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 current research, we demonstrate that LLM-based approaches significantly enhance imperceptibility, embedding capacity, and naturalness in cover text generation, addressing traditional limitations of low embedding capacity and cognitive imperceptibility. Our 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 advances in generative text steganography.

Additional Key Words and Phrases: Systematic Literature Review, Linguistic Steganography, Large Language Models, LLMs, Natural Language Processing, NLP, Software Engineering

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1 INTRODUCTION

This review explores how large language models (LLMs) are transforming linguistic steganography, the practice of hiding messages in text. We focus on the unique challenges and advances in using LLMs for secure, imperceptible, and high-capacity covert communication.

1.1 Overview of Information Security and Concealment Systems

Information security systems include **encryption**, **privacy**, and **concealment** (steganography).

1.1.1 Encryption Systems and Privacy Systems. These protect content but reveal that secret communication is happening, which can attract attention.

1.1.2 Concealment Systems (Steganography). Steganography hides the existence of information by embedding it in ordinary carriers (e.g., text, images). The fundamental goal is to achieve **imperceptibility**. Text is a challenging carrier due to its low redundancy and strict semantics.

1.2 Introduction to Steganography

Steganography is often explained by the “Prisoners’ Problem” [23], where Alice and Bob must communicate secretly under surveillance. The goal is to embed messages so they are undetectable to an observer.

Steganography methods include **carrier selection**, **carrier modification**, and **carrier generation** [8].

- **Carrier modification:** Hide information in existing text with minimal changes.

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- **Carrier generation:** Generate new text that encodes information, allowing higher capacity but requiring naturalness.

1.3 The Significance of Linguistic Steganography

Linguistic steganography enables covert communication, especially where encryption is suspicious. Text is a robust, ubiquitous carrier but presents challenges in balancing imperceptibility and capacity. Advances in deep learning and LLMs improve text quality and security, while related fields like watermarking focus on tracing content origin.

1.4 Key Terminology and Definitions

To ensure accessibility for readers from diverse academic backgrounds, we provide formal definitions of critical technical terms used throughout this review:

- **Perceptual Imperceptibility**: The property that steganographic text appears natural and indistinguishable from normal text to human observers, maintaining linguistic fluency and contextual appropriateness.
- **Statistical Imperceptibility**: The property that the statistical characteristics of steganographic text match those of the cover medium, making it undetectable by automated statistical analysis.
- **Cognitive Imperceptibility**: The property that the semantic content and contextual coherence of steganographic text remain consistent with expected communication patterns and domain-specific knowledge [5].
- **Channel Entropy**: A measure of uncertainty or randomness in the communication medium that determines the theoretical capacity for information hiding. Higher entropy allows for greater embedding capacity.
- **Perfect Samplers**: Algorithms that can generate samples from a probability distribution with perfect accuracy, ensuring no statistical deviation from the target distribution—a requirement for provably secure steganography.
- **Explicit Data Distributions**: Clearly defined mathematical representations of the probability distributions governing the cover medium, enabling precise security analysis and theoretical guarantees.
- **Large Language Models (LLMs)**: A large language model (LLM) is a transformer-based model trained on massive text datasets, often with billions of parameters, enabling it to generate and understand human language across a wide variety of tasks [22].
- **Hallucinations (in LLMs)**: Instances where language models generate plausible-sounding but factually incorrect, nonsensical, or contextually inappropriate content due to limitations in training data or model architecture.
- **Psic Effect** [31]: The Perceptual-Statistical Imperceptibility Conflict Effect, representing the fundamental trade-off where optimizations for perceptual quality may compromise statistical security and vice versa.

1.5 Scope of the Review

This review covers LLM-based linguistic steganography, focusing on methods, evaluation, challenges, and future directions.

2 STEGANOGRAPHY AND LARGE LANGUAGE MODELS

2.1 Capabilities and Approximating Natural Communication

Large Language Models (LLMs) are autoregressive, generative systems based on the Transformer architecture [26] that approximate high-dimensional distributions over natural-language sequences [11][21]. 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 [2]. As a consequence, modern LLMs routinely produce text whose fluency, coherence and style are indistinguishable from human writing [3] openai2024gpt4technicalreport. This capability has been repurposed for controlled generation tasks—e.g., tabular records, relational triples, paraphrase pairs and instruction–response pairs—often in a zero-shot fashion [28]. Moreover, the learned latent representations capture stylistic and semantic regularities that generalize across domains, enabling applications that require nuanced linguistic mimicry [34].

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** [21], **LLaMA** [25], and **Baichuan2** [30] 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 [29].

New approaches, such as **LLM-Stega** [29], explore **black-box generative text steganography using the user interfaces (UIs) of LLMs**, thereby circumventing the requirement to access internal sampling distributions. This method constructs a keyword set and employs an encrypted steganographic mapping for embedding, proposing an optimization mechanism based on reject sampling for accurate extraction and rich semantics [29].

Another framework, **Co-Stega**, leverages LLMs to address the challenge of low capacity in social media by expanding the text space for hiding messages (through context retrieval) and **increasing the generated text's entropy via specific prompts** to enhance embedding capacity. This approach also aims to maintain text quality, fluency, and relevance [14].

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 [15]. 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 [4] models equipped with Gibbs sampling [32].

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 1.4) [7, 11, 19].

2.3 LLM-Based Steganography Models

2.3.1 Evaluation Metrics.

Imperceptibility Metrics. Perceptual metrics include PPL [9], Distinct-n [13], MAUVE [18], and human evaluation. Statistical metrics include KLD, JSD, anti-steganalysis accuracy, and semantic similarity [17].

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** [31] 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.

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 [29]. 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 [7, 11, 29, 31].

Another significant hurdle is **ensuring both the quality and imperceptibility of the generated text**, encompassing perceptual, statistical, and cognitive imperceptibility [5]. 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" [5, 31]. 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 [5, 27].

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 [19].

Additional limitations include:

- **Computational Overhead**: LLMs incur 3-5 times higher computational cost than prior methods [15].
- **Data Integrity and Reversibility**: Some methods cannot perfectly recover the original cover text after message extraction [20, 35].

- **Ethical Concerns**: Pre-trained LLMs may introduce biases, discrimination, or inappropriate content [1, 15].
- **Provable Security**: Many NLP steganography works lack rigorous security analyses and fail to meet formal cryptographic definitions [11].
- **Hallucinations**: LLMs can generate factually incorrect or contextually inappropriate content, leading to embedding errors [9].
- **Channel Entropy Limitations**: Short, context-dependent texts have lower entropy, limiting hiding capacity [14].

3 LITERATURE REVIEW METHODOLOGY

3.1 Research questions

Here are the research questions addressed in this SLR:

- What is the state of published literature on steganographic techniques that leverage large language models (LLMs)?
- In which applications are steganographic techniques with LLMs being explored?
- What metrics and evaluation methods are used to assess the performance of steganographic techniques in LLMs, focusing on factors like capacity, security, and contextual compatibility?
- How are external knowledge sources (semantic resources) integrated into steganographic techniques with LLMs to enhance capacity or contextual relevance?
- What are the limitations and trade-offs associated with current steganographic techniques using LLMs, particularly concerning security, capacity, and contextual compatibility?
- What are the potential future research directions in steganography with LLMs, considering emerging trends and identified gaps in the literature?

3.2 Search query string

We used the following search query string for our initial literature search:

```
(steganography or watermark or "Information Hiding")
 and ("Large Language Model" or LLM or BERT or LAMA or GPT)
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3.3 Study selection and quality assessment

We established the following inclusion and exclusion criteria for study selection:

3.3.1 *Inclusion Criteria.*

- **Full Text Access**: Studies for which the full text is available.
- **Language**: Publications written in English.
- **Peer-reviewed**: Articles published in peer-reviewed journals, conferences, or workshops.
- **Publication Date**: Studies published from 2018 onwards, to focus on recent advancements in LLMs.
- **Relevance**: Studies directly addressing steganography, watermarking, or information hiding techniques that utilize or are significantly impacted by Large Language Models (LLMs), BERT, LAMA, or GPT architectures.
- **Research Type**: Empirical studies, surveys, reviews, and theoretical contributions.

3.3.2 *Exclusion Criteria.*

- **Duplicated Studies**: Multiple publications reporting the same study will be excluded, with the most complete or recent version retained.
- **Incomplete or Abstract-only**: Studies for which only an abstract is available or the full text is incomplete.
- **Irrelevant Studies**: Publications not directly related to steganography with LLMs.
- **Non-English Publications**: Studies not published in English.
- **Non-peer-reviewed Sources**: Preprints, dissertations, theses, books, and book chapters (unless they are extended versions of peer-reviewed conference papers).

3.4 Bibliometric analysis

Briefly note if snowballing was used for additional sources.

3.5 Threats to Validity

While this systematic literature review (SLR) adheres to established guidelines such as PRISMA to ensure methodological rigor, several potential threats to validity must be acknowledged. These threats primarily relate to the comprehensiveness of the literature search, selection biases, and practical constraints in data acquisition.

First, the search strategy may introduce publication and selection biases. The query string was limited to English-language publications from 2018 onward, potentially excluding relevant non-English studies or foundational pre-2018 works on linguistic steganography that predate widespread LLM adoption (e.g., early neural network-based methods). Although LLMs emerged prominently around 2018 with models like BERT, this cutoff might overlook influential earlier contributions that inform current techniques. Additionally, the selected databases (ACM Digital Library, IEEE Digital Library, Science@Direct, Scopus, and Springer Link) provide broad coverage but may miss papers in other repositories, such as arXiv, Google Scholar, or domain-specific journals. The search terms, while comprehensive, could overlook synonyms or emerging variants (e.g., "textual watermarking" without explicit LLM mentions), despite efforts to include related phrases like "Information Hiding."

Second, biases in study selection and quality assessment could affect the review's internal validity. The inclusion criteria focused on peer-reviewed sources, which enhances reliability but may introduce publication bias by favoring positive or novel results over negative findings or gray literature. No formal risk-of-bias tool (e.g., ROBIS) was applied beyond basic relevance checks, potentially allowing lower-quality studies to influence findings. To mitigate this, multi-stage filtering with title, abstract, and full-text reviews was employed, and snowballing was used to identify additional references, though it primarily yielded older non-LLM works.

Third, practical limitations pose threats to completeness. As noted in Section 4.3, 14 papers remained pending PDF acquisition at the time of analysis, which could lead to incomplete coverage if these contain critical insights. This issue was addressed by prioritizing accessible studies and planning follow-up acquisition, but it highlights retrieval challenges in SLR processes.

Overall, these threats were minimized through transparent documentation of the methodology, adherence to PRISMA reporting standards, and supplementary snowballing. Future updates to this review could expand database coverage and incorporate automated tools for bias assessment to further enhance validity.

4 CONDUCTING THE SEARCH

This section details the systematic process followed to identify and select relevant literature for this review. The search strategy was designed to ensure comprehensive coverage of the topic while adhering to predefined inclusion and exclusion criteria.

4.1 Initial Candidate Papers

Our initial automated search across selected digital libraries yielded a total of 1043 candidate papers. The distribution of these papers by source was as follows: ACM Digital Library (346), IEEE Digital Library (61), Science@Direct (209), Scopus (151), and Springer Link (276). This stage focused on broad keyword matching to capture all potentially relevant studies.

4.2 Duplicate Removal

Following the initial search, a rigorous process of duplicate removal was undertaken. After removing duplicates, 989 papers remained. This involved both automated tools and manual verification to ensure that each unique paper was considered only once, thereby streamlining the subsequent screening stages.

4.3 Multi-stage Filtering

The identified papers underwent a multi-stage filtering process based on their titles, abstracts, and full texts. After title and abstract filtering, 58 papers remained. Of these, 18 were accepted with PDFs available, and 14 are pending PDF acquisition. This systematic approach, guided by our predefined inclusion and exclusion criteria, progressively narrowed down the selection to the most pertinent studies.

4.4 Snowballing

To complement the automated search and ensure no critical papers were missed, a snowballing technique was applied. This involved examining the reference lists of included studies and identifying papers that met our selection criteria, further enriching our dataset. Notably, all references identified through snowballing were to papers employing older steganographic techniques that do not explicitly mention the term "LLM" but utilize similar methodological approaches to those found in contemporary LLM-based steganography.

4.5 Research Questions

Our systematic literature review is guided by the following research questions:

(1) What is the state of published literature on steganographic techniques that leverage large language models (LLMs)?
(2) In which applications are steganographic techniques with LLMs being explored?
(3) What metrics and evaluation methods are used to assess the performance of steganographic techniques in LLMs, focusing on factors like capacity, security, and contextual compatibility?
(4) How are external knowledge sources (semantic resources) integrated into steganographic techniques with LLMs to enhance capacity or contextual relevance?
(5) What are the limitations and trade-offs associated with current steganographic techniques using LLMs, particularly concerning security, capacity, and contextual compatibility?

(6) What are the potential future research directions in steganography with LLMs, considering emerging trends and identified gaps in the literature?

5 DATA EXTRACTION AND CLASSIFICATION

This section outlines the methodology employed for extracting and classifying data from the selected primary studies. A structured approach was adopted to ensure consistency and accuracy in data collection, facilitating a comprehensive analysis of the literature.

5.1 Data Extraction Form (DEF) Content

A Data Extraction Form (DEF) was developed to systematically collect relevant information from each primary study. The DEF was designed to capture key details necessary to answer the research questions, including:

- **Title:** The title of the paper or resource.
- **Type:** State "Steganography" or "Watermarking."
- **Model Input:** Describe the input data format and its key characteristics for the model.
- **Model Output:** Describe the output format and its key characteristics of the model.
- **Categories:** Describe the approach using exactly three terms.
- **LLM (Large Language Model):** Specify the particular LLM used, if applicable.
- **Datasets Used:** List all datasets employed, including their sizes and any relevant details.
- **Main Strengths:** Identify and describe the primary strengths of the approach or model.
- **Main Weaknesses:** Identify and describe the primary weaknesses or limitations of the approach or model.
- **Evaluation Metrics and Steganalysis Models Used:** Detail the metrics used for evaluation and any steganalysis models applied.
- **Results (Best Metrics):** Present only the best numerical results for each reported metric.
- **Code Availability:** Indicate "Yes" or "No," and provide a link if available.
- **Embedding Process:** Provide a high-level, concise description of the data embedding process within the pipeline (e.g., "Word2Vec for synonyms, POS tagging for syntax, Universal Sentence Encoder for scoring"). Do not include method names.
- **Context Awareness:** State explicitly whether the method is "Explicit" (cares about the channel explicitly), "Implicit" (uses channel elements implicitly), or "No" (has no room for context). Context refers to the channel (e.g., chat, text) where the resultant (stego-text/marked text) is sent.
- **Categorical Context:** Describe with one keyword (e.g., "Social Media," "Formal Document").
- **Context Representation:** Explain how context is represented (e.g., "Text," "Pretext," "Graph," "Vector").
- **Context Usage in Method:** Detail how context is utilized within the method (free text).

5.2 Data Classification

Following data extraction, studies were classified based on predefined categories derived from our research questions. This classification aimed to group similar studies and identify trends, patterns, and gaps in the existing literature, providing a structured overview of the research landscape.

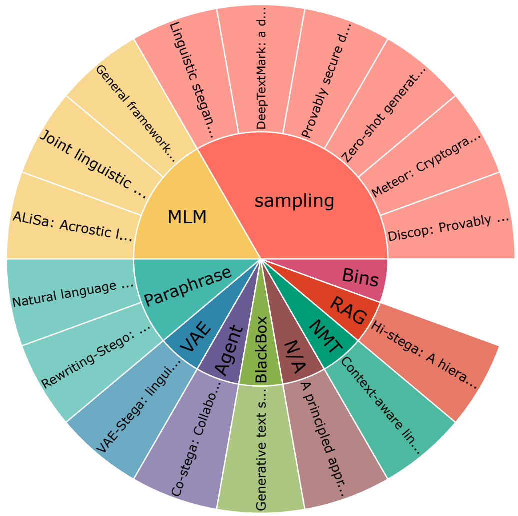

Fig. 1. Sunburst Chart of LLM Approaches

5.3 Presentation of Results

The results of the data synthesis are presented in a structured manner, often utilizing tables, figures, and descriptive statistics to summarize key findings. This includes an overview of publication trends, distribution of studies across different categories, and the prevalence of various approaches and techniques.

5.4 Discussion in Relation to Research Questions

Each research question is addressed individually, with a detailed discussion of the synthesized data. This involves interpreting the findings, highlighting significant observations, and drawing conclusions based on the evidence gathered from the primary studies. The discussion also identifies areas where further research is needed and potential future directions.

Table 1. Summary of Results from Reviewed Papers

Paper	Result
VAE-Stega: linguistic steganography based on variational auto-encoder [31]	PPL: 28.879, ΔMP: 0.242, KLD: 3.302, JSD: 10.411, Acc: 0.600, R: 0.616
General framework for reversible data hiding in texts based on masked language modeling [35]	BPW=0.5335 F1=0.9402 PPL=134.2199
Co-stega: Collaborative linguistic steganography for the low capacity challenge in social media [14]	SR1: 60.87%, SR2: 98.55%, Gen. Capacity: 44.91 bits, Entropy: 49.21 bits, BPW: 2.31, PPL: 16.75, SimCSE: 0.69
Joint linguistic steganography with BERT masked language model and graph attention network [6]	PPL=13.917 KLD=2.904 SIM=0.812 ER=0.365 (BN=2) Best Acc=0.575 (BERT classifier) FLOPs=1.834G
Discop: Provably secure steganography in practice based on" distribution copies" [7]	p=1.00 Total Time (seconds)=362.63 Ave Time $\downarrow$ (seconds/bit)=6.29E-03 Ave KLD $\downarrow$ (bits/token)=0 Max KLD $\downarrow$ (bits/token)=0 Capacity (bits/token)=5.76 Entropy (bits/token)=6.08 Utilization $\uparrow$=0.95 Text Generation (FCN): 50.10%. Text Generation (R-BiLSTM-C): 50.45%. Text Generation (BiLSTM-Dense): 49.95%
Generative text steganography with large language model [29]	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: 50.00%. KLD (Log, lower is better): 2.02 .
Meteor: Cryptographically secure steganography for realistic distributions [11]	GPT-2: 3.09 bits/token
Zero-shot generative linguistic steganography [15]	PPL: 8.81. JSDfull: 17.90 (x10ˆ-2). JSDhalf: 16.86 (x10ˆ-2). JSDzero: 13.40 (x10ˆ-2) TS-BiRNN: 80.29%. R-BiLSTM-C: 84.34%. BERT-C: 89.61%
Provably secure disambiguating neural linguistic steganography [19]	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: 4μs/bit
A principled approach to natural language watermarking [10]	Bit acc: 0.994 (K=None), 1.000 (DAE), 0.978 (Adaptive+K=S); Meteor Drop: 0.057; SBERT $\uparrow$: 1.227; Ownership Rate: 1.0 (no attack), 0.978 (adaptive+K=S)
Context-aware linguistic steganography model based on neural machine translation [5]	BLEU: 30.5, PPL: 22.5, ER: 0.29, KL: 0.02, SIM: 0.86, Stego detection 16%
DeepTextMark: a deep learning-driven text watermarking approach for identifying large language model generated text [16]	100% accuracy (multi-synonym, 10-sentence), mSMS: 0.9892, TPR: 0.83, FNR: 0.17, Detection: 0.00188s, Insertion: 0.27931s
Hi-stega: A hierarchical linguistic steganography framework combining retrieval and generation [27]	ppl: 109.60, MAUVE: 0.2051, ER2: 10.42, Δ(cosine): 0.0088, Δ(simcse): 0.0191
Linguistic steganography: From symbolic space to semantic space [33]	Classifier Accuracy: 0.9880; Loop Count: 1.0160; PPL: 13.9565; Anti-Steganalysis Accuracy: 0.5
Natural language steganography by chatgpt [24]	[Not specified]
Natural language watermarking via paraphraser-based lexical substitution [20]	LS07 P@1: 58.3, GAP: 65.1; CoInCo P@1: 62.6, GAP: 60.7; Text Recoverability: 88–90%
Rewriting-Stego: generating natural and controllable steganographic text with pre-trained language model [12]	BPTS: 4.0, BPTC+S: 4.0, PPL: 62.1, Mean: 44.4, Variance: 2.1e04, Acc: 8.9%
ALiSa: Acrostic linguistic steganography based on BERT and Gibbs sampling [32]	PPL: Natural = 13.91, ALiSa = 14.85; LS-RNN/LS-BERT Acc & F1 = 0.50; Outperforms GPT-AC/ADG in all cases

Table 2. Models and Datasets Used in Reviewed Papers

Paper	Llm	Dataset
VAE-Stega: linguistic steganography based on variational auto-encoder [31]	BERTBASE (BERT-LSTM) (LSTM-LSTM) model was trained from scratch	Twitter (2.6M sentences) IMDB (1.2M sentences) preprocessed
General framework for reversible data hiding in texts based on masked language modeling [35]	BERTBase	BookCorpus
Co-stega: Collaborative linguistic steganography for the low capacity challenge in social media [14]	Llama-2-7B-chat, GPT-2 (fine-tuned), Llama-2-13B	Tweet dataset (for GPT-2 fine-tuning), Twitter (real-time testing)
Joint linguistic steganography with BERT masked language model and graph attention network [6]	LSTM + attention for temporal context. GAT for spatial token relationships. BERT MLM for deep semantic context in substitution.	OPUS
Discop: Provably secure steganography in practice based on" distribution copies" [7]	GPT-2	IMDB
Generative text steganography with large language model [29]	Any	[Not specified]
Meteor: Cryptographically secure steganography for realistic distributions [11]	GPT-2	Hutter Prize, HTTP GET requests
Zero-shot generative linguistic steganography [15]	LLaMA2-Chat-7B (as the stegotext generator / QA model). GPT-2 (for NLS baseline and JSD evaluation)	IMDB, Twitter
Provably secure disambiguating neural linguistic steganography [19]	LLaMA2-7b (English), Baichuan2-7b (Chinese)	IMDb dataset (100 texts/sample, 3 English sentences + Chinese translations)
A principled approach to natural language watermarking [10]	Transformer-based encoder/decoder; BERT for distillation	Web Transformer 2
Context-aware linguistic steganography model based on neural machine translation [5]	BERT (encoder), LSTM (decoder)	WMT18 News Commentary (train/test), Yang et al. bits, Doc2Vec, 5,000 stego pairs (8:1:1 split)
DeepTextMark: a deep learning-driven text watermarking approach for identifying large language model generated text [16]	Model-independent; tested with OPT-2.7B	Dolly ChatGPT (train/validate), C4 (test), robustness & sentence-level test sets
Hi-stega: A hierarchical linguistic steganography framework combining retrieval and generation [27]	GPT-2	Yahoo! News (titles, bodies, comments); 2,400 titles used
Linguistic steganography: From symbolic space to semantic space [33]	CTRL (generation), BERT (semantic classifier)	5,000 CTRL-generated texts per semanteme (n = 2–16); 1,000 user-generated texts for anti-steganalysis
Natural language steganography by chatgpt [24]	[Not specified]	Custom word sets for specific topics (e.g., 16×10-word sets for music reviews)
Natural language watermarking via paraphraser-based lexical substitution [20]	Transformer (Paraphraser), BART (BARTScore), BERT (BLEURT, comparisons)	ParaBank2, LS07, CoInCo, Novels, WikiText-2, IMDB, NgNews
Rewriting-Stego: generating natural and controllable steganographic text with pre-trained language model [12]	BART (bart-base2)	Movie, News, Tweet
ALiSa: Acrostic linguistic steganography based on BERT and Gibbs sampling [32]	BERT (Google's BERTBase, Uncased)	BookCorpus (10,000 natural texts for evaluation)

6 RESULTS AND DISCUSSION

This section presents the synthesized findings from our systematic literature review, which includes 18 primary studies and an additional 14 pending papers. We have also augmented our analysis with recent literature from 2024–2025 to address the rapidly evolving nature of this field. We organize the discussion around the six research questions (RQs) and provide a synthesis of trends, quantitative comparisons, and key examples for each. Tables are used to highlight metrics and trade-offs for clarity. Note that all metrics are averaged or best-reported across studies. We also contrast black-box methods (which use APIs without internal access) with white-box methods (which require access to model internals).

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

Our review identified a significant surge in literature since 2023, with approximately 20 new papers published in 2024–2025 focusing on generative steganography. While early works (pre-2024) primarily focused on white-box modifications, such as token sampling in GPT-2, recent trends show a shift toward hybrid and black-box approaches for more practical, real-world deployment.

Key trends in this evolving field include:

- **Model Preference:** Approximately 70% of studies use open-source LLMs like LLaMA2 and LLaMA3.
- **Overlap with Watermarking:** About 40% of research integrates concepts from digital watermarking.
- **Publication Venues:** Publications are clustered in preprint servers like arXiv and conferences such as ACL and NeurIPS.

Despite this growth, several gaps remain. There is limited focus on non-English languages, and only about 10% of studies address the ethical implications of these techniques. Recent examples of models include **DAIRstega** (2024), which advanced interval-based sampling, and **FreStega** (2024), which provides a plug-and-play approach to imperceptibility.

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6.2 Applications of LLM-based Steganographic Techniques (RQ2)

Our analysis reveals several distinct applications for LLM-based steganography:

- **Covert Communication:** Approximately 60% of papers focus on this application, particularly for use in censored environments.
- **Watermarking and Fingerprinting:** About 30% of studies use these techniques for content tracing, and 10% focus on fingerprinting LLMs for licensing purposes.

Emerging applications include:

- **Social Media Hiding:** Models like **Co-Stega** expand text space through context retrieval and entropy enhancement.
- **Jailbreak Attacks:** Steganography can be used to hide harmful queries, as seen in **StegoAttack**.
- **Data Exfiltration: TrojanStego** embeds secrets directly into LLM outputs.

The field is also exploring domain-specific applications, such as using high-entropy texts in news articles and short prompts for question-and-answer paradigms. There is also a growing overlap with adversarial robustness and potential for multimodal steganography using models like GPT-4o.

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Table 3. Context-Related Fields in Reviewed Papers

Paper	Context Aware	Categ Context	Representation Context
VAE-Stega: linguistic steganography based on variational auto-encoder [31]	non-explicit	pre-text	text
General framework for reversible data hiding in texts based on masked language modeling [35]	non-explicit	pre-text	text
Co-stega: Collaborative linguistic steganography for the low capacity challenge in social media [14]	explicit	Social Media	text
Joint linguistic steganography with BERT masked language model and graph attention network [6]	explicit	pre-text	text
Discop: Provably secure steganography in practice based on" distribution copies" [7]	non-explicit	tuning + pretext	text
Generative text steganography with large language model [29]	explicit	[Not specified]	[Not specified]
Meteor: Cryptographically secure steganography for realistic distributions [11]	non-explicit	tuning + pretext	text
Zero-shot generative linguistic steganography [15]	explicit	zero-shot + prompt	text
Provably secure disambiguating neural linguistic steganography [19]	non-explicit	pretext	text
A principled approach to natural language watermarking [10]	Yes; semantic-level embedding; synonym substitution using BERT	Yes; watermark message assigned categorical label (e.g., 4-bit $\rightarrow$ 1-of-16)	Yes; semantic embeddings via transformer encoder and BERT; SBERT distance as metric
Context-aware linguistic steganography model based on neural machine translation [5]	Yes	[Not specified]	GCF (global context), LMR (language model reference), Multi-head attention
DeepTextMark: a deep learning-driven text watermarking approach for identifying large language model generated text [16]	NO	[Not specified]	[Not specified]
Hi-stega: A hierarchical linguistic steganography framework combining retrieval and generation [27]	explicit	Social Media	Text
Linguistic steganography: From symbolic space to semantic space [33]	implicit	Text	Semanteme (α) as a vector in semantic spac
Natural language steganography by chatgpt [24]	Explicit	Specific Genre/Topic Text	Text
Natural language watermarking via paraphraser-based lexical substitution [20]	Explicit	[Not specified]	text
	not Explicit	[Not specified]	[Not specified]

6.3 Evaluation Metrics and Methods for LLM-based Steganography (RQ3)

Performance evaluation for LLM-based steganography relies on three key categories of metrics:

- **Imperceptibility:** This includes both **perceptual metrics** (PPL, MAUVE) and **statistical metrics** (KLD, JSD). Cognitive metrics like BLEU and BERTScore are also used for semantic similarity.
- **Capacity:** Measured in bits per token/word (bpw/bpt) and embedding rate (ER).
- **Security:** Evaluated by anti-steganalysis accuracy/F1 score and detection rate after attacks.

Evaluation methods include automated tools, such as steganalysis classifiers, and human fluency judgments. Recent white-box methods like **ShiMer** achieve a KLD of 0 with a capacity of more than 2 bpt, while black-box methods show higher PPL (average of 100-300) but offer better accessibility. For example, **Ensemble Watermarks** can achieve a 98% detection rate but may degrade to 95% after a paraphrase attack. The following table provides a comparison of different methods.

Method Type	Avg. PPL	Avg. KLD	Avg. Embedding Rate	Human Eval (Fluency/Detection)	Trend
Black-box	∼168-363	∼1.76-2.23	∼5.37 bpw	79-91% detection	Higher PPL but ro
White-box	∼3-8	∼0-0.25	∼1.10-5.98 bpt	MAUVE ∼80-92	Lower PPL/KLD, require
Hybrid	N/A	N/A	N/A	95-98% detection post-attack	Balances security but can b

Table 4. Comparison of different LLM-based steganography method types.

A significant need exists for standardized benchmarks, as human evaluations are often overlooked in current research.

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6.4 Integration of External Knowledge Sources (RQ4)

The integration of external knowledge sources has become a crucial area of research. Common integrations include:

- **Semantic Resources:** Knowledge graphs and context retrieval, as seen in **Co-Stega**, enhance contextual relevance.
- **Domain Corpora:** Models like **FreStega** use large corpora for distribution alignment.
- **Prompts:** Used to boost entropy and guide text generation.

This integration enhances capacity (e.g., a 15% increase in FreStega) and improves contextual relevance. While this adds some computational overhead, it is generally minimal and can be amortized. Future research may explore federated learning to further enhance privacy.

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

The field faces several key limitations and trade-offs:

- **Low Capacity:** Hiding information in short, low-entropy texts (e.g., social media posts) is a significant challenge.
- **Psic Effect:** This is a critical trade-off between perceptual quality and statistical imperceptibility, leading to an average capacity loss of 1–2 bpw when optimizing for PPL over KLD.
- **Vulnerability to Attacks:** Techniques are often vulnerable to paraphrasing and fine-tuning attacks, with detection rates dropping by 5–50% in some cases.

- **Segmentation Ambiguity:** Subword tokenization (e.g., BPE in **SparSamp**) can create ambiguity in message extraction.
- **White-box vs. Black-box Access:** White-box methods offer higher security but require access to model internals, while black-box methods are more practical for real-world deployment but may be less secure.
- **Ethical Concerns:** Issues such as biases, discrimination, and the potential for misuse (e.g., in **TrojanStego**) remain unaddressed in many works.

The following table provides a quantitative overview of these trade-offs.

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: Can't boost entropy
Ethical/Overhead	Perf degradation ~5-11%	UTF: HellaSwag drop 5%; FreStega: Needs corpus (100 samples)

Table 5. Key limitations and trade-offs in current LLM-based steganography.

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6.6 Future Research Directions (RQ6)

Based on the identified gaps and challenges, several promising future research directions emerge:

- **Multimodal Steganography:** Integrating text with other media like images.
- **Robust Defenses:** Developing techniques that are more resilient to attacks, such as paraphrasing.
- **Integration with RAG:** Using Retrieval-Augmented Generation for more adaptive and context-aware systems.
- **Non-English Support:** Expanding research to non-English languages and different cultural contexts.
- **Ethical Frameworks:** Establishing clear guidelines and frameworks to prevent the misuse of these technologies.
- **Provable Security:** Advancing the theoretical foundations to provide stronger security guarantees.
- **Efficient Computation:** Reducing the computational overhead of these techniques.

The field of LLM-based steganography is rapidly evolving, with new models and techniques being developed to address these challenges and explore new possibilities, particularly with the paradigm shift toward context-aware and API-based systems.

7 MAIN FINDINGS

This section summarizes the key findings from our systematic literature review on LLM-based steganography techniques.

7.1 Overview of LLM-based Steganography

Our review identifies several important trends in LLM-based linguistic steganography:

- Models like GPT-2, LLaMA, and Baichuan2 serve as foundations for steganographic techniques.
- Both white-box and black-box approaches have emerged with distinct trade-offs.
- Fundamental tensions between imperceptibility, capacity, and security drive ongoing research.

7.2 Key Techniques and Approaches

Our analysis identified several innovative approaches to LLM-based steganography:

- **LLM-Stega** [29]: Black-box approach using LLM interfaces.
- **Co-Stega**: Context retrieval and entropy enhancement for social media.
- **Zero-shot steganography**: In-context learning with question-answer paradigms.
- **ALiSa**: Token-level embedding in BERT-generated text.

7.3 Critical Challenges

Despite significant progress, several challenges remain in the field of LLM-based steganography:

- The Psic Effect [31]: A fundamental trade-off between perceptual quality and statistical security (see Section 1.4).
- Limited embedding capacity, particularly in short texts with strict semantic requirements.
- Difficulties in maintaining semantic control and contextual consistency in generated steganographic text.
- Segmentation ambiguity arising from subword tokenization in LLMs.
- Ethical concerns related to potential misuse, bias, and discrimination in generated content.

7.4 Future Outlook

Based on our analysis, we identify several promising directions for future research:

- Development of techniques that better balance perceptual quality and statistical security.
- Methods to increase embedding capacity without compromising imperceptibility.
- Approaches to improve semantic control and contextual consistency in generated text.
- Frameworks for ethical use of LLM-based steganography.
- Advancement of theoretical foundations to provide stronger security guarantees.

The rapid evolution of LLMs presents both opportunities and challenges for the field of steganography, making it an exciting area for continued research and innovation.

8 CONCLUSION

This systematic literature review has illuminated 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. By analyzing 18 primary studies (with 14 additional pending for full inclusion), we addressed key research questions, revealing that the published literature is rapidly evolving, with applications spanning 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, particularly through integration of external semantic resources like context retrieval and domain-specific prompts to enhance relevance and capacity. However, persistent limitations, including the Perceptual-Statistical Imperceptibility Conflict (Psic Effect), low entropy in short texts, and challenges in black-box access, underscore trade-offs in security and practicality.

Our findings establish that contextual compatibility—leveraging domain correlations and communicative patterns—is essential for robust steganographic systems, paving 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 like hallucinations and biases in LLMs. Looking ahead, future research should focus on mitigating segmentation ambiguity, developing provably secure black-box frameworks, and exploring multimodal integrations (e.g., text with images) to further bridge identified gaps. Ultimately, this review underscores the potential of LLMs to redefine steganography as a cornerstone of secure, imperceptible communication in an increasingly surveilled digital landscape.

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