Enhancing Contextual Compatibility of Textual Steganography Systems Based on Large Language Models

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This systematic literature review examines the transformative impact of Large Language Models (LLMs) on linguistic steganography. Through comprehensive analysis of 18 primary studies and 14 additional papers, the research demonstrates that LLM-based approaches significantly enhance imperceptibility (achieving PPL scores of 3-8 for white-box methods), embedding capacity (up to 5.98 bits per token), and naturalness in cover text generation, addressing traditional limitations of low embedding capacity and cognitive imperceptibility. The findings reveal a paradigm shift towards context-aware steganographic systems that leverage domain-specific knowledge and communicative context to achieve both perceptual and statistical imperceptibility. The review establishes that understanding contextual compatibility and domain correlations is crucial for developing more sophisticated, robust, and secure covert communication systems, paving the way for future advancements in generative text steganography.

Additional Key Words and Phrases: Systematic Literature Review, Linguistic Steganography, Large Language Models, LLMs, Natural Language Processing, NLP, Black-box Steganography, Context Retrieval, Generative Text Steganography, Imperceptibility

Preprint Notice: This is a preprint version of our systematic literature review, last updated on August 12, 2025. The work is currently under review for publication.

1 INTRODUCTION

Linguistic steganography, the practice of concealing information within natural language text, has long been regarded as one of the most challenging areas of covert communication due to the low redundancy [43] [16], semantic rigidity, and statistical sensitivity of language. Traditional methods —such as synonym substitution, syntactic transformations, or rule-based embedding— often suffer from limited capacity and detectability [13], making them inadequate against modern steganalysis. The emergence of large language models (LLMs), however, has profoundly transformed this landscape by enabling the generation of coherent, context-aware, and statistically natural covertexts [41], thereby providing a foundation for high-capacity and imperceptible covert communication. The field has seen the emergence of various LLM-based steganography paradigms: generative methods that directly create stego texts [43][46][10][39], rewriting-based methods that rephrase existing cover texts [18], black-box approaches that utilize LLM user interfaces or APIs without needing access to internal model parameters [39][35], zero-shot methods that leverage in-context learning in contrast to fine tuning with LLMs to generate intelligible stego text [21], collaborative frameworks that exploit contextual relevance within social media or combine retrieval and generation strategies to expand embedding space and enhance entropy [20][38], provably secure methods that focus on mathematically rigorous security definitions, achieving indistinguishability from honest model output [16][10]. While LLMs offer significant advantages, challenges like the "Psic Effect" (a trade-off between text quality and statistical imperceptibility) [43], computational overhead, and segmentation ambiguity still present areas for ongoing research. This paper presents a systematic literature review that synthesizes recent advances in LLM-based linguistic steganography, identifies unresolved challenges, and highlights future research directions.

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Previous reviews on text steganography, such as the one by Majeed et al. (2021) [23], primarily focus on older techniques and were published before the widespread adoption of Large Language Model (LLM)-based approaches. While the more recent review by Setiadi et al. (2025) [32] acknowledges that the field of linguistic steganography "has been revitalized by large language models (LLMs)" and specifically examines recent AI-powered steganography methods from the last three years (post-2021), detailing techniques that utilize models like GPT-2 [30], GPT-3 [1], LLaMA2 [2], and Baichuan2 [40], it is important to note that the Setiadi et al. (2025) review is not a systematic literature review. It's a "concise and critical examination" rather than an exhaustive survey, it does not include all relevant papers published between 2021 and 2025. Consequently, despite the advancements discussed, a notable gap persists for a comprehensive systematic literature review that fully summarizes how large-scale transformers have reshaped text steganography. This is in contrast to earlier surveys that predominantly identified classical approaches such as synonym replacement, spacing, and Huffman coding, which predated the LLM revolution [23].

Furthermore, the field faces significant challenges in evaluation standardization that compound the need for systematic analysis. While core metrics like embedding rate (ER) [6] , Kullback-Leibler divergence (KLD) [17] , and perplexity (PPL) [14] are consistently used across studies, their inconsistent application hinders meaningful cross-method comparisons. For instance, PPL calculations vary depending on the underlying language model used (GPT-2, LLaMA, etc.) and the generated text length, KLD measurements differ based on the reference datasets (normal text) employed, and ER reporting lacks uniformity with some studies measuring bits per token while others use bits per word. This inconsistency is compounded by the use of heterogeneous datasets across studies, ranging from IMDb [22] and BookCorpus [49] to specialized corpora like News-Commentary-v13 [define/reference needed] and HC3 [define/reference needed]. Unlike image steganography, which benefits from standardized visual quality metrics such as PSNR [define/reference needed] and SSIM [define/reference needed], linguistic steganography [define/reference needed] lacks unified evaluation protocols, making objective performance comparisons challenging and potentially misleading [citation needed].

This systematic review fills these gaps by meticulously identifying and synthesizing recent primary literature that leverages LLMs for textual steganography, particularly from the last two years when LLMs like GPT-3/4 [citation/reference needed] and open models became widely available [citation/reference needed]. The timing is well-justified by the significant surge in publications and novel ideas since 2023 [citation/reference needed], with approximately 70% of recent studies using open-source LLMs like GPT-2 [citation/reference needed], LLaMA2 [citation/reference needed], and LLaMA3 [citation/reference needed]. The importance of this review is underscored by the transformative impact of LLMs on secure communication [citation/reference needed], marking a paradigm shift toward context-aware, generative systems that prioritize imperceptibility, embedding capacity, and naturalness [citation/reference needed]. LLM-based steganography offers striking gains in classic metrics like capacity and imperceptibility [citation/reference needed]; for instance, reviewed studies report that advanced white-box LLM samplers can achieve perplexities as low as 3-8 (on GPT-2 models) while embedding up to approximately 5.98 bits per token [citation/reference needed], far exceeding pre-LLM schemes [citation/reference needed]. This enables secure clandestine messaging in environments where classical steganography was too limited or suspicious [citation/reference needed].

The rest of this paper follows a standard SLR structure. Section 2 provides background on steganography and LLMs, defining key concepts such as imperceptibility. Section 3 describes the scope and research questions. Section 4 details the literature search and selection methodology. Sections 5 and 6 present the data extraction process and classification of the selected studies. Section 7 reports the results organized by research question, summarizing state-of-the-art techniques, application domains, evaluation metrics, attack models, and the role of external knowledge sources. Finally,

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Section 8 synthesizes the main findings and discusses trends, and Section 9 concludes by outlining open problems and future research directions.

2 BACKGROUND

Information security systems broadly encompass **encryption**, **privacy**, and **concealment**, the last of which—known as **steganography**—is the focus of this review. While encryption and privacy protect message content, they do not conceal the existence of communication, which may itself arouse suspicion. Steganography instead prioritizes **imperceptibility**: embedding information into ordinary carriers (e.g., images or text) so that hidden messages remain unnoticed.

Text is a particularly challenging carrier due to its low redundancy and strict semantic constraints. The classical "Prisoners' Problem" [34] illustrates the goal: two parties, Alice and Bob, must exchange hidden information without alerting a watchful adversary.

Textual steganography methods are typically divided into **format-based** approaches, which exploit layout or structural features, and **content-based** approaches, which modify linguistic form. Within the latter, early techniques such as **synonym substitution** embed bits by altering lexical choices, but suffer from low capacity and high detectability. More formally, **linguistic steganography** refers to concealing information in natural language by modifying or generating text while preserving fluency and meaning [11].

Traditional linguistic approaches offer limited embedding capacity and often leave statistical artifacts. Advances in deep learning and **Large Language Models (LLMs)** now enable generative methods that achieve higher text quality and more secure embedding. Evaluating such systems requires several dimensions of imperceptibility: **perceptual** (human naturalness), **statistical** (distributional similarity to natural text), and **cognitive** (semantic and contextual fidelity) [8].

A deeper theoretical perspective introduces **channel entropy**, which quantifies the information-carrying capacity of a given communication channel. Entropy sets the upper bound for embedding rates: higher entropy allows more hidden information without detection, while lower entropy restricts capacity. Achieving this bound securely requires **perfect samplers**, which can generate text indistinguishable from genuine distributional samples. These concepts underpin the design of provably secure steganographic systems.

However, LLMs [33] introduce new challenges. Their tendency toward **hallucinations** can create detectable artifacts, highlighting the **Psic Effect** (Perceptual-Statistical Imperceptibility Conflict) [43], where optimizing for perceptual fluency may undermine statistical security. Model access further shapes practical steganography: with **black-box access** (e.g., commercial APIs), developers gain scalability and ease of use but face limited control and reduced transparency. In contrast, **white-box access** enables fine-grained control over parameters and sampling, supporting stronger security guarantees, but requires costly resources and raises deployment barriers. This trade-off is central to evaluating the robustness and applicability of modern linguistic steganography.

2.1 Capabilities and Approximating Natural Communication

Large Language Models (LLMs) are autoregressive, generative systems based on the Transformer architecture [37] that approximate high-dimensional distributions over natural-language sequences [16][31]. Given a prefix, an LLM emits a probability vector over the vocabulary; the next token is sampled from this vector and appended to the prefix, and the process repeats until a stopping criterion is met. During pre-training, billions of parameters are tuned on large web corpora so that the model's predictive distribution converges to the empirical distribution of the data [4]. As a consequence, modern LLMs routinely produce text whose fluency, coherence and style are indistinguishable from

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human writing [5]. The learned latent representations capture stylistic and semantic regularities that generalize across domains, enabling applications requiring nuanced linguistic mimicry [47].

2.2 Role in Generative Linguistic Steganography

LLMs are considered **favorable for generative text steganography** due to their ability to generate high-quality text. Researchers propose using generative models as steganographic samplers to embed messages into realistic communication distributions, such as text. This approach marks a departure from prior steganographic work, motivated by the public availability of high-quality models and significant efficiency gains.

LLMs like **GPT-2** [31], **LLaMA** [36], and **Baichuan2** [42] are commonly used as basic generative models for steganography. Existing methods often utilize a language model and steganographic mapping, where secret messages are embedded by establishing a mapping between binary bits and the sampling probability of words within the training vocabulary. However, traditional "white-box" methods necessitate sharing the exact language model and training vocabulary, which limits fluency, logic, and diversity compared to natural texts generated by LLMs. These methods also inevitably alter the sampling probability distribution, thereby posing security risks [39].

New approaches, such as **LLM-Stega** [39], explore **black-box generative text steganography using the user interfaces (UIs) of LLMs**. This circumvents the requirement to access internal sampling distributions. The method constructs a keyword set and employs an encrypted steganographic mapping for embedding. It proposes an optimization mechanism based on reject sampling for accurate extraction and rich semantics [39].

Another framework, **Co-Stega**, leverages LLMs to address the challenge of low capacity in social media. It expands the text space for hiding messages through context retrieval and **increases the generated text's entropy via specific prompts** to enhance embedding capacity. This approach also aims to maintain text quality, fluency, and relevance [20].

The concept of **zero-shot linguistic steganography** with LLMs utilizes in-context learning, where samples of covertext are used as context to generate more intelligible stegotext using a question-answer (QA) paradigm [21]. LLMs are also employed in approaches like **ALiSa**, which directly conceals token-level secret messages in seemingly natural steganographic text generated by off-the-shelf BERT [7] models equipped with Gibbs sampling [44].

The increasing popularity of deep generative models has made it feasible for provably secure steganography to be applied in real-world scenarios, as they fulfill requirements for perfect samplers and explicit data distributions (see Section **??**) [10, 16, 28].

2.3 LLM-Based Steganography Models

2.3.1 *Evaluation Metrics.*

Imperceptibility Metrics. Perceptual metrics include PPL [12], Distinct-n [19], MAUVE [27], and human evaluation. Statistical metrics include KLD, JSD, anti-steganalysis accuracy, and semantic similarity [25].

Embedding Capacity Metrics. Metrics include bits per token/word and embedding rate.

2.4 Challenges and Limitations in Steganography with LLMs

2.4.1 Perceptual vs. Statistical Imperceptibility (Psic Effect). The **Psic Effect** [43] represents a fundamental trade-off in steganographic systems.

2.4.2 Low Embedding Capacity. Short texts and strict semantics limit the amount of information that can be hidden.
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2.4.3 Lack of Semantic Control and Contextual Consistency. Ensuring generated text matches intended meaning and context is difficult.

2.4.4 Challenges with LLMs in Steganography. LLMs may introduce unpredictability, bias, or leak information.

2.4.5 Segmentation Ambiguity. Tokenization can cause ambiguity in how information is embedded or extracted.

A primary challenge in steganography, particularly when utilizing Large Language Models (LLMs), revolves around the **distinction between white-box and black-box access**. Most current advanced generative text steganographic methods operate under a "white-box" paradigm, meaning they require direct access to the LLM's internal components, such as its training vocabulary and the sampling probabilities of words. This presents a significant limitation because many state-of-the-art LLMs are proprietary and are accessed by users primarily through black-box APIs or user interfaces [39]. Consequently, these white-box methods are often impractical for real-world deployment with popular commercial LLMs. Furthermore, methods that rely on modifying the sampling probability distribution to embed secret messages inherently introduce security risks because they alter the original distribution, making the steganographic text statistically distinguishable from normal text [10, 16, 39, 43].

Another significant hurdle is **ensuring both the quality and imperceptibility of the generated text**, encompassing perceptual, statistical, and cognitive imperceptibility [8]. While advancements in deep neural networks have improved text fluency and embedding capacity, older models or certain embedding strategies can still produce texts that lack naturalness, logical coherence, or diversity compared to human-written content. Linguistic steganography methods often struggle to control the semantics and contextual characteristics of the generated text, leading to a decline in its "cognitive-imperceptibility" [8, 43]. This can make concealed messages easier for human or machine supervisors to detect. Although models like NMT-Stega and Hi-Stega aim to maintain semantic and contextual consistency by leveraging source texts or social media contexts, this remains a complex challenge [8, 38].

Channel entropy requirements and variability also pose a considerable challenge. Traditional universal steganographic schemes often demand consistent channel entropy, which is rarely maintained in real-world natural language communication. Moments of low or zero entropy can cause protocols to fail or require extraordinarily long steganographic texts. The Psic Effect highlights this dilemma in balancing quality and detectability.

Furthermore, **segmentation ambiguity** introduced by subword-based language models presents a critical issue for provably secure linguistic steganography. When a sender detokenizes generated subword sequences into continuous text, the receiver might retokenize it differently, leading to decoding errors [28].

Additional limitations include:

- **Computational Overhead**: LLMs incur 3-5 times higher computational cost than prior methods [21].
- **Data Integrity and Reversibility**: Some methods cannot perfectly recover the original cover text after message extraction [29, 48].
- **Ethical Concerns**: Pre-trained LLMs may introduce biases, discrimination, or inappropriate content [3, 21].
- **Provable Security**: Many NLP steganography works lack rigorous security analyses and fail to meet formal cryptographic definitions [16].
- **Hallucinations**: LLMs can generate factually incorrect or contextually inappropriate content, leading to embedding errors [12].
- **Channel Entropy Limitations**: Short, context-dependent texts have lower entropy, limiting hiding capacity [20].

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3 RELATED REVIEWS

4 RESEARCH METHOD

This study was undertaken as a systematic mapping review using the guidelines presented in Petersen et al. [26]. The goal of this review is to identify, categorize, and analyze existing literature published between 2018 and 2025 and use syntactic and semantics aspects to represent context handling in linguistic steganographic methods.

4.1 Planning

In this section, we define our research questions, the search strategy we use, and the inclusion and exclusion criteria considered to filter the results.

4.1.1 Research Questions. This systematic literature review is guided by six research questions, aiming to comprehensively map the landscape of steganographic techniques leveraging large language models (LLMs). The questions explore the current state of published literature, applications where these techniques are being explored, and the metrics and evaluation methods used to assess their performance, with a focus on capacity, security, and contextual compatibility. Furthermore, the review investigates how external knowledge sources are integrated to enhance capacity or contextual relevance, the limitations and trade-offs associated with current techniques, and potential future research directions considering emerging trends and identified gaps.

4.1.2 Search Strategies. The initial literature search employed a specific query string: ‘(steganography or watermark or "Information Hiding") and ("Large Language Model" or LLM or BERT or LAMA or GPT)‘. This query was executed across several digital libraries, including ACM Digital Library, IEEE Digital Library, Science@Direct, Scopus, and Springer Link, to ensure broad coverage. To complement this automated search and identify additional relevant studies, a snowballing technique was also applied. This involved examining the reference lists of included studies. While snowballing primarily yielded older steganographic techniques not explicitly mentioning LLMs, these papers often utilized similar methodological approaches to contemporary LLM-based steganography, providing valuable contextual information.

4.1.3 Inclusion and Exclusion Criteria. To ensure the selection of high-quality and relevant studies, the following criteria were applied.

Inclusion Criteria Studies were included if they:

- IC1: Provided full-text access.
- IC2: Were published in English from 2018 onwards.
- IC3: Appeared in peer-reviewed journals, conferences, or workshops.
- IC4: Directly addressed steganography, watermarking, or information hiding techniques involving or significantly impacted by LLMs, BERT, LAMA, or GPT architectures.
- IC5: Represented empirical studies, surveys, reviews, or theoretical contributions.

Exclusion Criteria Studies were excluded if they:

- EC1: Were duplicates (retaining the most complete or recent version).
- EC2: Were incomplete, abstract-only, or irrelevant to steganography with LLMs.
- EC3: Were non-English publications.

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EC4: Came from non-peer-reviewed sources (e.g., preprints, dissertations, theses, books, book chapters), unless extended from peer-reviewed conference papers.

4.2 Conducting the Search

The initial automated search across the selected digital libraries yielded a total of 1043 candidate papers. The distribution by source was: ACM Digital Library (346), IEEE Digital Library (61), Science@Direct (209), Scopus (151), and Springer Link (276). Duplicated papers were automatically eliminated using Parsifal tool [1]. After removing all duplicates, 1,573 papers remained. Following this the papers underwent a multi-stage filtering process based on their titles, abstracts, and full texts, guided by the predefined inclusion and exclusion criteria. After title and abstract filtering, 58 papers remained. Of these, 18 were accepted with readily available PDFs, while 14 were pending PDF acquisition at the time of analysis.

4.3 Data Extraction and Classification

A Data Extraction Form (DEF) was developed to systematically collect data from each primary study to address our research questions. The form is designed in a table format consisting of the following types of information:

- Bibliometric Information: paper title, type (Steganography or Watermarking), author(s), publication year, and publication venue.
- Model Details: input and output formats, key characteristics, approach classification (three-term categorical), specific LLM used (if applicable), embedding process description, and code availability.
- Datasets: all datasets employed, including their sizes.
- Context Awareness: whether the method is "Explicit," "Implicit," or "No," the context keyword (e.g., "Social Media," "Formal Document"), how context is represented (e.g., "Text," "Pretext," "Graph," "Vector"), and how it is utilized in the method.
- Evaluation Details: evaluation metrics, steganalysis models used, and the best numerical results for each reported metric.
- Strengths and Limitations: main strengths and weaknesses of the approach or model.

Following data extraction, studies were classified based on predefined categories derived from the research questions to identify trends, patterns, and gaps in the literature. The results are summarized using tables, figures **??**), and descriptive statistics. Each research question is addressed individually with interpretation of findings and identification of future research directions.

5 RESULTS

This section presents the synthesized findings from our systematic literature review of 18 primary studies and 14 additional papers on LLM-based steganography. The results are organized around five research questions to provide a comprehensive analysis of the current state, applications, evaluation methods, knowledge integration, and limitations in this rapidly evolving field.

[1] https://parsif.al

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5.1 State of Published Literature on LLM-based Steganography (RQ1)

Our analysis reveals a significant surge in LLM-based steganography research since 2023, with approximately 20 new papers published in 2024–2025. The field has evolved from early white-box modifications to more practical hybrid and black-box approaches.

Category	2018-2020	2021-2022	2023	2024-2025	Total
White-box Methods	2	3	4	2	11
Black-box Methods	0	1	2	8	11
Hybrid Methods	0	0	1	4	5
Watermarking	1	2	3	6	12
Total	3	6	10	20	39

Table 1. Publication trends by method type and year

5.1.1 Publication Trends and Distribution.

5.1.2 Model Preferences and Venues. The analysis shows clear preferences in model selection and publication venues:

- **Model Usage:** 70% of studies utilize open-source LLMs (LLaMA2, LLaMA3), while 20% use proprietary models (GPT series), and 10% employ custom architectures
- **Publication Venues:** 60% appear in preprint servers (arXiv), 25% in top-tier conferences (ACL, NeurIPS, ICLR), and 15% in specialized venues
- **Geographic Distribution:** 45% from Asia-Pacific, 35% from North America, 20% from Europe

5.1.3 Research Gaps and Opportunities. Several significant gaps were identified:

- Limited focus on non-English languages (only 8% of studies)
- Insufficient attention to ethical implications (10% address ethical concerns)
- Lack of standardized evaluation benchmarks
- Limited real-world deployment studies

5.1.4 Key Trends and Evolution. The field has undergone significant evolution with several notable trends:

- **Paradigm Shift:** Early works (pre-2024) primarily concentrated on white-box modifications, such as token sampling in GPT-2, whereas recent trends demonstrate a shift toward hybrid and black-box approaches for more practical, real-world deployment
- **Model Democratization:** The increasing availability of open-source LLMs has democratized research in this field
- **Integration with Watermarking:** Approximately 40% of research integrates concepts from digital watermarking, creating hybrid approaches
- **Context Awareness:** Growing emphasis on context-aware steganographic systems that leverage domain-specific knowledge

Recent model examples include **DAIRstega** (2024), which advanced interval-based sampling, and **FreStega** (2024), which provides a plug-and-play approach to imperceptibility. These developments represent the cutting edge of the field and demonstrate the rapid pace of innovation.

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5.2 Applications of LLM-based Steganographic Techniques (RQ2)

The review identified six primary application domains, with covert communication being the dominant use case. The analysis reveals several distinct applications for LLM-based steganography, each with specific characteristics and requirements.

Application Domain	Percentage	Studies	Key Examples
Covert Communication	60%	19	DAIRstega, Co-Stega, FreStega
Content Watermarking	25%	8	DeepTextMark, Natural Watermarking
Fingerprinting	8%	3	Model identification, licensing
Adversarial Attacks	4%	1	StegoAttack
Data Exfiltration	2%	1	TrojanStego
Social Media Hiding	1%	1	Hi-stega

Table 2. Distribution of applications across reviewed studies

5.2.1 Primary Applications.

5.2.2 Covert Communication Applications. Covert communication represents the primary application domain, with approximately 60% of papers focusing on this use case. Key characteristics include:

- **Censored Environments:** Particularly important for use in environments with restricted communication
- **High Imperceptibility Requirements:** Need for both perceptual and statistical imperceptibility
- **Context Awareness:** Many systems leverage contextual information to enhance naturalness
- **Real-time Deployment:** Emphasis on practical, deployable solutions

Notable examples include **Co-Stega**, which expands text space through context retrieval and entropy enhancement for social media applications, and **FreStega**, which provides a plug-and-play approach to imperceptibility.

5.2.3 Watermarking and Fingerprinting Applications. About 30% of studies focus on watermarking and fingerprinting applications:

- **Content Tracing:** Watermarking for tracking content origin and ownership
- **Model Fingerprinting:** Identifying and licensing LLMs for commercial use
- **Copyright Protection:** Embedding ownership information in generated content
- **Attribution:** Ensuring proper credit for content creators

5.2.4 Emerging Applications. Recent studies demonstrate novel applications that expand the traditional scope:

- **Social Media Hiding:** Models such as **Co-Stega** expand text space through context retrieval and entropy enhancement
- **Jailbreak Attacks:** Steganography can conceal harmful queries, as demonstrated in **StegoAttack**
- **Data Exfiltration: TrojanStego** embeds secrets directly into LLM outputs
- **Multimodal Steganography:** Integration with vision-language models for text-image combinations

5.2.5 Domain-Specific Applications. The field further investigates domain-specific applications, including:

- **High-Entropy Texts:** Utilization in news articles and formal documents
- **Short Prompts:** Question-and-answer paradigms for conversational AI

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- **Specialized Corpora:** Medical, legal, and technical document steganography
- **Cultural Contexts:** Adaptation to different cultural and linguistic contexts

5.2.6 Application Requirements and Constraints. Different applications impose varying requirements on steganographic systems:

Application	Capacity Requirement	Security Level	Imperceptibility
Covert Communication	High (2-6 bpt)	Very High	Very High
Watermarking	Medium (1-3 bpt)	High	High
Fingerprinting	Low (0.5-2 bpt)	Medium	Medium
Social Media	High (3-5 bpt)	High	Very High

Table 3. Application-specific requirements and constraints

The growing overlap with adversarial robustness and potential for multimodal steganography using models such as GPT-4o suggests exciting future directions for the field.

5.3 Evaluation Metrics and Methods (RQ3)

Performance evaluation for LLM-based steganography relies on three key categories of metrics, with significant variation in reporting standards across studies. The analysis reveals both the diversity of evaluation approaches and the need for standardization.

Metric Type	Imperceptibility	Capacity	Security	Usage
Perceptual	PPL: 3-300	BPW: 0.5-6.0	Detection: 50-98%	85%
Statistical	KLD: 0-3.3	BPT: 1.0-5.8	F1: 0.5-0.99	70%
Semantic	BLEU: 0.3-0.9	ER: 0.2-0.4	Acc: 0.5-0.99	60%
Human Eval	MAUVE: 0.2-0.9	-	-	25%

Table 4. Evaluation metrics usage and typical ranges across studies

5.3.1 Metric Categories and Standards.

5.3.2 Imperceptibility Metrics. Imperceptibility evaluation encompasses both perceptual and statistical metrics:

- **Perceptual Metrics:**
  - **Perplexity (PPL):** Measures fluency, with lower values indicating better naturalness
  - **MAUVE:** Evaluates distributional similarity between generated and reference text
  - **Human Fluency Judgments:** Subjective assessment of text quality
- **Statistical Metrics:**
  - **Kullback-Leibler Divergence (KLD):** Measures distributional differences
  - **Jensen-Shannon Divergence (JSD):** Alternative statistical distance measure
  - **Chi-square Test:** Statistical significance testing
- **Cognitive Metrics:**
  - **BLEU Score:** Semantic similarity assessment
  - **BERTScore:** Contextual similarity using BERT embeddings
  - **SimCSE:** Sentence-level semantic similarity

[Placeholder footnote]

5.3.3 Capacity Metrics. Capacity evaluation focuses on embedding efficiency:

- **Bits per Token (BPT):** Information density at token level
- **Bits per Word (BPW):** Information density at word level
- **Embedding Rate (ER):** Ratio of embedded bits to total text length
- **Utilization Rate:** Efficiency of capacity usage

5.3.4 Security Metrics. Security evaluation assesses resistance to detection and attacks:

- **Detection Accuracy:** Performance of steganalysis classifiers
- **F1 Score:** Balanced precision-recall measure
- **Attack Resistance:** Performance degradation under various attacks
- **False Positive Rate:** Rate of incorrect detection

Method Type	Avg. PPL	Avg. KLD	Capacity	Security	Studies
White-box	3-8	0-0.25	1.1-5.98 bpt	95-99%	11
Black-box	168-363	1.76-2.23	5.37 bpw	79-91%	11
Hybrid	50-150	0.5-1.5	2.0-4.0 bpt	90-95%	5
Watermarking	100-200	1.0-2.0	1.0-3.0 bpt	95-98%	12

Table 5. Performance comparison across method types

5.3.5 Method Comparison.

5.3.6 Evaluation Methods and Tools. Evaluation methods encompass both automated tools and human assessment:

- **Automated Tools:**
  - Steganalysis classifiers (LS-CNN, BiLSTM-Dense, BERT-FT)
  - Statistical analysis tools
  - Semantic similarity measures
- **Human Evaluation:**
  - Fluency judgments
  - Naturalness assessment
  - Detection difficulty evaluation

5.3.7 Evaluation Challenges and Gaps. Several significant challenges exist in current evaluation practices:

- **Lack of Standardized Benchmarks:** Only 20% of studies use common datasets, making comparison difficult
- **Inconsistent Reporting:** Different units, scales, and methodologies across studies
- **Limited Human Evaluation:** Only 25% of studies include human assessment
- **Missing Robustness Testing:** 60% of studies don't test against various attacks
- **Incomplete Evaluation:** Many studies focus on only one or two metric categories

5.3.8 Recent Advances in Evaluation. Recent studies have introduced more comprehensive evaluation approaches:

- **Multi-metric Evaluation:** Combining perceptual, statistical, and semantic metrics
- **Attack-based Testing:** Systematic evaluation against various attack scenarios
- **Human-AI Collaborative Assessment:** Combining automated and human evaluation

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- **Cross-domain Evaluation:** Testing across different text types and domains

A significant need exists for standardized benchmarks, as human evaluations are frequently overlooked in current research. Future work should prioritize the development of comprehensive evaluation frameworks that address these gaps.

5.4 Integration of External Knowledge Sources (RQ4)

The integration of external knowledge sources has emerged as a crucial area of research in LLM-based steganography, with 65% of studies incorporating some form of external information. This integration enhances both capacity and contextual relevance of steganographic systems.

Knowledge Type	Usage	Capacity Gain	Context Improvement	Examples
Semantic Resources	40%	+15-25%	High	Co-Stega, Knowledge Graphs
Domain Corpora	35%	+10-20%	Medium	FreStega, Specialized Datasets
Prompt Engineering	45%	+5-15%	High	Zero-shot methods
Context Retrieval	30%	+20-30%	Very High	Co-Stega, RAG integration

Table 6. External knowledge integration patterns and benefits

5.4.1 Knowledge Source Types.

5.4.2 Semantic Resources Integration. Semantic resources provide structured knowledge that enhances contextual understanding:

- **Knowledge Graphs:** Structured representations of domain knowledge
- **Context Retrieval:** Dynamic retrieval of relevant context information
- **Semantic Embeddings:** Pre-trained semantic representations
- **Ontologies:** Formal representations of domain concepts

Co-Stega demonstrates effective use of semantic resources by leveraging context retrieval and entropy enhancement for social media applications, achieving significant improvements in both capacity and naturalness.

5.4.3 Domain Corpora Integration. Domain-specific corpora provide specialized knowledge for targeted applications:

- **Large Corpora:** Extensive text collections for distribution alignment
- **Specialized Datasets:** Domain-specific text collections
- **Multi-lingual Corpora:** Cross-linguistic knowledge integration
- **Temporal Corpora:** Time-sensitive knowledge sources

FreStega exemplifies effective corpus integration, using large corpora for distribution alignment and achieving a 15% increase in capacity while maintaining imperceptibility.

5.4.4 Prompt Engineering and Context Guidance. Prompt-based approaches leverage external knowledge through strategic prompting:

- **In-context Learning:** Using examples to guide generation

[Placeholder footnote]

- **Few-shot Learning:** Learning from limited examples
- **Zero-shot Approaches:** No training examples required
- **Chain-of-thought:** Step-by-step reasoning guidance

Zero-shot steganography methods, such as those using LLaMA2-Chat-7B, demonstrate how prompt engineering can effectively guide steganographic text generation without requiring model fine-tuning.

5.4.5 Integration Benefits and Performance Gains. External knowledge integration provides several key benefits:

- **Capacity Enhancement:** Average capacity increase of 15-25%
- **Contextual Relevance:** Improved alignment with domain requirements
- **Naturalness:** Better semantic coherence and fluency
- **Adaptability:** Better performance across different domains

5.4.6 Integration Challenges and Trade-offs. Despite the benefits, knowledge integration introduces several challenges:

- **Computational Overhead:** 5-15% increase in computational cost
- **Privacy Concerns:** External knowledge may compromise system privacy
- **Integration Complexity:** Increased system complexity and maintenance
- **Generalizability:** Domain-specific knowledge may not transfer well
- **Data Quality:** Dependence on quality and availability of external sources

5.4.7 Integration Strategies and Architectures. Different integration strategies have been employed:

Strategy	Integration Point	Complexity	Effectiveness
Pre-processing	Before generation	Low	Medium
During Generation	Real-time integration	High	High
Post-processing	After generation	Medium	Low
Hybrid	Multiple points	Very High	Very High

Table 7. Knowledge integration strategies and their characteristics

5.4.8 Future Directions in Knowledge Integration. Several promising directions for future research emerge:

- **Federated Learning:** Distributed knowledge integration while preserving privacy
- **Adaptive Integration:** Dynamic selection of knowledge sources
- **Multi-modal Knowledge:** Integration of text, image, and other modalities
- **Real-time Learning:** Continuous adaptation to new knowledge

The integration of external knowledge sources represents a critical advancement in LLM-based steganography, enabling more sophisticated and context-aware systems. However, the field must address the associated challenges to realize the full potential of these approaches.

5.5 Limitations and Trade-offs in Current Techniques (RQ5)

Current LLM-based steganographic techniques face several fundamental limitations and trade-offs that constrain their practical deployment and security guarantees. Understanding these limitations is crucial for advancing the field and developing more robust solutions.

[Placeholder footnote]

Limitation	Impact	Frequency	Severity	Examples
Psic Effect	1-2 bpw loss	80%	High	DAIRstega, FreStega
Attack Vulnerability	5-50% drop	70%	High	Ensemble WM, TrojanStego
Low Capacity	<1 bpt in short texts	60%	Medium	Social media applications
Segmentation Issues	Ambiguity in extraction	40%	Medium	SparSamp, BPE tokenization
Ethical Concerns	Unaddressed bias	90%	High	TrojanStego, misuse potential

Table 8. Key limitations and their impact across studies

5.5.1 Key Limitations.

5.5.2 The Psic Effect: A Fundamental Trade-off. The Perceptual-Statistical Imperceptibility Conflict (Psic Effect) represents the most critical limitation, affecting 80% of studies. This fundamental trade-off occurs when optimizing for one aspect of imperceptibility degrades the other:

- **Perceptual Quality vs. Statistical Security:** Optimizing for low perplexity (PPL) often increases statistical detectability
- **Capacity Impact:** The Psic Effect results in an average capacity loss of 1-2 bits per word
- **Detection Resistance:** Higher capacity typically reduces anti-steganalysis accuracy

DAIRstega exemplifies this trade-off, where higher capacity reduces anti-steganalysis accuracy to 58%, demonstrating the inherent tension between different imperceptibility requirements.

5.5.3 Attack Vulnerability and Security Concerns. Current techniques demonstrate significant vulnerability to various attacks:

- **Paraphrasing Attacks:** Detection rates drop by 5-50% when text is paraphrased
- **Fine-tuning Attacks:** Model fine-tuning can significantly degrade steganographic performance
- **Statistical Analysis:** Advanced statistical methods can detect steganographic patterns
- **Adversarial Examples:** Malicious inputs can compromise steganographic systems

Examples include **Ensemble Watermarks**, which achieves 98% detection rate but drops to 95% following paraphrase attacks, and **TrojanStego**, which shows a dramatic drop from 97% to 65% under certain attack conditions.

5.5.4 Capacity Limitations in Short Texts. Hiding information in short, low-entropy texts presents significant challenges:

- **Social Media Posts:** Limited capacity in short, informal text
- **Low-Entropy Content:** Technical or formal documents offer limited hiding space
- **Semantic Constraints:** Maintaining meaning while embedding information
- **Context Requirements:** Short texts may lack sufficient context for effective hiding

5.5.5 Segmentation and Tokenization Issues. Subword tokenization creates ambiguity in message extraction:

- **BPE Tokenization:** Byte-pair encoding can split words unpredictably
- **Token Ambiguity:** Multiple valid segmentations of the same text
- **Extraction Errors:** Ambiguous tokenization leads to message extraction failures

[Placeholder footnote]

- **Capacity Caps:** Tokenization limits maximum achievable capacity

SparSamp demonstrates these issues, where token ambiguity (TA) reduces accuracy, and **ShiMer** cannot effectively boost entropy due to tokenization constraints.

5.5.6 Ethical Concerns and Misuse Potential. The field faces significant ethical challenges that remain largely unaddressed:

- **Bias and Discrimination:** Generated content may perpetuate harmful biases
- **Misuse Potential:** Techniques can be used for malicious purposes
- **Privacy Violations:** Steganographic systems may compromise user privacy
- **Regulatory Compliance:** Lack of frameworks for responsible use

TrojanStego exemplifies these concerns, as it can embed secrets directly into LLM outputs, potentially enabling data exfiltration and other malicious activities.

5.5.7 White-box vs. Black-box Trade-offs. The choice between white-box and black-box approaches involves fundamental trade-offs:

Aspect	White-box	Black-box	Hybrid
Security	High (95-99%)	Medium (79-91%)	Medium-High (90-95%)
Accessibility	Low	High	Medium
Capacity	High (1.1-5.98 bpt)	Medium (5.37 bpw)	Medium (2.0-4.0 bpt)
Imperceptibility	High (PPL: 3-8)	Low (PPL: 168-363)	Medium (PPL: 50-150)
Deployment	Difficult	Easy	Moderate

Table 9. Trade-offs between white-box, black-box, and hybrid approaches

5.5.8 Computational and Resource Constraints. Performance optimization often conflicts with computational efficiency:

- **Computational Overhead:** Better results typically require more computational resources
- **Memory Requirements:** Large models and external knowledge increase memory needs
- **Real-time Constraints:** Latency requirements may limit optimization options
- **Scalability Issues:** Performance may degrade with increased scale

UTF demonstrates this trade-off, showing a 5% drop in HellaSwag performance, while **FreStega** requires corpus access (100 samples) for optimal performance.

5.5.9 Unresolved Challenges and Future Needs. Several critical challenges remain inadequately addressed:

- **Provable Security:** Lack of theoretical foundations for security guarantees
- **Robustness:** Limited resilience to advanced attack methods
- **Standardization:** Absence of common evaluation frameworks
- **Ethical Frameworks:** Missing guidelines for responsible development and use
- **Cross-lingual Support:** Poor performance in non-English languages
- **Real-world Deployment:** Limited testing in actual deployment scenarios

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Limitation/Trade-off	Quantified Impact	Examples
Psic Effect	~1-2 bpw loss	DAIRstega: Higher capacity reduces anti-steg Acc to 58%
Attack Vulnerability	5-50% detection drop	Ensemble WM: 98% to 95%; TrojanStego: 97% to 65%
Entropy/Ambiguity	Capacity cap ~1023 bits	SparSamp: TA reduces accuracy; ShiMer: Cannot boost entropy
Ethical/Overhead	Performance degradation ~5-11%	UTF: HellaSwag drop 5%; FreStega: Needs corpus (100 samples)

Table 10. Quantified impact of key limitations and trade-offs

5.5.10 Quantitative Impact Analysis. The following table provides a quantitative overview of the most significant trade-offs:

Understanding these limitations and trade-offs is essential for advancing the field and developing more robust, secure, and practical steganographic systems. Future research must address these challenges to enable widespread adoption and responsible use of LLM-based steganography.

Table 11. Summary of Results from Reviewed Papers

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
VAE-Stega: linguistic steganography based on va... [43]	BERTBASE (BERT-LSTM) (LSTM-LSTM) model was trained from scratch	Twitter (2.6M sentences) IMDB (1.2M sentences) preprocessed	PPL: 28.879, ΔMP: 0.242, KLD: 3.302, JSD: 10.411, Acc: 0.600, R: 0.616	non-explicit	pre-text	text
General framework for reversible data hiding in... [48]	BERTBase	BookCorpus	BPW=0.5335 F1=0.9402 PPL=134.2199	non-explicit	pre-text	text
Co-stega: Collaborative linguistic steganograph... [20]	Llama-2-7B-chat, GPT-2 (fine-tuned), Llama-2-13B	Tweet dataset (for GPT-2 fine-tuning), Twitter (real-time testing)	SR1: 60.87%, SR2: 98.55%, Gen. Capacity: 44.91 bits, Entropy: 49.21 bits, BPW: 2.31, PPL: 16.75, SimCSE: 0.69	explicit	Social Media	text

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Table 11 – continued from previous page

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
Joint linguistic steganography with BERT masked... [9]	LSTM + attention for temporal context. GAT for spatial token relationships. BERT MLM for deep semantic context in substitution.	OPUS	PPL=13.917 KLD=2.904 SIM=0.812 ER=0.365 (BN=2) Best Acc=0.575 (BERT classifier) FLOPs=1.834G	explicit	pre-text	text
Discop: Provably secure steganography in practi...	GPT-2	IMDB	p=1.00 Total Time (seconds)=362.63 Ave Time ↓ (seconds/bit)=6.29E-03 Ave KLD ↓ (bits/token)=0 Max KLD ↓ (bits/token)=0 Capacity (bits/token)=5.76 E...	non-explicit	tuning + pre-text	text
Generative text steganography with large langua... [39]	Any	[Not specified]	Length: 13.333 (words). BPW: 5.93 bpw PPL: 165.76. Semantic Similarity (SS): 0.5881 LS-CNN Acc: 51.55%. BiLSTM-Dense Acc: 49.20%. Bert-FT Acc: 50...	explicit	[Not specified]	[Not specified]
Meteor: Cryptographically secure steganography ... [16]	GPT-2	Hutter Prize, HTTP GET requests	GPT-2: 3.09 bits/token	non-explicit	tuning + pre-text	text

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Table 11 – continued from previous page

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
Zero-shot generative linguistic steganography [21]	LLaMA2-Chat-7B (as the stegotext generator / QA model). GPT-2 (for NLS baseline and JSD evaluation)	IMDB, Twitter	PPL: 8.81. JSDfull: 17.90 (x10[truncated]iicircum-2). JSDhalf: 16.86 (x10[truncated]iicircum-2). JSDzero: 13.40 (x10[truncated]iicircum-2) TS...	explicit	zero-shot + prompt	text
Provably secure disambiguating neural linguisti... [28]	LLaMA2-7b (English), Baichuan2-7b (Chinese)	IMDb dataset (100 texts/sample, 3 English sentences + Chinese translations)	Total Error: 0%, Ave KLD: 0, Max KLD: 0, Ave PPL: 3.19 (EN), 7.49 (ZH), Capacity: 1.03–3.05 bits/token, Utilization: 0.66–0.74, Ave Time: [truncat...	non-explicit	pretext	text
A principled approach to natural language water... [15]	Transformer-based encoder/decoder; BERT for distillation	Web Transformer 2	Bit acc: 0.994 (K=None), 1.000 (DAE), 0.978 (Adaptive+K=S); Meteor Drop: [truncated]iitilde0.057; SBERT ↑: [truncated]iitilde1.227; Ownership R...	Yes; semantic-level embedding; synonym substitution using BERT	Yes; watermark message assigned categorical label (e.g., 4-bit → 1-of-16)	Yes; semantic embeddings via transformer encoder and BERT; SBERT distance as metric
Context-aware linguistic steganography model ba... [8]	BERT (encoder), LSTM (decoder)	WMT18 News Commentary (train/test), Yang et al. bits, Doc2Vec, 5,000 stego pairs (8:1:1 split)	BLEU: 30.5, PPL: 22.5, ER: 0.29, KL: 0.02, SIM: 0.86, Stego detection [truncated]iitilde16%	Yes	[Not specified]	GCF (global context), LMR (language model reference), Multi-head attention

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Table 11 – continued from previous page

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
DeepTextMark: a deep learning-driven text water... [24]	Model-independent; tested with OPT-2.7B	Dolly ChatGPT (train/validate), C4 (test), robustness & sentence-level test sets	100% accuracy (multi-synonym, 10-sentence), mSMS: 0.9892, TPR: 0.83, FNR: 0.17, Detection: 0.00188s, Insertion: 0.27931s	NO	[Not specified]	[Not specified]
Hi-stega: A hierarchical linguistic steganograp... [38]	GPT-2	Yahoo! News (titles, bodies, comments); 2,400 titles used	ppl: 109.60, MAUVE: 0.2051, ER2: 10.42, Δ(cosine): 0.0088, Δ(simcse): 0.0191	explicit	Social Media	Text
Linguistic steganography: From symbolic space t... [45]	CTRL (generation), BERT (semantic classifier)	5,000 CTRL-generated texts per semanteme (n = 2–16); 1,000 user-generated texts for anti-steganalysis	Classifier Accuracy: 0.9880; Loop Count: 1.0160; PPL: 13.9565; Anti-Steganalysis Accuracy: [truncated]iitilde0.5	implicit	Text	Semanteme (α) as a vector in semantic spac
Natural language steganography by chatgpt [35]	[Not specified]	Custom word sets for specific topics (e.g., 16×10-word sets for music reviews)	[Not specified]	Explicit	Specific Genre/Topic Text	Text

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Table 11 – continued from previous page

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
Natural language watermarking via paraphraser-b... [29]	Transformer (Paraphraser), BART (BARTScore), BERT (BLEURT, comparisons)	ParaBank2, LS07, CoInCo, Novels, WikiText-2, IMDB, NgNews	LS07 P@1: 58.3, GAP: 65.1; CoInCo P@1: 62.6, GAP: 60.7; Text Recoverability: [truncated]iitilde88–90%	Explicit	[Not specified]	text
Rewriting-Stego: generating natural and control... [18]	BART (bart-base2)	Movie, News, Tweet	BPTS: 4.0, BPTC+S: 4.0, PPL: 62.1, Mean: 44.4, Variance: 2.1e04, Acc: 8.9%	not Explicit	[Not specified]	[Not specified]
ALiSa: Acrostic linguistic steganography based ... [44]	BERT (Google's BERTBase, Uncased)	BookCorpus (10,000 natural texts for evaluation)	PPL: Natural = 13.91, ALiSa = 14.85; LS-RNN/LS-BERT Acc & F1 = [truncated]iitilde0.50; Outperforms GPT-AC/ADG in all cases	No	[Not specified]	[Not specified]

6 DISCUSSION

This section provides a comprehensive discussion of the findings presented in the results section, synthesizing insights across all research questions and identifying implications for future research and practice.

6.1 Synthesis of Key Findings

The systematic review reveals a rapidly evolving field that has undergone significant transformation since 2023. The shift from white-box to black-box approaches represents a paradigm change toward more practical, real-world deployable steganographic systems. This evolution is driven by the increasing accessibility of large language models through APIs and the need for covert communication in censored environments.

6.2 Implications for Research and Practice

6.2.1 Methodological Implications. The findings suggest several important methodological considerations:

- **Standardization Need:** The lack of standardized evaluation metrics and benchmarks represents a critical barrier to progress. Future research should prioritize the development of common evaluation frameworks.

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- **Evaluation Completeness:** The limited use of human evaluation (only 25% of studies) and robustness testing (40% missing) indicates a need for more comprehensive evaluation practices.
- **Reproducibility:** The variation in reporting standards and missing implementation details in many studies hampers reproducibility and comparison.

6.2.2 Practical Implications. For practitioners and developers:

- **Method Selection:** The choice between white-box and black-box methods should be based on security requirements vs. deployment constraints.
- **Capacity Planning:** The Psic Effect and capacity limitations in short texts should be carefully considered in system design.
- **Security Considerations:** The vulnerability to attacks (5-50% detection rate drops) requires robust defense mechanisms.

6.3 Addressing the Psic Effect

The Perceptual-Statistical Imperceptibility Conflict emerges as the most significant challenge in the field. This fundamental trade-off between perceptual quality and statistical security affects 80% of studies and results in an average capacity loss of 1-2 bits per word. Future research should focus on:

- Developing techniques that minimize this trade-off
- Creating adaptive systems that balance both aspects dynamically
- Exploring novel approaches that decouple perceptual and statistical imperceptibility

6.4 The Role of Context and External Knowledge

The integration of external knowledge sources has proven crucial for enhancing both capacity and contextual relevance. However, this integration introduces new challenges:

- **Privacy Concerns:** External knowledge integration may compromise the privacy of the steganographic system
- **Computational Overhead:** The 5-15% increase in computational cost may limit real-time applications
- **Generalizability:** Domain-specific knowledge may not transfer well across different contexts

6.5 Ethical Considerations and Responsible Development

The review reveals a concerning gap in ethical considerations, with only 10% of studies addressing ethical implications. This represents a significant oversight given the potential for misuse in:

- Censorship evasion in authoritarian regimes
- Covert communication for malicious purposes
- Data exfiltration and information leakage
- Bias propagation through generated content

Future research must prioritize the development of ethical frameworks and responsible use guidelines.

6.6 Limitations of the Review

Several limitations of this systematic review should be acknowledged:

- **Incomplete Coverage:** 14 papers remained pending PDF acquisition, potentially missing important insights

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- **Language Bias:** The focus on English-language publications may have excluded relevant non-English research
- **Recency Bias:** The rapid evolution of the field means some recent developments may not be fully captured
- **Quality Assessment:** The lack of formal quality assessment tools may have influenced the synthesis

6.7 Future Research Directions

Based on the synthesis of findings, several promising research directions emerge:

6.7.1 Technical Advancements.

- **Multimodal Steganography:** Integration with vision-language models for text-image combinations
- **Robust Defense Mechanisms:** Development of attack-resistant techniques
- **Provable Security:** Theoretical foundations for stronger security guarantees
- **Efficient Computation:** Reducing computational overhead for real-time applications

6.7.2 Methodological Improvements.

- **Standardized Evaluation:** Development of common benchmarks and evaluation protocols
- **Human-Centered Design:** Greater emphasis on human evaluation and usability
- **Cross-Language Support:** Extension to non-English languages and cultural contexts
- **Real-World Testing:** Evaluation in actual deployment scenarios

6.7.3 Ethical and Social Considerations.

- **Ethical Frameworks:** Development of guidelines for responsible use
- **Bias Mitigation:** Techniques to prevent discrimination and bias propagation
- **Transparency:** Methods for detecting and auditing steganographic content
- **Regulatory Compliance:** Alignment with emerging AI regulations and standards

6.8 Conclusion

This systematic review has provided a comprehensive analysis of the current state of LLM-based steganography, revealing both significant progress and critical challenges. The field has evolved rapidly, with clear trends toward more practical and context-aware systems. However, fundamental limitations such as the Psic Effect, attack vulnerability, and ethical concerns remain inadequately addressed.

The findings suggest that future research should prioritize the development of standardized evaluation frameworks, robust defense mechanisms, and ethical guidelines. The integration of external knowledge sources shows promise but requires careful consideration of privacy and computational constraints. Most importantly, the field must address the ethical implications of these technologies to ensure their responsible development and deployment.

As LLMs continue to evolve and become more accessible, the field of linguistic steganography will likely see continued growth and innovation. The challenges identified in this review provide a roadmap for future research directions, while the opportunities suggest exciting possibilities for advancing both the technical capabilities and practical applications of these systems.

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7 CONCLUSION

This systematic literature review illuminates the profound impact of Large Language Models (LLMs) on linguistic steganography, demonstrating a clear paradigm shift toward context-aware, generative systems that prioritize imperceptibility, embedding capacity, and naturalness. Through analysis of 18 primary studies (with 14 additional pending for full inclusion), key research questions were addressed, revealing that the published literature is rapidly evolving. Applications now span secure communication in social media, zero-shot generation, and watermarking overlaps.

Evaluation metrics such as Perplexity (PPL), Kullback-Leibler Divergence (KLD), and bits per token/word consistently show LLM-based methods outperforming traditional approaches. This improvement is particularly evident through integration of external semantic resources like context retrieval and domain-specific prompts to enhance relevance and capacity. However, persistent limitations remain, including the Perceptual-Statistical Imperceptibility Conflict (Psic Effect), low entropy in short texts, and challenges in black-box access. These underscore fundamental trade-offs in security and practicality.

The findings establish that contextual compatibility—leveraging domain correlations and communicative patterns—is essential for robust steganographic systems. This development paves the way for more sophisticated covert channels resistant to both human and automated detection. These advancements hold significant implications for information security, enabling high-capacity hidden messaging in everyday digital interactions while mitigating risks such as hallucinations and biases in LLMs.

Future research should concentrate on several key areas: mitigating segmentation ambiguity, developing provably secure black-box frameworks, and exploring multimodal integrations (e.g., text with images) to bridge identified gaps. This review underscores the potential of LLMs to redefine steganography as a cornerstone of secure, imperceptible communication in an increasingly surveilled digital landscape.

Table 12. Summary of Results from Reviewed Papers

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
VAE-Stega: linguistic steganography based on va... [43]	BERTBASE (BERT-LSTM) (LSTM-LSTM) model was trained from scratch	Twitter (2.6M sentences) IMDB (1.2M sentences) preprocessed	PPL: 28.879, ΔMP: 0.242, KLD: 3.302, JSD: 10.411, Acc: 0.600, R: 0.616	non-explicit	pre-text	text
General framework for reversible data hiding in... [48]	BERTBase	BookCorpus	BPW=0.5335 F1=0.9402 PPL=134.2199	non-explicit	pre-text	text

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Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
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Joint linguistic steganography with BERT masked... [9]	LSTM + attention for temporal context. GAT for spatial token relationships. BERT MLM for deep semantic context in substitution.	OPUS	PPL=13.917 KLD=2.904 SIM=0.812 ER=0.365 (BN=2) Best Acc=0.575 (BERT classifier) FLOPs=1.834G	explicit	pre-text	text
Discop: Provably secure steganography in practi...	GPT-2	IMDB	p=1.00 Total Time (seconds)=362.63 Ave Time ↓ (seconds/bit)=6.29E-03 Ave KLD ↓ (bits/token)=0 Max KLD ↓ (bits/token)=0 Capacity (bits/token)=5.76 E...	non-explicit	tuning + pre-text	text
Generative text steganography with large langua... [39]	Any	[Not specified]	Length: 13.333 (words). BPW: 5.93 bpw PPL: 165.76. Semantic Similarity (SS): 0.5881 LS-CNN Acc: 51.55%. BiLSTM-Dense Acc: 49.20%. Bert-FT Acc: 50...	explicit	[Not specified]	[Not specified]

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Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
Meteor: Cryptographically secure steganography ... [16]	GPT-2	Hutter Prize, HTTP GET requests	GPT-2: 3.09 bits/token	non-explicit	tuning + pretext	text
Zero-shot generative linguistic steganography [21]	LLaMA2-Chat-7B (as the stegotext generator / QA model). GPT-2 (for NLS baseline and JSD evaluation)	IMDB, Twitter	PPL: 8.81. JSDfull: 17.90 (x10[truncated]iicircum-2). JSDhalf: 16.86 (x10[truncated]iicircum-2). JSDzero: 13.40 (x10[truncated]iicircum-2) TS...	explicit	zero-shot + prompt	text
Provably secure disambiguating neural linguisti... [28]	LLaMA2-7b (English), Baichuan2-7b (Chinese)	IMDb dataset (100 texts/sample, 3 English sentences + Chinese translations)	Total Error: 0%, Ave KLD: 0, Max KLD: 0, Ave PPL: 3.19 (EN), 7.49 (ZH), Capacity: 1.03–3.05 bits/token, Utilization: 0.66–0.74, Ave Time: [truncat...	non-explicit	pretext	text
A principled approach to natural language water... [15]	Transformer-based encoder/decoder; BERT for distillation	Web Transformer 2	Bit acc: 0.994 (K=None), 1.000 (DAE), 0.978 (Adaptive+K=S); Meteor Drop: [truncated]iitilde0.057; SBERT ↑: [truncated]iitilde1.227; Ownership R...	Yes; semantic-level embedding; synonym substitution using BERT	Yes; watermark message assigned categorical label (e.g., 4-bit → 1-of-16)	Yes; semantic embeddings via transformer encoder and BERT; SBERT distance as metric

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Table 12 – continued from previous page

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
Context-aware linguistic steganography model ba... [8]	BERT (encoder), LSTM (decoder)	WMT18 News Commentary (train/test), Yang et al. bits, Doc2Vec, 5,000 stego pairs (8:1:1 split)	BLEU: 30.5, PPL: 22.5, ER: 0.29, KL: 0.02, SIM: 0.86, Stego detection [truncated]iitilde16%	Yes	[Not specified]	GCF (global context), LMR (language model reference), Multi-head attention
DeepTextMark: a deep learning-driven text water... [24]	Model-independent; tested with OPT-2.7B	Dolly ChatGPT (train/validate), C4 (test), robustness & sentence-level test sets	100% accuracy (multi-synonym, 10-sentence), mSMS: 0.9892, TPR: 0.83, FNR: 0.17, Detection: 0.00188s, Insertion: 0.27931s	NO	[Not specified]	[Not specified]
Hi-stega: A hierarchical linguistic steganograp... [38]	GPT-2	Yahoo! News (titles, bodies, comments); 2,400 titles used	ppl: 109.60, MAUVE: 0.2051, ER2: 10.42, Δ(cosine): 0.0088, Δ(simcse): 0.0191	explicit	Social Media	Text
Linguistic steganography: From symbolic space t... [45]	CTRL (generation), BERT (semantic classifier)	5,000 CTRL-generated texts per semanteme (n = 2–16); 1,000 user-generated texts for anti-steganalysis	Classifier Accuracy: 0.9880; Loop Count: 1.0160; PPL: 13.9565; Anti-Steganalysis Accuracy: [truncated]iitilde0.5	implicit	Text	Semanteme (α) as a vector in semantic spac

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Table 12 – continued from previous page

Paper	Llm	Dataset	Result	Context Aware	Categ Context	Representation Context
Natural language steganography by chatgpt [35]	[Not specified]	Custom word sets for specific topics (e.g., 16×10-word sets for music reviews)	[Not specified]	Explicit	Specific Genre/Topic Text	Text
Natural language watermarking via paraphraser-b... [29]	Transformer (Paraphraser), BART (BARTScore), BERT (BLEURT, comparisons)	ParaBank2, LS07, CoInCo, Novels, WikiText-2, IMDB, NgNews	LS07 P@1: 58.3, GAP: 65.1; CoInCo P@1: 62.6, GAP: 60.7; Text Recoverability: [truncated]iitilde88–90%	Explicit	[Not specified]	text
Rewriting-Stego: generating natural and control... [18]	BART (bart-base2)	Movie, News, Tweet	BPTS: 4.0, BPTC+S: 4.0, PPL: 62.1, Mean: 44.4, Variance: 2.1e04, Acc: 8.9%	not Explicit	[Not specified]	[Not specified]
ALiSa: Acrostic linguistic steganography based ... [44]	BERT (Google's BERTBase, Uncased)	BookCorpus (10,000 natural texts for evaluation)	PPL: Natural = 13.91, ALiSa = 14.85; LS-RNN/LS-BERT Acc & F1 = [truncated]iitilde0.50; Outperforms GPT-AC/ADG in all cases	No	[Not specified]	[Not specified]

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