational policies, and subjective human judgement rather than by dynamic user-generated or AI-mediated processes [6], [7]. Consequently, they lack the conceptual tools to address newer concerns such as misinformation, bias, hallucination, or explainability, which are central to GAI systems. Furthermore, many prior reviews were conducted using narrative approaches that lack methodological rigour and reproducibility [8]. To address this limitation, the present study is based on the systematic literature review approach, which provides a transparent, replicable process that can be used to identify, appraise, and synthesise evidence. To address these gaps, the review is structured around two guiding research questions, as

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presented in Table I (Section III-B). These questions were developed to examine the factors influencing information quality in the context of Generative AI-enabled e-government services (GAIGS).

Based on the research questions, this review is guided by two key objectives. The first objective is to identify and synthesise the factors that influence information quality in GAIGS, grounded in a comprehensive review of existing academic literature. The second objective is to develop thematic categories of these identified factors through qualitative analysis, thereby enhancing conceptual clarity and guiding future investigations within the context of GAI-supported electronic government services.

This study makes several significant contributions. From an academic perspective, it advances theoretical insights by revisiting information quality factors in light of the emerging capabilities and constraints of Generative AI. For policymakers, it highlights critical information quality indicators that can strengthen transparency, accountability, and public trust in digital service delivery. For practitioners, including system developers and government administrators, the findings offer practical guidance for assessing and improving information quality in GAI-supported service environments. Ultimately, this review addresses the urgent need to ensure that as eGovernment systems continue to evolve through the adoption of Generative AI, the quality of information they generate remains accurate, trustworthy, and aligned with the expectations of citizens and public institutions.

II. Literature Review

Electronic government (e-Government or e-G) has transformed the operations of the government and redefined the delivery, access, and experience of the public services. E-Government can be defined as the use of digital technologies, especially Internet-based systems, in the organisation of administrative activities, the provision of public services and interaction of governmental units with their stakeholders [9]. Transactional and informational services provided by means of such platforms are called e-government services. Such services are presented in certain areas like Government-to-Citizen (G2C), Government-to-Government (G2G), and Government-to-Business (G2B), which are marked with different user needs, expectations, and complexities of interaction with the service [10], [11].

The advent of Generative Artificial Intelligence (GAI) in the digital landscape of the public sector sets new demands and requirements in terms of information quality that is being generated. The traditional information quality characteristics, accuracy, completeness, relevance, timeliness, and credibility, are still fundamental, but their use in GAI-enabled services requires them to be reevaluated carefully [12], [13]. Empirical studies have established that generative models can generate results that seem to be coherent yet inaccurate or misleading in substance [14]. In addition, the completeness of information may be hampered when generative reactions do not have contextual richness or local detail in the multilingual or high-complexity contexts [15], [16].

The speed at which GAI is implemented in e-Government service platforms has raised vital issues over the quality of information being supplied to the citizens, businesses, and government agencies, as identified by Straub et al. [17]. Although traditional sources of information quality remain relevant as assessment standards, their relevance to GAI-enhanced services has been increasingly questioned [18]-[20]. Zhang and Gosline [21] indicate that in many instances, the language models generate outputs with a semblance of coherence but lack truth and accuracy, a phenomenon commonly referred to as hallucination, which severely compromises the confidence and reliability of users and systems. This issue is additionally supported by the results of Temsah et al. [22] and Sun et al. [23], who state that the content created by GAI does not always comply with the requirements of factual correctness. Moreover, the generative processes of such systems can be opaque and thus yield output that is not in the context, culturally appropriate, or policy-congruent. Such a problem is especially prevalent in multilingual and diverse sociotechnical government settings, according to Banerjee et al. [24], Torkamaan et al. [25], and Huang et al. [26]. According to Zhao et al. [27], this misalignment may lead to disengagement or even misuse of public services. In a similar vein, Hutahaean et al. [28] and Esposito and Tse [29] state that these gaps can negatively affect the service quality, legality, and citizen confidence. These risks demonstrate the necessity to find certain criteria that can differentiate high-quality information in the framework of GAI-generated content in e-government services.

Previous studies underline the necessity to shift the traditional definition of information quality and focus on those factors that represent the essence of generative outputs [18], [30], [31]. Drawing on the evidence synthesised in this review, the authors observe that foundational information quality frameworks developed for structured, human-managed data environments do not adequately account for the generative, probabilistic nature of AI-produced content. Specifically, dimensions such as hallucination susceptibility, bias amplification, and explainability are not captured by conventional quality models, highlighting the need to extend the theoretical landscape to accommodate the unique characteristics of GAIGS. Nevertheless, the recognition and confirmation of such factors lack consistent results in what has already been done, particularly in the implementation of the factors in the public sector [32]-[36]. This ambiguity and non-standardisation make it difficult to implement systematic evaluation or enhancement of the quality of the information produced by GAI in e-Government services. On the user side, information quality is one of the main predictors of satisfaction, behavioural intention, and future use of digital services [37], [38]. As soon as users believe that GAI-created content is truthful, understandable, and useful, their trust in working with the system rises considerably [33], [39]-[41]. On the other hand, low-quality or unclear content will build distrust and undermine the bond between citizens and digital government services.

Efforts to create GAI applications that are accountable and trusted by the citizens are not coherent without a firm base of clearly laid out information quality aspects. In addition, Chen and Wen [42], Afroogh et al. [43], and Zhu [44] pointed out that the tendency to evaluate the quality of information in e-government supported by GAI is a complex task that reveals the urgency of determining the features appropriate in this changing environment. Quality information is also important in promoting initial satisfaction through delivering information of quality that users expect in terms of clarity, relevance, and reliability [45], [46]. Once the users are satisfied, they tend to have a positive behavioural intention towards using the service. Such intent is not only before actual usage but also enhances chances of making further usage in the future, as Prasetya et al. [47] elaborate. In GAI-supported platforms, Al-Haddad et al. [48] found that the behavioural intention is dependent not only on the technical accuracy of the information, but also on the capability of the user to interpret and contextualise the information. Such a systematic literature review is thus required to summarise the existing body of knowledge, find regularities, and suggest a consistent set of information quality indicators that could be used to effectively exploit GAI in e-Government environments. Taken together, the extant literature demonstrates a developing and divided knowledge on the quality of information in GAI-based e-Government services [49]. This gap is crucial to fill in order to advance the theoretical insights as well as the practical application of high-quality, reliable GAI-enabled public services.

III. Methodology

The study involved a systematic literature review methodology to determine, appraise, and summarise extant research regarding the determinants of the quality of information in GAIGS. This methodology was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines that have been developed by Moher et al. [50] and offer a standardised structure that guarantees methodological rigour, transparency, and replicability of a review. The process of selecting articles was recorded by the PRISMA 2009 flow diagram (see Fig. 1), which graphically shows the steps of identification, screening, eligibility, and inclusion.

The process was also divided into seven key phases, as suggested by Shaffril et al. [51], including the development of review protocols, the development of research questions, systematic searching tactics, quality evaluation, data extraction, data synthesis, and data demonstration. Other sources used in informing the methodology are Kitchenham and Charters [52], Petticrew and Roberts [53], and Hong et al. [54], which provide practical advice on the screening of articles and quality evaluation in non-health research studies.

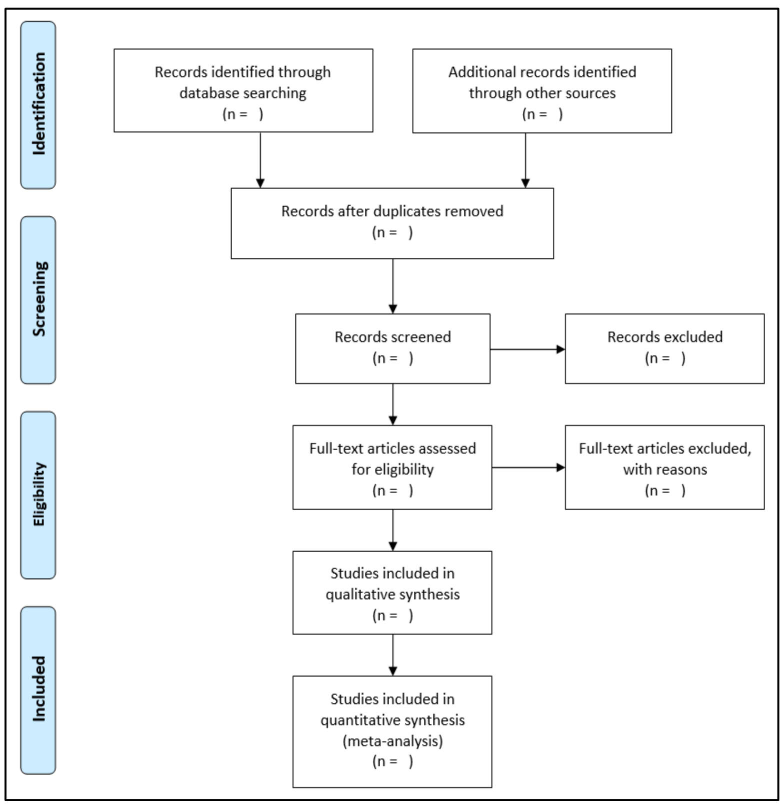

Fig. 1. PRISMA 2009 flow diagram for the systematic review process [50].

A. Review Protocol

As its main guideline during the systematic review process, the PRISMA reporting protocol [50] was also adopted. PRISMA is an established protocol for performing transparent and complete literature reviews in various academic sectors. Since the study is interdisciplinary in nature, additional information was also obtained in the form of software engineering and social science review guidelines to make the study domain relevant.

B. Formulation of Research Questions

This systematic review was developed using the PICo framework of research questions, which are more appropriate in qualitative and exploratory reviews. PICo is an acronym of Population, Interest, and Context, a structured method of formulating clear, targeted, and answerable questions in evidence-based research [55]. Users and stakeholders of GAIGS are referred to as the Population in the study; the Interest is the key factor affecting the quality of information; the Context is the application of Generative AI technologies in e-government service environments. It is also important because PICo will make the objectives of the review clearer and relevant, which will ensure that the synthesised and extracted data answers the main questions that are being explored. Table I presents these research questions that were formulated using the PICo framework.

TABLE. I. RESEARCH QUESTIONS

No.	Question
RQ1	What are the key factors that influence information quality in Generative AI-enabled e-government Services (GAIGS)?
RQ2	How are these factors thematically categorised to reflect the current understanding of information quality in the context of eGovernment services?

C. Systematic Searching Strategies

In order to achieve a thorough and replicable evidence base, a systematic search strategy was used in the various academic databases. The approach was designed to identify peer-reviewed journal articles that address the intersection of information quality, Generative AI technologies, and e-government services. Following established systematic review protocols, the process involved clear stages of identification, screening, eligibility assessment, and quality appraisal, as detailed in the subsequent subsections.

1) Identification: The identification process involved a systematic search across four academic databases: Web of Science (WoS), IEEE Xplore, Scopus, and Wiley Online Library. The reason for selecting these databases was their ability to index a wide list of quality journals in the information systems, artificial intelligence, and technology in the public sector. To ensure comprehensive coverage, core keywords were first established, and related terms were further developed by consulting academic thesauri, domain-specific dictionaries, encyclopaedias, and relevant prior studies. This strategy enabled a thorough representation of key concepts related to information quality, Generative AI, and electronic government services. Boolean operators were applied to combine search terms strategically. The detailed search strings used for each database are presented in Table II. The initial search process yielded a total of 664 articles, comprising 114 from Web of Science, 122 from Scopus, 67 from IEEE Xplore, and 361 from Wiley Online Library.

TABLE. II. THE SEARCH STRINGS

Keywords	**Generative AI, e-Government Services, Information Quality, Factors, and Dimensions**
Database	**Search String**
Web of Science (WoS)	TS=("Information Quality" AND ("Generative AI" OR "Large Language Model*" OR "ChatGPT") AND ("e-Government" OR "electronic government" OR "digital government")) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article) AND PUBLICATION YEARS: (2021 OR 2022 OR 2023 OR 2024 OR 2025)
Scopus	TITLE-ABS-KEY (("Information Quality") AND ("Generative AI" OR "Large Language Model*" OR "ChatGPT") AND ("e-Government" OR "electronic government" OR "digital government")) AND PUBYEAR > 2020 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (SRCTYPE, "j"))
IEEE Xplore	"All Metadata":"Information Quality" AND ("Generative AI" OR "Large Language Model*" OR "ChatGPT") AND ("e-Government" OR "electronic government" OR "digital government") AND Publication Year: 2021–2025 AND Content Type: Journals AND Language: English
Wiley Online Library	(“Information Quality”) AND (“Generative AI” OR “Large Language Model*” OR “ChatGPT”) AND (“e-Government” OR “electronic government” OR “digital government”) AND Publication Date: 2021–2025 AND Publication Type: Journal Article AND Language: English

TABLE. III. THE SELECTION CRITERIA

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2021 – 2025	< 2021
Literature type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press, Early Access

2) Screening: The screening process represents the initial stage of study selection in a systematic review. At this stage, all records retrieved from the database searches were first subjected to duplicate removal, resulting in the exclusion of 24 duplicate articles. The screening process applied predefined inclusion and exclusion criteria, specifically restricting the results to English-language journal articles published between 2021 and 2025, limited to final-stage publications. The detailed screening conditions are summarised in Table III. Following this screening phase, a total of 371 articles were deemed relevant and eligible for further assessment. This ensured that only studies meeting the specified screening criteria were carried forward.

3) Eligibility: After the screening process, the complete texts of the 371 articles that were retrieved were carefully analysed. This step was referred to as the eligibility assessment and sought to confirm that every article was in line with the inclusion criteria identified in the review protocol. The author and co-authors tested the objectives of the study, the context of the investigation, and the existence of the relevant factors, such as the quality of information, in GAIGS. Using this evaluation, 226 articles were eliminated since they did not qualify according to the inclusion criteria. In all, 121 articles were taken to the next phase to be evaluated in terms of quality.

D. Quality Assessment of the Selected Articles

The author and the co-authors independently evaluated the quality of the chosen articles, paying attention to the abstract, methodology, and main findings. In accordance with Petticrew and Roberts [53], each article was qualitatively evaluated and classified into one of three categories: high, moderate, or low quality. Only articles rated as high or moderate were considered eligible for inclusion in the review. To ensure consistency and objectivity in assessment, this study adapted quality evaluation criteria based on the guidelines by Hong et al. [54]. The evaluation focused on five key questions:

For each criterion, the author and co-authors responded using one of three options: Yes, No, or Can't tell. Articles that fulfilled four or more of these criteria were categorised as high quality, while those that met exactly three were considered moderate quality. Articles meeting only one or two criteria were classified as low quality. To maintain the credibility of the findings, only studies rated as high or moderate quality were included in the synthesis process. Out of the 121 articles shortlisted for quality assessment, only those that met the required level of methodological soundness, specifically, those rated 4 or 5, advanced to the synthesis stage. A total of 33 articles satisfied these quality assessment criteria. These studies exhibited adequate rigour and relevance to the investigation of information quality in GAIGS. Articles that did not meet the quality threshold were excluded to ensure the reliability of the synthesis. The distribution of quality scores across all assessed articles is displayed in Fig. 2, which summarises the results of the quality appraisal conducted using a five-point scoring system based on the predefined criteria outlined in Table IV.

E. Data Extraction

Data extraction was conducted systematically using a structured data form. For each article, key details were recorded, including the author's name, year of publication, article title, the type of Generative AI technology used, and the category of e-government services. The extraction was conducted independently by the lead authors, with regular consultation and validation from the co-authors to ensure consistency and accuracy across all entries. For this study, a systematic integrative analysis served as the primary evaluation method, emphasising the synthesis of diverse research approaches, particularly those employing quantitative methods. The primary objective was to identify essential themes and subthemes, starting with the data collection phase, which presents an in-depth analysis of the 33 selected publications related to the study's focus. The subsequent analysis followed a thematic synthesis approach, with themes developed deductively based on pre-identified aspects of information quality and their intersection with Generative AI technologies in electronic government contexts. The research team cooperated in theme formulation, basing it on the evidence that was extracted.

TABLE. IV. QUALITY ASSESSMENT CRITERIA

No	Assessment Criteria
1	Are the main objectives of the article aligned with the investigation of information quality in Generative AI-enabled e-Government Services (GAIGS)?
2	Does the article clearly describe its research design and methodological approach?
3	Are the constructs or factors influencing information quality well-defined and contextually appropriate?
4	Is there sufficient justification for the selection and use of Generative AI technologies within e-Government settings?
5	Does the article provide practical insights or implications that contribute to the development or measurement of information quality in AI-enabled systems?

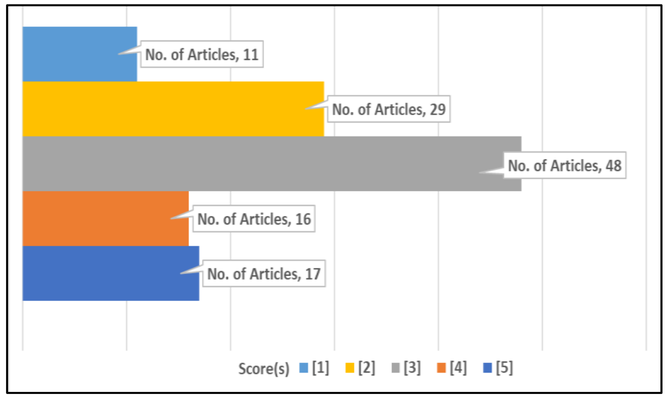

Fig. 2. Quality assessment results.

During the analysis, a reflective log was kept in order to capture different interpretations, difficulties, and emerging thoughts that are crucial in exploring data. All the differences or conceptual inconsistencies that were experienced throughout the process of developing the themes were addressed jointly with an aim of attaining coherence and reliability within the final thematic structure.

The expert review step also helped to improve the thematic framework. The suitability, the relevance, and the clarity of the identified subthemes were confirmed in this stage; therefore, the domain validity was established. Expert feedback was also included in order to improve the structure and make sure that it is consistent with the scope of the review.

F. Thematic Analysis

This study has established 22 important factors that determine the quality of information in GAIGS. This was based on a critical assessment of 33 chosen journal articles, and the results were analysed through thematic analysis on the basis of the six-step method suggested by Dawadi [56]. This method of analysis allowed the critical organisation of the factors into logical and sensible themes, providing a systematic meaning of how the quality of information is handled in the outputs of Generative AI in the context of delivering services to the people. The following is how it works:

In Step 1: Data Familiarisation, the process started with the repetition of the reading and reflecting on the 22 factors and how many times they appear in the 33 reviewed studies. Each factor was considered concerning its definition, role, and usage in the GAIGS context. This action made the research team form a general concept of the factors; hence, early conceptual overlaps and patterns could be identified, which would shape further analysis.

In Step 2: Generating Initial Codes, all the factors were given initial codes according to their conceptual contribution to the quality of information. As an illustration, credibility and reliability, factual correctness, and reference validity were paired with each other, whereas bias, transparency, and security were classified under ethical safeguards. These preliminary codes were the role of each of these factors within the context of AI-generated content within the setting of public service.

In Step 3: Seeking Themes, the first codes were clustered into concept-similar categories, leading to the discovery of five main themes that reflect the key areas of concern with information quality in Generative AI applications. Trustworthiness and verifiability are the first theme and comprise reliability, factual accuracy, reference validity, traceability, verifiability, and authoritativeness. These considerations apply to the reliability and accuracy of GAI-created content and how users can challenge its authenticity, which is especially critical in the case of public services where misinformation may undermine institutional trust. The second theme, security and ethics, is composed of bias, transparency, security, compliance, and detectability. These considerations are an indication of the necessity of responsible system behaviour and ethical measures that safeguard users, foster fairness, and encourage accountability in the provision of AI services. The third theme, content quality and structure, includes such aspects as consistency, timeliness, completeness, interpretability, and granularity, which focus on the necessity of well-organised, clear, and timely content addressed to the informational needs of users. The fourth theme, user perception and value, entails relevance, accessibility, value-added, and uniqueness. These aspects demonstrate the user experiences and assessments of GAI-produced outputs with special reference to the utility, inclusiveness, and novelty of the information presented. Lastly, the fifth theme is adaptability and system behaviour, which encompasses hallucination and interoperability and touches on the ability of GAI systems to work on multiple platforms and act in response to various situations and handle risk arising out of content creation or inconsistency. Collectively, these themes give a complete picture of the landscape of factors that affect information quality in GAIGS.

In Step 4: Reviewing Themes, the research team re-examined every theme to achieve internal consistency and conceptual clarity. The individual factors were evaluated to ensure that they fit the targeted theme. As an example, hallucination was discussed in more than one category but eventually categorised under Adaptability and System Behaviour because of its direct relation to unpredictable GAI outputs. This action made respective themes unique and thematic boundaries clear.

In Step 5: Defining and Naming Themes, the five themes were narrowed down and were clearly named to indicate their focus on analysis. Trustworthiness and verifiability are used to describe the credibility and the reliability of GAI products. Security and ethics consist of measures that maintain fairness, transparency, and data protection. Content quality and structure measure the technical delivery and organisational clarity of the information. User perception and value are aspects of user-centred issues like usefulness and inclusiveness. Adaptability and system behaviour include the capability of the system to change with regard to user context and cross-platform functionality.

In the final step, Step 6: Producing the Report, the five themes identified were integrated into a coherent story that summarises the larger trends within the literature. Collectively, all these themes offer a complete picture of the various interrelated factors that constitute information quality in GAIGS. The thematic framework resulting from this process will serve as a starting point to further formulate the model and provide guidance to practitioners on how to design citizen-centred, effective, and trustworthy AI systems to serve the public sector.

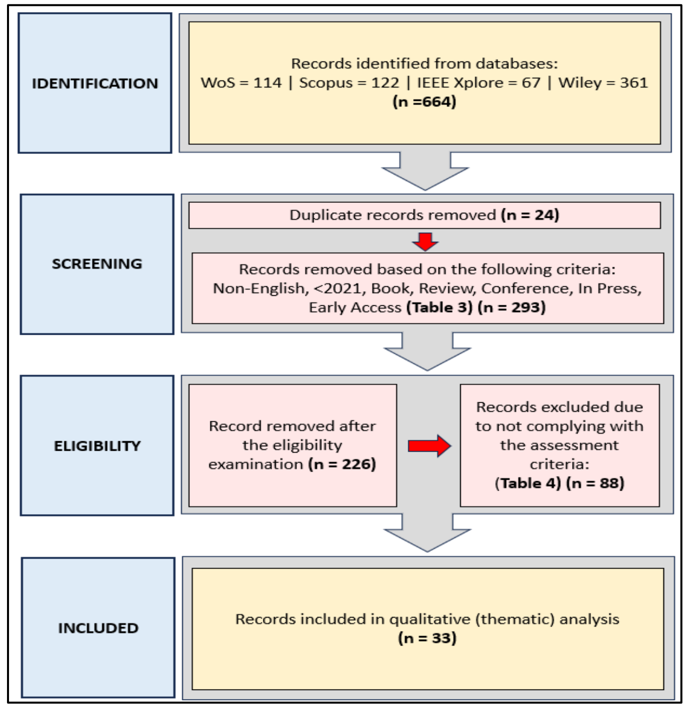

Fig. 3. PRISMA flow diagram applied for this study (adapted from [50]).

G. Data Demonstration

To maintain transparency and facilitate reproducibility, a PRISMA flow diagram was developed to illustrate the article identification, screening, eligibility, and inclusion stages, as depicted in Fig. 3. A supplementary table (Table VI) was also prepared to present the database results, screening outcomes, inclusion criteria, quality evaluation summary, and thematic classification of the 22 information quality factors. These visualisations support the interpretability and clarity of the systematic review, while providing a structured foundation for future empirical validation and model development.

IV. Results and Discussion

This section presents the findings derived from a systematic review and thematic analysis of 33 selected journal articles that focus on information quality in GAIGS. The results are synthesised through two key outputs. Table V provides an overview of the selected articles, detailing the types of Generative AI technologies examined and the corresponding context of e-government services. This table establishes the empirical foundation for the thematic synthesis.

Table VI consolidates the frequency and distribution of the 22 identified information quality factors, accompanied by references to the supporting articles. To provide quantitative grounding for the thematic findings, the frequency with which each factor was cited across the 33 reviewed studies was recorded. Among the 22 identified factors, Timeliness emerged as the most frequently cited (n=10), followed by Reliability (n=8), Interpretability (n=8), Hallucination (n=8), Relevance (n=8), and Consistency (n=8). These high-frequency factors indicate areas of strongest consensus in the literature regarding what constitutes information quality in GAIGS. The authors further observed co-occurrence patterns in which Reliability, Factual Accuracy, and Transparency were repeatedly cited together, reinforcing their conceptual alignment within the Trustworthiness and Verifiability theme. Similarly, Hallucination and Bias were frequently co-cited, reflecting interrelated concerns about GAI output integrity. Together, these tables illustrate the diversity and recurrence of specific information quality concerns across different public sector domains, setting the stage for a deeper thematic exploration of how these factors cluster into broader conceptual themes.

TABLE. V. OVERVIEW OF SELECTED ARTICLES HIGHLIGHTING INFORMATION QUALITY FACTORS, GENERATIVE AI TYPES, AND E-GOVERNMENT SERVICE CONTEXT

References	Title	Type of GAI	e-G Services Context
[57]	Survey of Hallucination in Natural Language Generation	Natural Language Generation (NLG)	Healthcare, Education, Legal
[58]	Exploring the Boundaries of Reality: Investigating the Phenomenon of Artificial Intelligence Hallucination in Scientific Writing Through ChatGPT References	Large Language Models (LLM)	Education
[59]	Hallucinations in ChatGPT: A Cautionary Tale for Biomedical Researchers	Large Language Models (LLM)	Healthcare
[60]	High Rates of Fabricated and Inaccurate References in ChatGPT-Generated Medical Content	Large Language Models (LLM)	Healthcare
[61]	Comparing Scientific Abstracts Generated by ChatGPT to Real Abstracts with Detectors and Blinded Human Reviewers	Large Language Models (LLM)	Healthcare, Education
[62]	Solving Real-Time Information Updates and Mitigating Bias in Generative AI Models	General GAI	Public Information
[63]	Understanding and Addressing AI Hallucinations in Healthcare and Life Sciences	Large Language Models (LLM)	Healthcare
[64]	Bane and Boon of Hallucinations in the Context of Generative AI	General GAI	Public Information
[65]	Assessment of the Bias of Artificial Intelligence Generated Images and Large Language Models on Their Depiction of a Surgeon	Large Language Models (LLM)	Healthcare
[66]	An Analysis of the Accuracy and Bias of a Generative AI Model	General GAI	Public Information
[67]	From Automation to Innovation: Harnessing the Synergy of Generative AI and Retrieval-Augmented Generation for Citizen-Centric Governance	Retrieval-Augmented Generation (RAG) with Large Language Models (RAG-LLM)	Public Information
[68]	Improving citizen-government interactions with generative artificial intelligence: Novel human-computer interaction strategies for policy understanding through large language models	Human-Computer Interaction with Large Language Models (HCI–LLM)	Public Administration
[69]	Comparative Analysis of Generative AI Risks in the Public Sector	General GAI	Public Administration
[70]	Understanding the Interplay Between Trust, Reliability, and Human Factors in the Age of Generative AI	Human Factors and Large Language Models (LLM)	Public Administration
[71]	Tribal Knowledge Cocreation in Generative Artificial Intelligence Systems	Knowledge Co-Creation with Large Language Models (LLM)	Public Administration
[72]	Ethical Challenges and Solutions of Generative AI: An Interdisciplinary Perspective	AI Ethics and Natural Language Processing (NLP)	Public Administration
[73]	Elevating E-Government: Unleashing the Power of AI and IoT for Enhanced Public Services	General GAI	Public Administration
[74]	Beyond Algorithmic Disclosure for Generative AI	General GAI	Legal
[75]	Measuring Service Quality in Generative AI Environments: A Comprehensive GAISQUAL Framework	General GAI	Business, Information Science
[76]	Transparency for AI Systems: A Value-Based Approach	General GAI	Legal, Ethics
[77]	Generative Conversational AI Agent for Managerial Practices: The Role of IQ Dimensions, Novelty Seeking, and Ethical Concerns	Large Language Models (LLM)	Business, Management
[78]	Information Quality Dimensions in Generative Conversational AI for Financial Inclusion	General GAI	Financial Inclusion
[79]	Adoption challenges to artificial intelligence literacy in public healthcare: An evidence-based study in Saudi Arabia	Literacy Adoption and General GAI	Healthcare
[80]	Public opinion and the rise of digital minds: Perceived risk, trust, and regulation support	Governance, Public Trust and General GAI	Public Administration
[81]	Proficiency, Clarity, and Objectivity of Large Language Models Versus Specialists' Knowledge on COVID-19's Impacts in Pregnancy: Cross-Sectional Pilot Study	Large Language Models (LLM)	Healthcare
[82]	AI Can Be a Powerful Social Innovation for Public Health if Community Engagement Is at the Core	Natural Language Processing (NLP)	Public Health
[83]	Era of Generalist Conversational Artificial Intelligence to Support Public Health Communications	Large Language Models (LLM)	Public Health

References	Title	Type of GAI	e-G Services Context
[84]	Generative Artificial Intelligence (ChatGPT & Bard) in Public Administration Research: A Double-Edged Sword for Street-Level Bureaucracy Studies	Large Language Models (LLM)	Public Administration
[85]	Generative AI in Public Administration in Light of the Regulatory Awakening in the US and EU	General GAI	Public Administration
[86]	Unlocking the Power and Future Potential of Generative AI in Government Transformation	General GAI	Public Administration
[87]	Public Service with Generative AI: Exploring Features and Applications	General GAI	Public Administration
[88]	Evaluating public sector employee perceptions towards artificial intelligence and generative artificial intelligence integration	General GAI	Public Administration
[89]	E-Government 3.0: An AI Model to Use for Enhanced Local Democracies	General GAI	Public Administration, Local Governance

TABLE. VI. INFORMATION QUALITY FACTORS IDENTIFIED FROM SELECTED STUDIES

Factor	References
Reliability	[57], [58], [59], [70], [77], [83], [86], [89]
Factual Accuracy	[58]; [60], [62], [65], [68], [80], [82]
Interpretability	[57], [60], [63], [68], [69], [77], [83], [89]
Relevance	[58], [59], [61], [65], [66], [70], [74], [82]
Timeliness	[58], [59], [61], [64], [69], [72], [74], [79], [80], [82]
Consistency	[57], [60], [61], [65], [68], [71], [72], [77]
Transparency	[60], [61], [65], [70], [71], [75], [83]
Hallucination	[57], [59], [60], [75], [80], [81], [83], [87]
Bias	[58], [62], [66], [67], [81], [84]
Granularity	[65], [72], [73], [81], [85]
Accessibility	[59], [67], [69], [83], [85]
Security	[59], [60], [76], [81], [82]
Completeness	[73], [78], [84]
Compliance	[61], [67], [75], [79], [86]
Value-Added	[59], [80], [83], [88]
Detectability	[57]; [62], [65], [72], [79]
Traceability	[60], [62], [65], [85]
Authoritativeness	[58]; [64], [66], [82]
Uniqueness	[58], [65], [71]
Interoperability	[62], [80]
Verifiability	[60], [66], [67]
Reference Validity	[64], [84]

The themes identified in this review, as depicted in Fig. 4, are strongly supported by recurring patterns across the selected studies on Generative AI in e-government services. The need for trust, factual accuracy, and source validation is repeatedly emphasised in GAI applications deployed in domains such as healthcare, education, and public administration [57], [58], [60], [62]. These studies reinforce the critical role of factors under the theme of trustworthiness and verifiability in ensuring the credibility of GAI-generated content. The perceived reliability of the system decreases when trust is violated, and this factor can adversely affect the user's desire to embrace or trust GAI to deliver critical services to society. Likewise, the theme of security and ethics is supported in findings that investigate the risks of bias, lack of transparency, and non-adherence in outputs produced by GAI [65], [84], [85]. Such ethical issues are especially of concern in the domain of e-government, where accountability and equity are of paramount importance in terms of system acceptance by the populace.

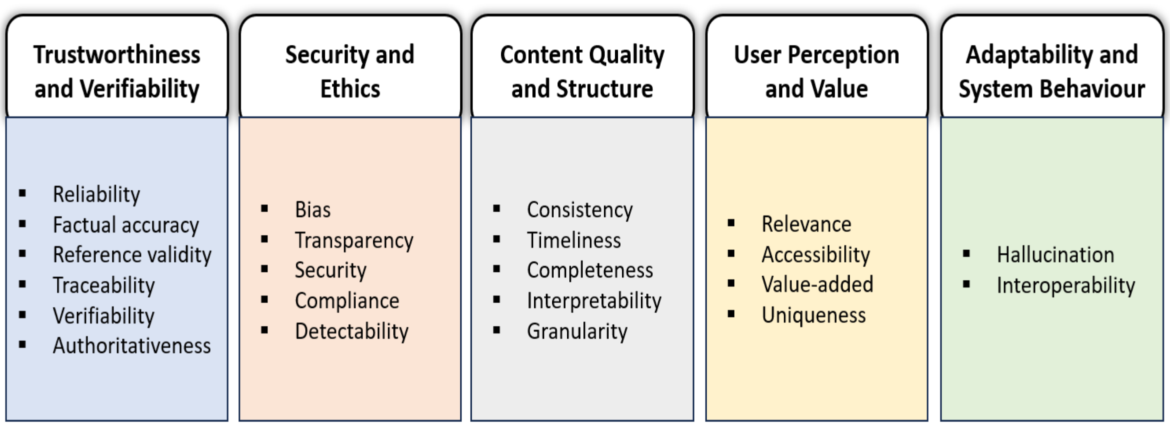

Fig. 4. Themes of factors influencing information quality in generative AI-enabled e-government services (GAIGS).

Moreover, the concept of content quality and structure is complemented by the findings that emphasise the necessity of consistency, timeliness, and interpretability to make the information actionable and the interactions in the service context smooth [68], [69]. The GAI systems that provide clear and well-structured information regularly are more likely to create positive perceptions that may contribute to the increase in the intention to use and further use such services. A similar user perception and value theme is supported by the literature that refers to the role of accessibility, relevance, and usefulness in satisfaction with e-government platforms [12], [59], [81]. These are key elements in creating confidence in GAI-assisted interactions and maintaining interest on the part of users. Furthermore, the topic of adaptability and system behaviour is confirmed by articles on hallucination, system integration, and context-sensitive output requirements [83]. Such features affect not only the current usability but also the long-term confidence in the work of the system. Collectively, the results indicate that the quality of GAI-generated information plays an important role in influencing the initial user acceptance as well as the intent to use the GAI-enabled eGovernment services further [90]. Based on the synthesised evidence, the authors propose the following system design guidelines for GAIGS practitioners. First, for Trustworthiness and Verifiability, platforms should incorporate source-attribution layers and explainability mechanisms that enable users to trace and verify the provenance of AI-generated content. Second, for Security and Ethics, developers are advised to embed bias-detection pipelines and conduct periodic algorithmic audits, supported by compliance monitoring aligned to national e-government standards. Third, for Content Quality and Structure, knowledge-grounding mechanisms should be adopted to reduce hallucination and improve the timeliness and consistency of outputs. Fourth, for User Perception and Value, accessibility-by-design principles, including multilingual support and plain-language generation, should be applied to serve diverse citizen populations. Fifth, for Adaptability and System Behaviour, systems should be designed with context-sensitive response tuning and cross-platform interoperability standards to ensure consistent quality across different service delivery channels.

V. Conclusion

The review has synthesised evidence of thirty-three identified articles published in 2021-2025 to determine twenty-two main factors contributing to information quality in GAI-enabled eGovernment services (GAIGS). Through a structured thematic analysis, these factors were grouped into five major themes, namely trustworthiness and verifiability, security and ethics, content quality and structure, user perception and value, and adaptability and system behaviour. The themes capture the varying methods in the conceptualisation of the information quality of the AI-generated outputs of public services in the literature. It is shown in the findings that credible, ethical, convenient, and contextually responsive information is critical to the improvement of user satisfaction and to the desire and persistence in the use of GAI-assisted platforms.

Several limitations of this review should be acknowledged. The corpus is restricted to peer-reviewed journal articles, which may exclude relevant insights available in grey literature and government reports. The thematic classification process, while guided by an established six-step method, involves a degree of interpretive judgement. Furthermore, given the rapid pace of GAI development, emerging capabilities may introduce quality dimensions not yet captured in the existing literature. Notwithstanding these limitations, the authors identify three priority directions to guide future inquiry. First, the 22 factors identified in this review should be subjected to empirical validation through the development and psychometric testing of measurement instruments in real GAIGS deployment contexts. Second, domain-specific information quality models should be constructed for distinct e-government service areas, recognising that quality priorities may vary considerably across healthcare, legal, taxation, and social welfare services. Third, future research should examine user-side moderating variables, including digital literacy, trust disposition, and prior experience with AI systems, to better understand how these factors mediate the relationship between information quality and citizen satisfaction, adoption, and continued engagement. Despite these limitations, the authors are confident that the findings of this review offer a timely, structured, and practical foundation for advancing both the theoretical understanding and the responsible implementation of high-quality, trustworthy, and citizen-centred GAIGS.

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