A Comprehensive Survey on Linguistic Steganography: Methods, Countermeasures, Evaluation, and Challenges

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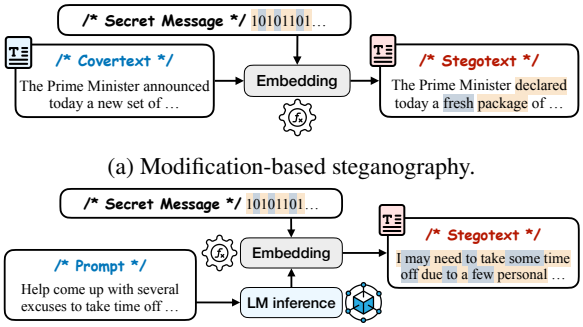
Abstract

Linguistic steganography hides secret messages in natural language text. Large language models (LLMs) have reshaped the field, but a systematic account of how these scattered advances collectively reshape the field in this new era is still missing. We provide one along four axes: 148 steganographic methods, 60 linguistic steganalysis countermeasures, 23 evaluation metrics, and 9 open challenges, each with taxonomies, reviews, and adoption analyses. Cutting across these axes, we identify five specific **paradigm shifts in the LLM era**: (1) from covertext modification to prompt-only generation, (2) from heuristic to provable security, (3) from white-box symmetric LMs to black-box or asymmetric access, (4) from security-centric designs to joint optimization, and (5) from text-quality concerns to engineering issues. The survey aims to serve as both a reference and a roadmap for practical and responsible linguistic steganography in the LLM era.

1 Introduction

While cryptography conceals the content of a message, encrypted traffic itself remains identifiable and can be blocked in repressive environments (Kaptchuk et al., 2021). Steganography instead conceals the *existence* of the message by embedding it in innocuous carriers (Mishra and Bhanodiya, 2015). In the modern era, with the advancements of digital technology, steganography has been commonly based on digital carriers, including images (Subramanian et al., 2021), audio (Djebbar et al., 2012), video (Liu et al., 2019), and text (Majeed et al., 2021).

Among these steganographic techniques, **linguistic steganography** (currently the dominant category in text steganography) has attracted increasing research attention for several reasons: (1) Textual content is ubiquitous on social networks (Aggarwal and Wang, 2011). (2) Recent advances in large language models (LLMs) have significantly improved the fluency, coherence, and naturalness of generated steganographic texts (*stegotexts*) (Radford et al., 2019; Brown et al., 2020; Achiam et al., 2023). (3) Compared to steganography based on images, audio, or video (Cox et al., 1997), linguistic steganography is often less affected by compression-related distortion during transmission (Majeed et al., 2021). Figure 1 illustrates schematic diagrams of linguistic steganography, respectively, based on two primary frameworks: modification and generation.



(a) Modification-based steganography.

(b) Generative steganography based on language model(s).

Figure 1: An overview of how to achieve linguistic steganography based on two main frameworks.

In the era of large language models (LLMs), some influential open-weight models have been released (Zhang et al., 2022; Touvron et al., 2023), which have demonstrated strong performance across a wide range of downstream tasks, thereby enabling new possibilities for linguistic steganography (Ding et al., 2024a; Zeng and Wang, 2025). However, a comprehensive survey of linguistic steganography in the LLM era is still missing. In particular, previous surveys (Majeed et al., 2021; Xiang et al., 2022b; Badawy et al., 2023; Wu et al., 2024a) exhibit two main limitations: (1) the absence of LLM-era coverage and (2) coarse-grained, paper-narrow analyses.

Survey	Year	Steganographic methods		Steganalysis methods		Evaluation metrics	
		Number	Categories (L1/L2/L3)	Number	Categories (L1/L2)	Number	Categories (L1/L2)
Majeed et al. (2021)	2021	50	3	–	–	–	–
Xiang et al. (2022b)	2022	37	4/11/–	–	–	11	4/–
Badawy et al. (2023)	2022	18	–	–	–	12	3/–
Wu et al. (2024a)	2023	28	2/4/8	29	2/7	8	–
Ours	**2026**	**148**	**2/6/17**	**60**	**2/8**	**23**	**3/6**

Table 1: Quantitative comparison of this survey with existing surveys, in which "–" indicates that relevant information on this dimension is not substantially or formally provided in the survey, and "L1/L2/L3" denotes the layer 1st/2nd/3rd for categorization.

Survey	Steganalysis taxonomy	Evaluation taxonomy	Robustness consideration	Analyses of targeted metrics	Analyses of metric adoption	Analyses of steganalysis adoption	Features of the LLM era
Majeed et al. (2021)	✗	✗	✓	✓	✗	✗	✗
Xiang et al. (2022b)	✗	✓	✗	✗	✗	✗	✗
Badawy et al. (2023)	✗	✓	✗	✗	✗	✓	✗
Wu et al. (2024a)	✓	✗	✗	✗	✗	✗	✗
Ours	✓	✓	✓	✓	✓	✓	✓

Table 2: Qualitative comparison of this survey with existing surveys.

Motivated by these limitations, we present **the first survey that systematically situates linguistic steganography in the LLM era**. This survey provides a broad coverage and systematic analyses of current linguistic steganographic **methods** based on modification and generation, **counter-measures** (steganalysis methods), **evaluation** metrics, and **challenges**. Table 1 presents quantitative comparisons, highlighting our contribution on comprehensiveness. Table 2 presents qualitative comparisons, revealing our in-depth and fine-grained features. The main structure of this survey is shown in Figure 2. *To ensure both timeliness and comprehensiveness, this survey is motivated by the LLM era rather than being confined exclusively to LLM-based methods.* This broader scope is supported by an asymmetry discovered in this survey: Although most generative linguistic steganographic methods are adaptable to LLMs, most steganalysis methods have not yet. Further, we summarize the paradigm shifts in the LLM era, which motivate the scope and structure of this survey, as follows:

- The shift from modifying a covertext to *prompt-only generation*, removing the modification budget as a fundamental capacity bottleneck (especially since Yang et al. (2019a); Ziegler et al. (2019), see Section 3 and 4).
- The shift from heuristic to *provable security*, realized through information-theoretic mechanisms (since Zhang et al. (2021b), see Section 4.3 and Appendix E.1).
- The shift from white-box, symmetric LMs to *black-box* or *asymmetric* access, including API-only sender scenarios (since Wu et al. (2024c), see Appendix E and Table 7).
- The shift from security-centric designs to the *joint optimization* of security, efficiency, and robustness (since Yi et al. (2022a); Yan et al. (2023), see Section 6 and Appendix H).
- The shift from concerns of pure text quality to LM *engineering realities*, especially tokenization inconsistency and computational indeterminism (since Nozaki and Murawaki (2022), see Section 7 and Appendix I).

2 Preliminaries and Background

2.1 Steganography System

A classic scenario used to illustrate steganography is Simmons' *Prisoners' Problem* (Simmons, 1984). In this setting, Alice and Bob (the steganographers) are confined in prison and attempt to hatch an escape plan. Their only way of communication is monitored by the warden Eve (the steganalyzer), who monitors all messages. If Eve detects anything unusual or suspicious, she will block the exchange and impose punishment. Therefore, to evade detection, Alice and Bob must embed their secret messages into an *innocent-looking*

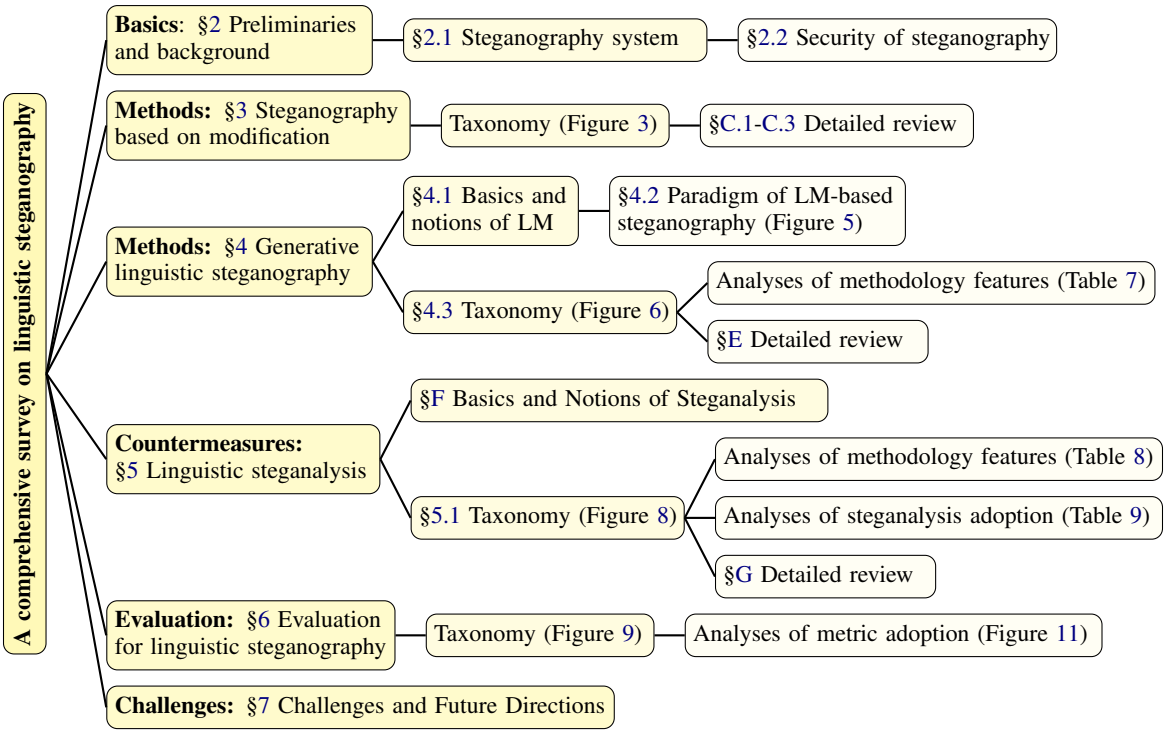


Figure 2: The main content flow and structure of this survey.

cover object to obtain a stego object. Formally, a steganography system $\sum_{\mathcal{D}}$ with the channel distribution $\mathcal{D}$ is a triple of algorithms, $\sum_{\mathcal{D}} = (\text{KeyGen}_{\mathcal{D}}, \text{Embed}_{\mathcal{D}}, \text{Extract}_{\mathcal{D}})$, in which:

- $\text{KeyGen}_{\mathcal{D}}(1^{\lambda})$ takes arbitrary input with length λ and generates a shared key $K \in \{0,1\}^k$ with length k.
- $\text{Embed}_{\mathcal{D}}(K, \mathbf{m}, \mathcal{H})$ takes a shared key K, a secret message $\mathbf{m} \in \{0,1\}^*$, and a channel history $\mathcal{H}$ as the input. It returns the steganographic content, $\mathbf{s}$.
- $\text{Extract}_{\mathcal{D}}(K, \mathbf{s}, \mathcal{H})$ takes a shared key K, a steganographic content $\mathbf{s}$, and a channel history $\mathcal{H}$ as the input. It returns the message extracted from the steganographic content, $\mathbf{s}$.

To clarify the scope of steganography, we distinguish it from related concepts: cryptography and watermarking in Appendix A.

2.2 Security of Steganography

To better understand linguistic steganography, it is important to first introduce a key property of steganographic systems: security. In the literature, two common definitions of steganographic security have been proposed. Cachin (1998) was the first to model steganographic security from an **information-theoretic** perspective. Hopper et al. (2002) and Katzenbeisser and Petitcolas (2002) proposed the **complexity-theoretic** definition of steganographic security. The detailed introduction of these two definitions is shown in Appendix B.

3 Steganography Based on Modification

Text steganographic methods based on modifying existing texts had dominated the field before the emergence of generative LMs. These approaches embed secret messages through alterations to a covertext, while aiming to preserve its readability and naturalness. We begin with **non-linguistic** format-based methods (e.g., manipulating spaces, punctuation, or text layout) and then move to **linguistic** methods, including lexicon-based (e.g., replacing words with synonyms or semantically similar alternatives) and rewriting-based methods (e.g., paraphrasing or restructuring sentences). Figure 3 presents the content flow and taxonomy of modification-based methods in this section. Figure 4 shows an example in each category of these modification-based steganographic methods. The detailed introduction of methods based on modification is provided in Appendix C. Although such methods are generally lightweight, they suffer from inherent limitations: the embedding capacity is low, and the modifications can be vulnerable to detec-

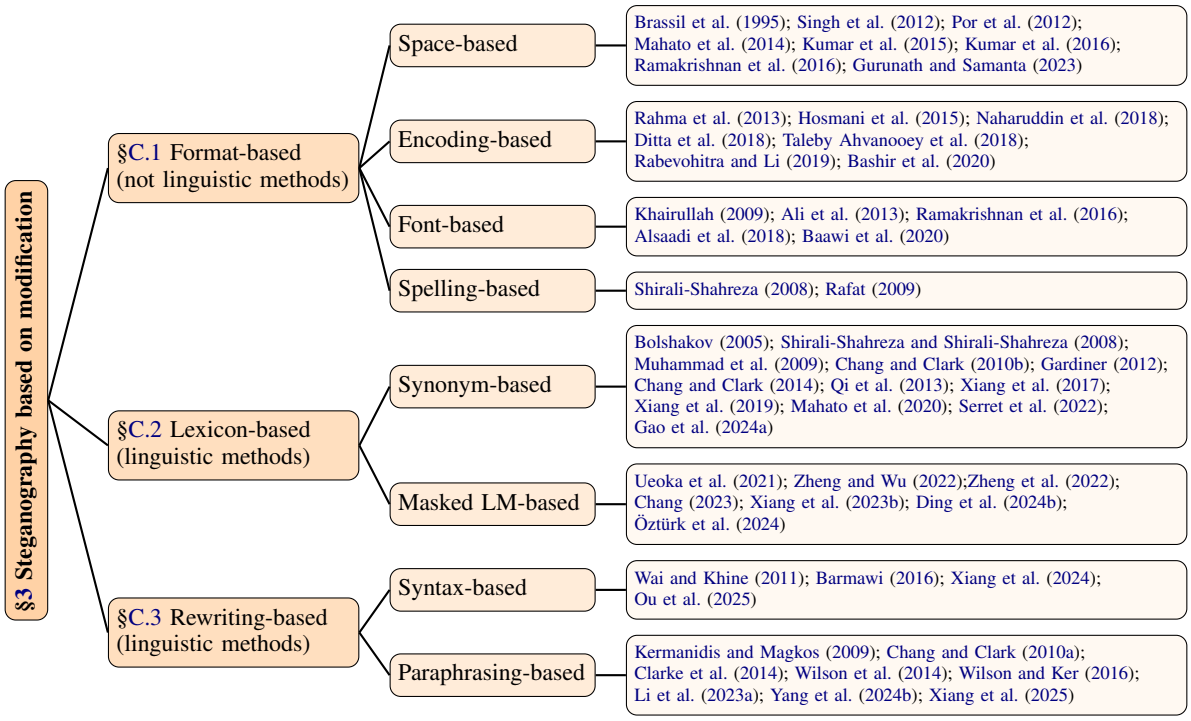


Figure 3: The main content flow and categorization of steganographic methods based on modification.

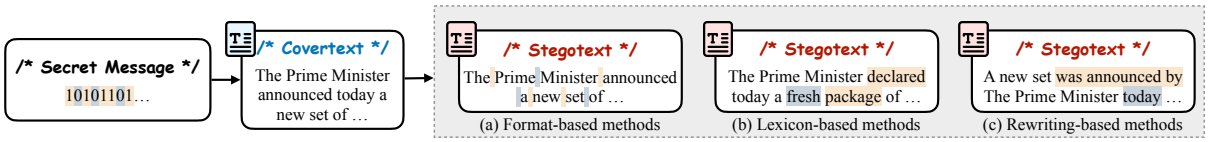


Figure 4: Modification-based steganographic methods which are categorized into three types, where an example is shown in each type.

tion by statistical steganalysis.

4 Generative Linguistic Steganography

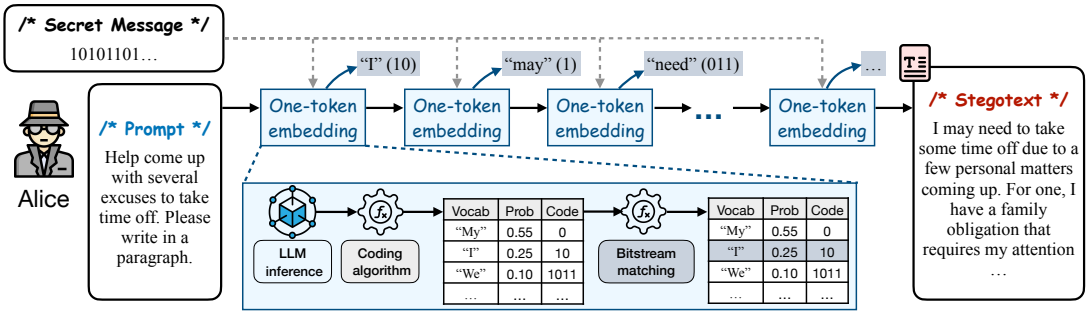
As discussed in Section 3, existing modification-based methods generally face the challenge of low embedding capacity, as the redundancy in the covertext is restricted. Besides, in these methods, security is not proved or ensured according to the security definition discussed in Section 2.2. These limitations have motivated **a shift toward generative approaches**, which offer greater flexibility and high imperceptibility. Generative methods overcome or mitigate the capacity and security problems of modification-based ones. The detailed introduction of these reasons is provided in Appendix D.

4.1 Basics and Notions of LM

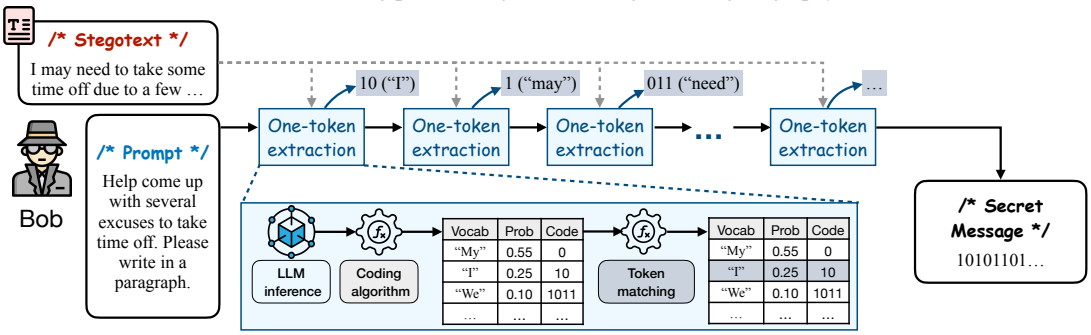
A language model (LM) has a vocabulary $\mathcal{V}$ consisting of $|\mathcal{V}|$ *tokens*. Consider a sequence of LM-generated T tokens $\{s^{(t)}\} \in \mathcal{V}^T$. Entries with negative indices, $[s^{(-N_p)}, \ldots, s^{(-1)}]$, represent a *prompt* of length N_p and $[s^{(0)}, \ldots, s^{(T-1)}]$ are tokens generated by an LM in response to the prompt.

Using an LM for the next-token prediction at position t, is a function defined as: $f_{\text{LM}}(\boldsymbol{s}^{(t-1)}; \theta) = \boldsymbol{l}^{(t)}$, in which $\boldsymbol{s}^{(t-1)}$ is the previous context $[s^{(-N_p)}, \ldots, s^{(t-1)}]$ at $t-1$, θ is the model parameters, and $\boldsymbol{l}^{(t)} = (l_1^{(t)}, \ldots, l_{|\mathcal{V}|}^{(t)}) \in \mathbb{R}^{|\mathcal{V}|}$ is the logit vector, corresponding to each token in $\mathcal{V}$. This discrete probability distribution can be calculated through the logit vector and the softmax function, i.e., $\boldsymbol{p}^{(t)} = (p_1^{(t)}, \ldots, p_{|\mathcal{V}|}^{(t)}) = \text{softmax}(\boldsymbol{l}^{(t)}) = (\frac{\exp(l_1^{(t)})}{\sum_{j=1}^{|\mathcal{V}|} \exp(l_j^{(t)})}, \ldots, \frac{\exp(l_{|\mathcal{V}|}^{(t)})}{\sum_{j=1}^{|\mathcal{V}|} \exp(l_j^{(t)})})$ over the vocabulary. The next token is then sampled from $\boldsymbol{p}^{(t)}$ (e.g., multinomial sampling).

We provide only a limited overview of LMs, without detailing their internal structures, because most LM-based linguistic steganographic methods interact with the model solely through the post-softmax next-token distribution. This abstraction



(a) Embedding process of generative linguistic steganography.



(b) Extraction process of generative linguistic steganography.

Figure 5: Overall framework of generative linguistic steganography, in which the example is operated autoregressively based on the Huffman coding.

has become even more prominent in the LLM era, where access to model internals can be further restricted to API-only settings.

4.2 Paradigm of LM-based Steganography

Alice (the sender) wants to communicate a secret message $\mathbf{m} \sim U(\{0,1\}^l)$ with Bob (the receiver) by embedding it in a natural-language text $\mathbf{s}$ (a stegotext). According to the notions and definitions of the steganographic system in Section 2.1, Alice and Bob have agreed on an embedding function $\text{Embed}_{\mathcal{D}}(K, \mathbf{m}, \mathcal{H})$ and an extracting function $\text{Extract}_{\mathcal{D}}(K, \mathbf{s}, \mathcal{H})$ that perform steganography. Specifically, in the scenario of LM-based generative linguistic steganography, $\mathcal{D}$ is commonly defined as the same shared language model $\mathcal{M}^o$, $\mathcal{H}$ is the token sequence of the prompt $[s^{(-N_p)}, \ldots, s^{(-1)}]$, $\mathbf{s}$ is the generated stegotext. These two functions are designed to be mutually consistent. In other words, $\text{Embed}_{\mathcal{D}}(K, \mathbf{m}, \mathcal{H}) = \mathbf{s}$ and $\text{Extract}_{\mathcal{D}}(K, \mathbf{s}, \mathcal{H}) = \mathbf{m}'$, in which the ideal result is $\mathbf{m} = \mathbf{m}'$.

Figures 5a and 5b respectively illustrate the embedding framework and the extraction framework of LM-based steganography, using the method based on the Huffman coding (Yang et al., 2019a). From the figures, we can notice that the cover carrier, which is necessary in traditional steganography, is not required in generative linguistic steganography. Instead, the prompt is shared in the steganographic protocol. Although generative linguistic steganographic methods generally follow the above frameworks, they can be classified according to the targeted performance metrics, methodology features, or the specific steganographic scenarios in which they are applied.

4.3 Taxonomy of Existing Methods

In this section, we categorize existing generative linguistic steganographic methods into three types: (1) methods toward higher security, (2) methods toward higher efficiency, and (3) methods toward higher robustness. **Security** can be assessed using various text-quality metrics (such as perplexity (Jelinek et al., 1977) and ROUGE (Lin, 2004)) or by measuring imperceptibility and indistinguishability that prevent humans or machine classifiers (steganalysis) from detecting stegotexts from normal texts. **Efficiency** refers to the embedding capacity of the stegotext as well as the embedding and extraction speeds. **Robustness** evaluates whether, and to which extent, the extracted message $\mathbf{m}'$ remains consistent with the embedded message $\mathbf{m}$, particularly under active attack scenarios, such as

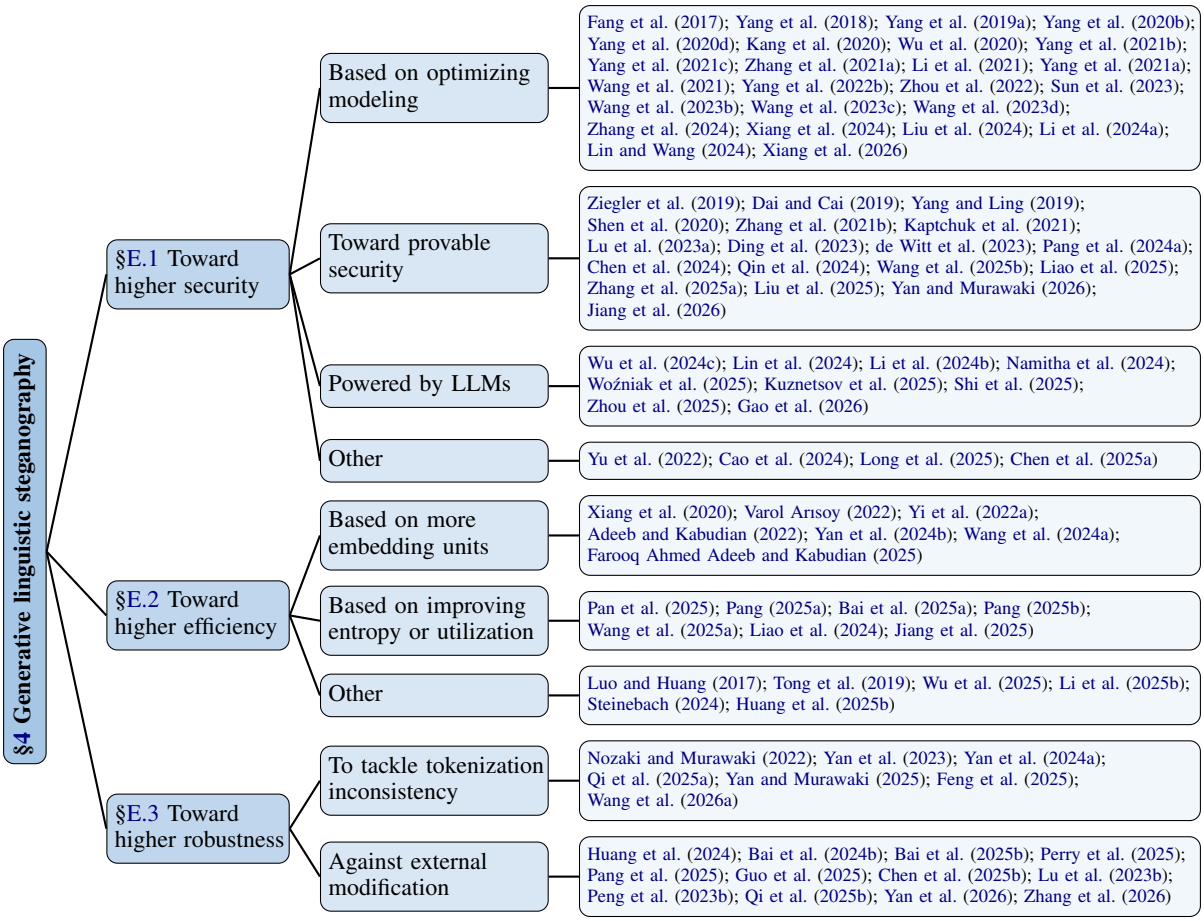


Figure 6: The main content flow and categorization of generative linguistic steganography.

Method	Dist. unchanged (KL = 0)?	Complexity (per token)	Mode
ADG (Zhang et al., 2021b)	✗	$O(N \log N)$	Stream
Meteor (Kaptchuk et al., 2021)	✗	$O(N)$, $O(2^{\lceil H(P) \rceil} N)$ with reorder	Stream
iMEC (de Witt et al., 2023)	✓	$O(2^B N)$	Block
Discop (Ding et al., 2023)	✓	$O(N)$, $O(N \log N)$ with reorder	Stream
SparSamp (Wang et al., 2025a)	✓	$O(2^B)$	Block
RRC (Yan and Murawaki, 2026)	✓	$O(N)$, $O(N \log N)$ with reorder	Block

Table 3: Methodology features of provably secure linguistic steganographic methods. The Dist. unchanged (KL = 0) column marks whether the method keeps the original distribution at each generation step. In the complexity column, N denotes the number of candidate tokens considered at each step; $H(P)$ denotes the entropy of the next-token distribution P; B denotes the block size used by block-mode methods.

substitution, deletion, or insertion.

Following Fang et al. (2017), which marked a milestone for RNN-based generative linguistic steganography, only modern methods (after Fang et al. (2017)) are included for taxonomy. Figure 6 presents the main content flow and categorization of generative linguistic steganographic methods, organized according to the *primary targeted metrics* and further methodology features. Among the three axes, security has undergone **a notable shift from heuristic to provable security**. Table 3 compares the methodology features of provably secure generative methods. We can observe a clear evolutionary trajectory from non-zero KL to KL = 0, and then toward lower complexity and higher efficiency. The detailed review of modern generative linguistic steganographic methods is provided in Appendix E.

5 Linguistic Steganalysis

Linguistic steganography is dual-use in nature, which can be used not only to protect personal

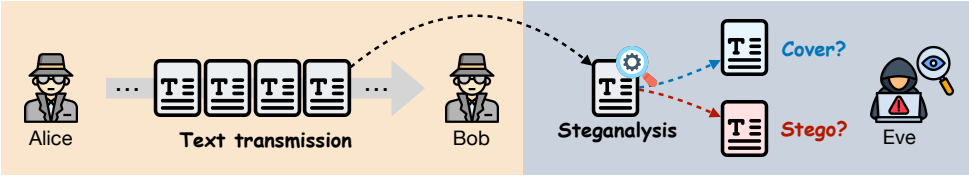


Figure 7: A sketch of how Eve operates steganalysis.

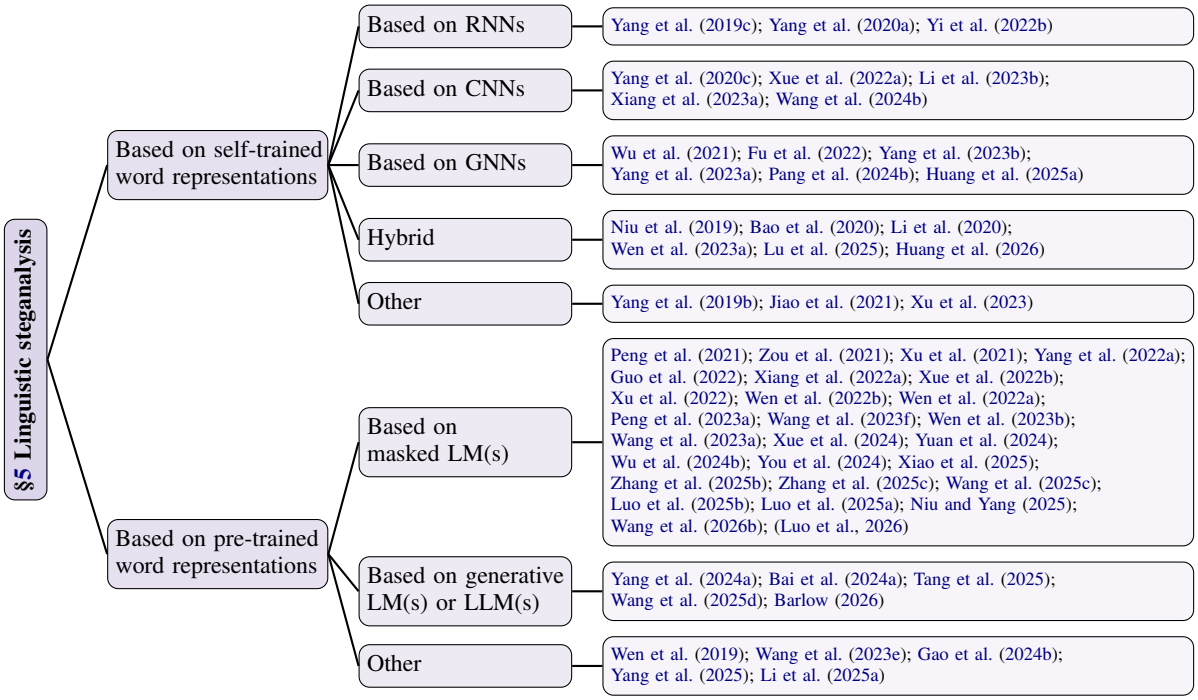


Figure 8: The main content flow and categorization of linguistic steganalysis methods.

privacy but also to enable malicious covert communication. Its countermeasures, **linguistic steganalysis** methods, are essential for detecting the presence of steganography, particularly in security-critical contexts (Fridrich and Goljan, 2002; Nissar and Mir, 2010). Figure 7 shows a sketch of steganalysis. The introduction of basics and notions of steganalysis is provided in Appendix F.

5.1 Taxonomy of Existing Methods

We categorize existing linguistic steganalysis methods along two axes. First, we distinguish whether a method relies on pre-trained word representations or models, such as Word2Vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014), or BERT (Devlin et al., 2019). Second, we further group methods by the type of backbone model they adopt. Following these principles, Figure 8 presents the resulting taxonomy of linguistic steganalysis methods. To keep the taxonomy focused on recent developments, our taxonomy and review only includes methods based on neural networks that are proposed after current representative methods, **FCN** (Yang et al., 2019b) and **TS-RNN** (Yang et al., 2019c). Table 8 (in the Appendix) lists the features of these linguistic steganalysis methods, revealing the following trends:

(1) The **IMDB** (Maas et al., 2011), **Twitter** (Go et al., 2009), and **News** (Kaggle, 2017) datasets have become mainstream for evaluation.

(2) Chronologically, methods based on **pre-trained** models (especially BERT (Devlin et al., 2019)) gradually **dominate** the field.

(3) **LLM-based** linguistic steganalysis methods have emerged only recently and remain relatively **underexplored**.

In addition, Table 9 (in the Appendix) summarizes the steganalysis methods adopted to evaluate generative linguistic steganography. Among them, **FCN** (Yang et al., 2019b) **CNN** (Wen et al., 2019), **R-BiLSTM-C** (Niu et al., 2019), **TS-RNN** (Yang et al., 2019c), **TS-CSW** (Yang et al., 2020c) are the five most commonly adopted steganalysis methods. The detailed review of linguistic steganalysis meth-

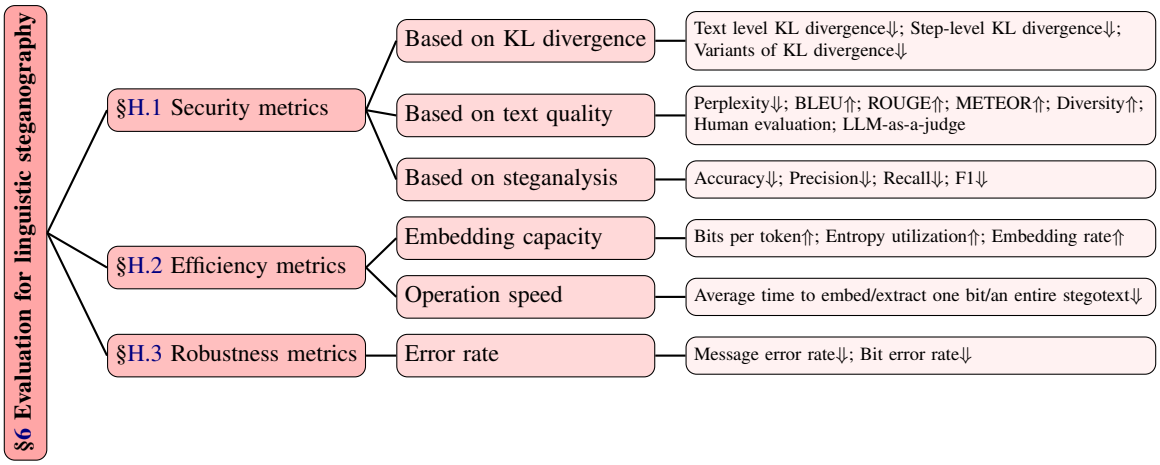


Figure 9: An overview of evaluation metrics. ⇑/⇓ indicate that higher/lower values correspond to better performance.

ods is provided in Section G. In particular, Table 6 (in Appendix) summarizes the features of LLM-adaptable linguistic steganalysis methods which are representative in the LLM era.

6 Evaluation for Linguistic Steganography

Following the taxonomy of generative linguistic steganography in Section 4.3, this section details the main metrics for evaluating linguistic steganography, which are categorized into security metrics, efficiency metrics, and robustness metrics.

Figure 9 presents an overview and their taxonomy of these evaluation metrics. Figure 11 (in the Appendix) summarizes the chronological trend on adoption rates of the major evaluation approaches in 95 papers of modern generative linguistic steganographic methods. Tables 10 and 11 (in the Appendix) present metrics chosen to evaluate these generative methods. From these tables, we draw the following key observations:

(1) Entropy utilization is gaining emphasis because model-agnostic methods compatible with diverse LLMs require **fair cross-model assessments** of embedding capacity.

(2) Metrics based on error rates are used increasingly with the growing focus on **robustness**.

Chronologically, the increasing focus on evaluating efficiency and robustness reflects **the shift from security-centric to joint optimization**. More details about evaluation are shown in Appendix H.

7 Challenges and Future Directions

Despite the rapid progress surveyed above, the field still lacks ready-to-use software and engineering-aware designs. We identify the open challenges and group them into three themes (details shown in Appendix I):

- *Engineering realities and issues*: (1) computational indeterminism, (2) tokenization inconsistency, (3) abrupt termination, and (4) challenges of synchronizing prompts.

- *Impractical assumptions and evaluations*: (5) limited embedding capacity, (6) high dependence on white-box LLMs, and (7) unrealistic security evaluations.

- *Community and ethical concerns*: (8) lack of unity in benchmarks and (9) ethics and use restrictions of LLM licenses.

8 Conclusion

In this survey, we provide a systematic overview of linguistic steganography in the LLM era along three aspects: (1) modification-based and generative steganographic methods, (2) linguistic steganalysis methods, and (3) evaluation metrics. Across these axes we identify five paradigm shifts that mark the LLM era, most notably the rise of **provably secure generative** methods, **robustness-oriented** designs, and emerging **black-box** and **asymmetric** schemes. Besides, we identify and group the remaining open challenges into three themes spanning (1) engineering realities, (2) impractical assumptions and evaluations, and (3) community and ethical concerns. This survey aims to catalyze further work on linguistic steganography that is practical to deploy and responsible to use.

Limitations

We acknowledge the following limitations of our survey. (1) We focus exclusively on linguistic (text) steganography and do not cover image/audio/video or cross-modal schemes. (2) We synthesize results as reported by the original authors and do not re-implement or re-benchmark methods under a unified protocol; building such a benchmark is itself one of the open challenges identified in Section 7.

Ethical Considerations

Although linguistic steganography can serve legitimate purposes, such as embedding and tracing copyright information, it can also be misused to evade legal censorship. This dual-use nature underscores the urgent need for effective regulation. In this survey, we highlight the ethics and use restrictions (Section 7 and Appendix I) and advocate for research on both responsible defensive capabilities and legitimate privacy-preserving uses, thereby promoting responsible use of steganography.

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A Comparison with Related Concepts

(1) **Cryptography** protects the content of a message, ensuring confidentiality, integrity, and authenticity, by transforming plaintext into ciphertext using mathematical algorithms and keys (RIVEST, 1990).

(2) **Watermarking** embeds information into a carrier to prove ownership, authenticity, or traceability, by inserting robust marks or patterns that survive common transformations (e.g., compression, distortion) (Honsinger, 2002).

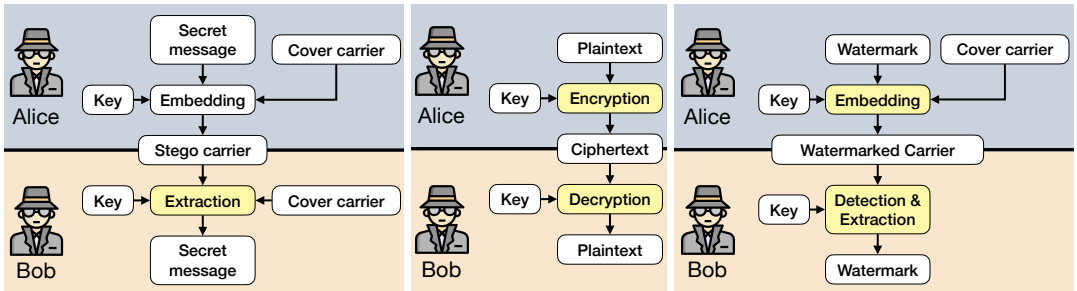
In summary, Table 4 compares the features of steganography, cryptography, and watermarking. In addition, Figure 10 illustrates their procedures, respectively.

B Two Definitions of Steganographic Security

(1) Cachin (1998) was the first to model steganographic security from an **information-theoretic** perspective. Given an observation $\mathbf{x}$, the security

Feature	Steganography	Cryptography	Watermarking
Goal	Hide the existence of communication	Protect the content of communication	Assert ownership or authenticity
Carrier	Multimedia	Plaintext → ciphertext	Multimedia
Visibility	Definitely not (ideally undetectable)	Obvious (ciphertext is visible)	Optional (depending on the watermarking type)
Adversary	Detect whether a given object contains hidden information	Recover the plaintext or secret key from the ciphertext	Destroy, alter, or remove the embedded watermark without significantly degrading the carrier quality
Robustness	Important (but optional in some work)	Strong against brute force	Designed to withstand distortion
Uses	Covert messaging, censorship evasion	Secure communication, authentication	Copyright protection, forensic tracking, digital rights management (DRM)

Table 4: Comparison of steganography, cryptography, and watermarking.



(a) Steganography. (b) Cryptography. (c) Watermarking.

Figure 10: Common procedures of both sides (Alice and Bob) in steganography, cryptography, and watermarking.

of a steganographic system can be quantified by the Kullback–Leibler (KL) divergence between the cover distribution P_c and the stego distribution P_s:

$$D_{\mathrm{KL}}(P_c||P_s) = \sum_{\mathbf{x}\in\mathcal{D}} P_c(\mathbf{x}) \log \frac{P_c(\mathbf{x})}{P_s(\mathbf{x})}, \quad (1)$$

which measures the statistical difference between the two distributions. When $D_{\mathrm{KL}}(P_c||P_s) = 0$, the steganographic system is considered to be *perfectly secure*, as $P_c = P_s$ and thus the steganalyzer cannot distinguish the stego object from the cover object better than by random guessing.

(2) Hopper et al. (2002) and Katzenbeisser and Petitcolas (2002) proposed the **complexity-theoretic** definition of steganographic security: A steganographic system is computationally secure if, for all probabilistic polynomial-time (PPT) adversaries $\mathcal{A}$ in distinguishing between the output of steganography sampler $\mathcal{O}_s$ and the output of random sampler $\mathcal{O}_r$ is negligible.

$$\left|\Pr[\mathcal{A}^{\mathcal{O}_s}(1^\lambda) = 1] - \Pr[\mathcal{A}^{\mathcal{O}_r}(1^\lambda) = 1]\right| < \mathrm{negl}(\lambda), \quad (2)$$

where λ is the security parameter, 1^λ denotes its unary encoding, and $\mathrm{KeyGen}_{\mathcal{D}}(1^\lambda)$ is the key-generation algorithm run on this parameter. The function $\mathrm{negl}(\lambda)$ is negligible in λ, i.e., for every polynomial $p(\cdot)$ there exists an $N \in \mathbb{N}$ such that for all $\lambda > N$ it holds that $\mathrm{negl}(\lambda) < \frac{1}{p(\lambda)}$. Intuitively, this means that any PPT adversary can only distinguish the two oracles with at most negligible advantage as a function of the security parameter.

C Review of Modification-Based Methods

C.1 Format-Based Methods

Format-based methods exploit the physical features of text symbols (e.g., spaces, encoding, fonts, spelling) without altering the linguistic content; they are therefore visually unobtrusive but, strictly speaking, lie outside the scope of linguistic steganography. We summarize them here for completeness.

Space-based methods hide bits in line/character/word/inter-paragraph spacing or invisible whitespace, by either inserting null spaces, shifting text vertically/horizontally, or jointly mapping multiple spacing operations to symbol blocks (Brassil et al., 1995; Singh et al., 2012; Por et al., 2012; Mahato et al., 2014; Kumar et al., 2015, 2016; Ramakrishnan et al., 2016; Gurunath and Samanta, 2023).

Encoding-based methods exploit the fact that

visually identical glyphs may correspond to different code points, e.g., Unicode homoglyphs of English/Arabic letters, ASCII variants, and zero-width characters or joiners (Rahma et al., 2013; Hosmani et al., 2015; Naharuddin et al., 2018; Ditta et al., 2018; Taleby Ahvanooey et al., 2018; Rabevohitra and Li, 2019; Bashir et al., 2020).

Font-based methods carry bits via font color, mixed-case typesetting, character spacing, font-color formatting in spreadsheets, or specially designed fonts with hiding-friendly properties (Khairullah, 2009; Ali et al., 2013; Ramakrishnan et al., 2016; Alsaadi et al., 2018; Baawi et al., 2020).

Spelling-based methods substitute spellings (e.g., US/UK variants) to embed bits (Shirali-Shahreza, 2008; Rafat, 2009).

Despite their simplicity, format-based methods are (i) fragile under text normalization, document conversion, or copy–paste; (ii) detectable by statistical steganalysis on spacing, punctuation, or font usage (Xiang et al., 2007); and (iii) highly platform- and language-dependent (e.g., spelling-based methods only apply to selected languages).

C.2 Lexicon-Based Methods

Lexicon-based methods modify individual words or word forms while preserving semantics and fluency. They divide into synonym-based and masked-LM-based methods.

Synonym-based methods exploit lexical redundancy: bits are embedded by selecting among synonyms or regional variants subject to contextual, frequency, or grammatical constraints. Representative work uses collocation-verified synonyms (Bolshakov, 2005), US/UK variants (Shirali-Shahreza and Shirali-Shahreza, 2008), language-specific grammar (Muhammad et al., 2009), n-gram-checked contextual substitution (Chang and Clark, 2010b; Qi et al., 2013; Chang and Clark, 2014), WordNet-based substitution (Gardiner, 2012), frequency-preserving encodings to defeat statistical steganalysis (Xiang et al., 2017, 2019; Mahato et al., 2020), messaging-oriented covertext extension (Serret et al., 2022), and IoT-oriented ambiguous-token selection (Gao et al., 2024a).

Masked-LM-based methods mask tokens in the covertext and use a masked language model (typically BERT (Devlin et al., 2019)) to predict context-appropriate replacements that encode bits, going well beyond classical synonym substitution (Ueoka et al., 2021; Zheng and Wu, 2022; Zheng et al., 2022; Chang, 2023; Xiang et al., 2023b; Ding et al., 2024b; Öztürk et al., 2024).

Lexicon-based methods preserve the surface semantics of the covertext, but suffer from (i) limited capacity, since only words with valid lexical variants can be substituted under context constraints; and (ii) poor language generalizability, as many methods rely on language-specific resources (thesauri, WordNet) unavailable for low-resource languages.

C.3 Rewriting-Based Methods

Rewriting-based methods alter the syntactic structure of sentences or paraphrase them while preserving meaning, e.g., reordering constituents, switching voice, or inserting subordinate clauses, thus operating beyond the lexical level. They divide into syntax-based and paraphrasing-based methods.

Syntax-based methods choose among alternative grammatical structures of the same sentence, e.g., via syntax banks combined with Shannon–Fano coding or signatures (Wai and Khine, 2011), joint lexical-syntactic transformations to lift capacity (Barmawi, 2016), or multi-granularity hiding across syntactic and symbolic spaces (Ou et al., 2025).

Paraphrasing-based methods select among alternative phrasings of the same meaning. Representative ideas include rule-based paraphrasing followed by supervised filtering (Kermanidis and Magkos, 2009), paraphrase dictionaries with n-gram and CCG-parser checks (Chang and Clark, 2010a), hash-chain-driven interactive rewriting (Clarke et al., 2014), hierarchical-LM unilingual translation for Twitter (Wilson et al., 2014; Wilson and Ker, 2016), BART-based token-level rewriting (Li et al., 2023a), Seq2Seq2Seq pivot-translation rewriting (Yang et al., 2024b), and attribute-controlled paraphrase generation (Xiang et al., 2025).

Rewriting-based methods are particularly strong at preserving semantics and readability, often yielding the best imperceptibility among modification-based approaches. Their main drawback is **low embedding capacity**, as redundancy must come from entire sentences or syntactic structures rather than localized lexical slots.

D Reasons of Researching Generative Linguistic Steganography

(1) **High capacity.** Generative language models can utilize the redundancy of the whole vocabu-

lary and flexibly choose a token conditioned on the targeted secret message at each inference position, enabling a much higher embedding rate than modification-based approaches that rely only on limited redundant positions in existing text.

(2) **Advances of language models.** A milestone marking the entry into the era of LLMs was the release of OpenAI's GPT-3 (Brown et al., 2020), the first widely recognized model to demonstrate that scaling transformer architectures to hundreds of billions of parameters and training them on massive corpora could achieve unprecedented performance across various tasks. Building on it, subsequent open-weight LLMs are used to generate stegotexts that are both indistinguishable from human writing and adaptable across domains and languages.

(3) **Imperceptibility and security.** The capabilities of LLMs directly support higher imperceptibility. Moreover, recent advances have shown that provably secure steganographic methods (e.g., Zhang et al. (2021b) and Ding et al. (2023)) can be realized within generative frameworks. These approaches equip generative steganography with strict security guarantees, thereby advancing it beyond empirical validation toward theoretical resilience against steganalysis.

E Review of Modern Generative Linguistic Steganographic Methods

Table 7 presents a detailed taxonomy of modern generative linguistic steganographic methods, which supplements the rough taxonomy shown in Figure 6. It is based on the following seven dimensions:

- **Targeted metric(s).** This dimension refers to what kind of improvements are aimed at by the proposed method. Explanations of these three types (security, efficiency, and robustness) are introduced in Section 4.3.

- **Scenario(s).** This dimension refers to the designated scenarios in which the steganographic method is proposed. The methods that can be applied to general generation scenarios are labeled *General*.

- **Backbone model(s).** This dimension refers to each method's language-model requirements or assumptions. Methods that apply across generative autoregressive LMs (for example, those optimizing embedding algorithm and extraction algorithm without relying on a particular architecture) are labeled *Model-agnostic*.

- **LLM-adaptable.** This dimension indicates whether the method proposed is implemented based on LLM(s) or it has the model-agnostic feature can be transferred to LLMs. *Notably, methods which are LLM-adaptable but not model-agnostic can be considered as LLM-specific methods.*

- **Training-free.** This dimension indicates whether the method operates without additional training or fine-tuning of the language model (i.e., using an off-the-shelf LM).

- **Asymmetric.** This dimension indicates whether embedding and extraction are not mirror operations, i.e., the extraction procedure fundamentally differs from embedding. For example, embedding requires LM inference, while extraction does not.

- **Black-box.** This dimension indicates whether the method operates without access to an LM's internal states (e.g., next-token probabilities) and can be implemented through an API-only interaction.

Organized chronologically, Table 7 reveals the following trends in this field:

(1) **Efficiency**, **robustness**, or multi-metric optimization has received growing emphasis. Earlier studies mainly focused on improving security, while more recent methods increasingly consider practical performance under multiple objectives.

(2) **Model-agnostic**, **LLM-adaptable** and **training-free** methods started dominating since 2024. This trend is closely related to the rapid adoption of large language models, where methods are expected to work across different backbones without costly retraining or architecture-specific modification.

(3) **Asymmetric** and **black-box** methods enable lightweight implementations, but almost remain underexplored. These settings better reflect practical interactions with commercial LLM APIs, where users often only have access to generated text rather than to the model internals.

(4) Most methods fall under the **general scenarios**, which means that they are not tied to a single language and can support multiple languages based on the underlying language model. Therefore, beyond a few language-specific studies on Arabic,

Malay, and Chinese poetry, the majority of recent methods can be regarded as multilingual in scope. This suggests that multilingual applicability has become an implicit feature of modern generative linguistic steganography.

In this section, we review several representative methods for each target metric.

E.1 Toward Higher Security

(1) **Methods based on optimizing modeling.** These methods mark the first wave of neural linguistic steganography emerging alongside neural language models. Fang et al. (2017) are one of the earliest attempts to directly use LSTMs for language modeling to generate stegotexts, and its embedding and extraction are based on block coding. Building on this line, Yang et al. (2019a) formalize the RNN-based embedding paradigm and improve the coding strategy: It ranks next-token probabilities to form a candidate pool, but embeds bits using fixed-length or variable-length Huffman coding. Further, Yang et al. (2021b) discover the *Psic effect*, i.e., perceptual-imperceptibility and statistical-imperceptibility conflict effect in linguistic steganography, and propose a new linguistic steganography based on Variational Auto-Encoder to guarantee both the perceptual-imperceptibility and statistical-imperceptibility.

(2) **Methods toward provable security.** These methods aiming at provable security largely pursue distribution-preserving at each generative step after steganographic encoding. Without considering language modeling, these methods are generally **training-free**. The early baseline is arithmetic coding (AC) (Ziegler et al., 2019), which maps a bitstream to successive token intervals so that sampling closely follows the LM's next-token distribution, yielding low per-step KL distortion and thus strong statistical imperceptibility. Building on this, self-adjusting arithmetic coding (Shen et al., 2020) dynamically trims/reshapes the candidate pool to meet a user-specified imperceptibility (KL divergence) threshold, improving the security–capacity trade-off over vanilla AC. ADG (Adaptive Dynamic Grouping) (Zhang et al., 2021b) aims at provably perfect matching by recursively grouping tokens into equal-probability bins and selecting within bins. For broader cryptographic guarantees under realistic settings, Meteor (Kaptchuk et al., 2021) provides a symmetric-key scheme that achieves computational security while sampling from generative approximations of natural language. iMEC (de Witt et al., 2023) shows that a steganography procedure is perfectly secure under an information-theoretic model of steganography if and only if it is induced by a coupling. To make perfect security practical, Discop (Ding et al., 2023) constructs multiple "distribution copies" and samples from the chosen copy indexed by message bits, preserving the original distribution (**zero KL divergence**) while improving efficiency. Recently, SparSamp (Wang et al., 2025a) further reduces overhead via sparse, message-derived sampling intervals, maintaining provable security but significantly boosting efficiency of embedding and extraction. Recently, Yan and Murawaki (2026) proposes an efficient provably secure method based on rotation range coding (RRC) of which approximate 100% entropy utilization for embedding capacity is empirically validated.

(3) **Methods powered by LLMs.** These methods are marked by black-box access, prompt-driven control, or higher-level strategy design beyond the basic token-by-token generation. Wu et al. (2024c) propose LLM-Stega, the first method tailored to **API-only** LLMs: instead of relying on internal logits, it builds keyword sets and an encrypted mapping at the interface level, showing that practical steganography is feasible even without probability access (**black-box**). Lin et al. (2024) propose a **prompt-driven** linguistic steganography with an **in-context learning** framework, explicitly targeting both perceptual and statistical imperceptibility. Most recently, Zhou et al. (2025) frame LLM steganography as a **self-evolving agent system**: an agent loop automatically discovers, composes, and updates a library of embedding strategies at inference time, allowing adaptation to domains and constraints.

E.2 Toward Higher Efficiency

(1) **Methods based on more embedding units.** These methods mainly push linguistic steganography below the word or token level, exploiting characters and script-specific symbols as basic embedding units to boost capacity. Xiang et al. (2020) use an LSTM-based character-level language model to embed at least one bit per character, achieving faster generation and significantly higher embedding rates than earlier word-level neural methods. Adeeb and Kabudian (2022) hide multiple bits per Arabic letter by modulating fine-grained script features such as elongation, pseudo-spaces, and dotted/diacritic patterns, realizing high-capacity, letter-

based embedding tailored to Arabic and related scripts. Yan et al. (2024b) apply a tokenization-free character-level scheme with entropy-based candidate construction and lexical emphasis, which substantially reduces out-of-vocabulary cases and improves imperceptibility. Farooq Ahmed Adeeb and Kabudian (2025) combine character-level embedding with foundation LLMs, designing a stegosystem that operates at the character granularity and reports large gains in bits-per-word and bits-per-character over prior neural methods while maintaining comparable security and imperceptibility.

(2) **Methods based on improving entropy or utilization.** These methods mainly aim to make full use of the entropy provided by generative models rather than creating more embedded positions. Pan et al. (2025) revisit prefix-based schemes (e.g., AC/Meteor) and propose two enhancements: security-enhanced and efficiency-enhanced variants. The first optimizes quantization distortion to minimize KL divergence. The second redesigns the sampling mechanism via distribution coupling to improve the steganographic capacity. Bai et al. (2025a) introduce a mechanism of entropy collection that gathers residual entropy left unused in each embedding step and recycles it in subsequent steps, resulting in higher capacity than prior distribution-preserving methods. Pang (2025b) improves entropy utilization in **black-box** settings: instead of requiring access to model's logits, it embeds messages across multiple candidate samples while keeping the generator's output behavior statistically unchanged, achieving provable security and competitive capacity with only API-level access. Wang et al. (2025a) propose sparse, message-driven sampling, which combines the message with pseudo-random numbers to form sampling indices and increasing sampling intervals. It preserves the original probability distribution and introduces minor additional complexity per sampling step and nearly full entropy utilization, enabling the fastest embedding speed without compromising generation speed.

E.3 Toward Higher Robustness

(1) **Methods to tackle tokenization inconsistency.** These methods address incorrect results or failures extraction when the sent tokens are different from received tokens after the **detokenization-retokenization** pipeline between Alice and Bob. Nozaki and Murawaki (2022) first show that subword-based generators can produce multiple valid segments for the same surface text, causing occasional extraction errors (called **segmentation ambiguity**). They propose simple, language-agnostic disambiguation tricks that prune prefix-confusable tokens so that detokenization is unique without heavily modifying existing systems. Yan et al. (2023) design a distribution-aware pruning strategy that resolves segmentation ambiguity while preserving the probability mass of remaining candidates, improving both security and imperceptibility. The method is realized by finding out a maximum weight independent set (MWIS) in each candidate graph. Yan et al. (2024a) further reduce distortion by adding a verification stage: instead of actively modifying candidate pools, an all-case extraction method is proposed to obtain possible true extracted results. Further, verification is adopted to filter wrong extracted results caused by segmentation ambiguity. Qi et al. (2025a) (SyncPool) then show how to eliminate segmentation ambiguity without sacrificing provable security by grouping all tokens with prefix relationships into ambiguity pools and using a shared CSPRNG to synchronously sample from these pools, keeping both candidate set size and token distribution exactly unchanged. Yan and Murawaki (2025) generalize from segmentation ambiguity to full tokenization inconsistency between Alice and Bob's models. Recently, Wang et al. (2026a) propose ReTokSync, a self-synchronizing disambiguation framework, which triggers a corrective reset only when ambiguity actually occurs to mitigate the performance reduction caused by disambiguation. Table 5 summarizes the features of these methods to tackle tokenization inconsistency, according to which several findings stand out:

- Jointly achieving (a) distribution-preserving guarantees (KL = 0 or provable security), (b) strict 100% extraction correctness, and (c) low complexity, remains an open challenge. SyncPool achieves this at the cost of a super-linear $O(N \log N)$ which is still heavier than the linear-time alternatives.
- A clear trend from high to low computational complexity is emerging across successive works.

(2) **Methods against external modification.** These methods target robustness when a stego-text is perturbed by active tampering. Pang et al. (2025) propose an adaptive robust enhancement

Method	Strict 100% correctness?	Dist. unchanged (KL = 0)?	Complexity (per token)
Basic (Nozaki and Murawaki, 2022)	✓	✗	$O(N^2)$
MWIS (Yan et al., 2023)	✓	✗	$O(N^2)$
All-case verification (Yan et al., 2024a)	✗	✓	$O(N \times 2^N)$
SyncPool (Qi et al., 2025a)	✓	✓	$O(N \log N)$
Stepwise verification (Yan and Murawaki, 2025)	✓	✗	$O(N)$
ReTokSync (Wang et al., 2026a)	✗	✓	$O(L)$

Table 5: Methodology features of methods to tackle tokenization inconsistency. Strict 100% correctness column marks whether the method can 100% eliminate extraction errors caused by tokenization inconsistency. The Dist. unchanged (KL = 0) column marks whether the method keeps the original distribution at each generation step. In the complexity column, N denotes the number of candidate tokens considered at each step; L denotes the number of generated tokens in the real-time sequence.

framework using a sliding window approach, that can be applied on top of existing generative linguistic steganography schemes. Bai et al. (2025b) present an **asymmetric** framework in which only the encoder has access to the model. Specifically, the encoder uses various permutations of distribution to hide secret bits, while the decoder relies on a sampling function to extract the hidden bits by guessing the permutation used. Guo et al. (2025) integrate classical error-correcting codes into a generative linguistic stegosystem. Qi et al. (2025b) leverage **diffusion language models** to achieve robust and provable security. Their method identifies robust positions in the partially parallel denoising trajectory. Furthermore, they introduce an error correction strategies, including pseudo-random error correction and neighborhood search correction, during steganographic extraction.

F Basics and Notions of Steganalysis

According to Simmons' *Prisoners' Problem* (Simmons, 1984) discussed in Section 2.1, in the steganographic scenarios, Eve (the steganalyzer) uses steganalysis methods to distinguish stegotexts from covertexts to determine whether or not she needs to block Alice and Bob's communication. Linguistic steganalysis is a text binary classifier that maps an observed text to a decision on whether it is steganographic or not.

Formally, let $\mathcal{V}$ denote the vocabulary and $\mathcal{X} = \mathcal{V}^*$ the set of all finite-length texts, i.e., $x_i \in \mathcal{X}$. Let $\mathcal{Y} = \{0, 1\}$ be the label set, i.e., $y_i \in \mathcal{Y}$ where $y_i = 0$ indicates that x_i is a covertext and $y_i = 1$ indicates that x_i is a stegotext. The linguistic steganalysis is then modeled as a binary classifier:

$$g(\theta) : \mathcal{X} \to \mathcal{Y},\ g(x;\theta) = \mathbf{1}[f(x;\theta) \geq \tau], \quad (3)$$

in which $f(x;\theta)$ is a scoring function, τ is a decision threshold, and θ is the learnable parameters. Figure 7 shows a sketch of steganalysis. Note that Eve does not need to extract the embedded message and is unable to edit the sent text. Among the classical typology of steganalysis attacks (e.g., stego-only, known-cover, known-stego, and chosen-stego attacks), the online decision problem faced by Eve in our setting is stego-only: at test time she only observes a single text $x \in \mathcal{X}$ and must decide whether $y = 0$ or $y = 1$ without access to the corresponding cover or the embedded message.

G Review of Linguistic Steganalysis Methods

In this section, we review representative linguistic steganalysis methods and introduce the features of various categories.

G.1 Methods Based on Self-Trained Word Representations

This category mainly includes early methods based on neural modeling methods to extract and analyze text features, consisting of recurrent neural networks (RNNs), convolutional neural networks (CNNs), graph neural networks (GNNs), and hybrid modeling methods. RNN-based detectors typically model the conditional distribution of the next token given previous context, and then use likelihood-based or perplexity-based criteria to identify abnormal sequences introduced by embedding operations. For example, LSTM (Niu et al., 2019; Yang et al., 2019c, 2020a) or GRU (Xu et al., 2023) architectures can be trained on large collections of clean carrier texts to learn typical syntactic and semantic patterns. CNN-based models (Yang et al., 2020c; Xue et al., 2022a; Xu et al., 2023), on the other hand, focus more on local text fragments and are effective at capturing stego-induced changes in short n-grams, such as unusual phrase constructions or statistically rare word combina-

tions. With the introduction of GNNs into linguistic steganalysis, researchers began to represent texts as graphs, where nodes may correspond to words, sentences, or documents, and edges encode semantic similarity, syntactic dependencies, or user–post relationships in social media platforms (Wu et al., 2021; Yang et al., 2023a; Pang et al., 2024b). GNN-based steganalysis then performs message passing over these structures to aggregate multi-hop contextual information, enabling the detection of more global, structure-level anomalies that are difficult to capture using purely sequential models.

G.2 Methods Based on Pre-Trained Word Representations

This category mainly includes modern methods based on pre-trained language models, consisting of masked LMs and generative LMs (or LLMs). Method based on masked language modeling (Peng et al., 2021; Zou et al., 2021; Yang et al., 2022a; Xiang et al., 2022a; Wang et al., 2023a), such as those built on BERT-like architectures, typically exploit the contextualized token representations and token-level prediction probabilities learned from large-scale unlabeled corpora. In a common pipeline, the pre-trained model is either frozen as a feature extractor or lightly fine-tuned on clean carrier texts, and then a simple classifier (e.g., MLP or shallow CNN) is trained on top of its hidden states to discriminate between stegotexts and covertexts. Generative LMs (or LLMs) extend this idea by modeling the full left-to-right generation process. Instead of relying on hand-crafted or shallow neural features, Yang et al. (2024a) treat linguistic steganalysis as an LLM-based generative task. They fine-tune open LLMs with LoRA (Hu et al., 2022) for stego vs. cover detection and analyze text distributions via length, perplexity and log-probability. Bai et al. (2024a) treat ChatGPT as a black-box few-shot classifier: supply a prompt with up to 32 labeled examples and ask it whether a new sentence is steganographic or not. Tang et al. (2025) target strongly concealed stegotexts, especially those generated by LLM-based steganography, and proposes an LLM-based steganalysis framework with two operation modes: generation and classification. Wang et al. (2025d) move from isolated sentences to social media settings, and propose STLC-KG, which fuses an LLM with a commonsense knowledge graph to catch logical inconsistencies introduced by steganography.

In particular, Table 6 summarizes the features of LLM-adaptable linguistic steganalysis methods, as they constitute a promising yet still underexplored direction in linguistic steganalysis.

G.3 Dataset Resources

In this section, we introduce the three datasets which are mainstream for evaluating linguistic steganalysis: **IMDB** (Maas et al., 2011), **Twitter** (Go et al., 2009), and **News** (Kaggle, 2017).

IMDB is applied by 43 out of 60 steganalysis methods (shown in Table 8). It contains up to 50,000 movie reviews. This dataset is initially designed for binary sentiment classification.

Twitter is applied by 46 out of 60 steganalysis methods (shown in Table 8). It is a short-text dataset collected from the Twitter platform, and contains 1.6 million training tweets, including 800,000 positive and 800,000 negative samples. Twitter is widely used to evaluate the robustness of text analysis models in noisy short-text scenarios.

News is applied by 31 out of 60 steganalysis methods (shown in Table 8). It consists of up to 2.7 million news articles and essays from 27 American publications.

Generally, the evaluation protocol uses sentences from the dataset as covertexts and uses prefixes of these covertexts to prompt steganographic models to generate stegotexts. Although these three datasets are not modern, they remain the only widely adopted benchmarks. We suggest a limitation that *although a degree of benchmark consistency is shown, the evolution of contemporary text domains and generation scenarios is lacked in steganalysis*.

H Review of Evaluation Metrics

Following the terminology in Section 4.1, we denote the generated stegotext by the token sequence $[s^{(0)}, \ldots, s^{(T-1)}]$.

H.1 Security

H.1.1 Metrics Based on KL Divergence

According to the information-theoretic perspective of steganography security in Section 2.2, the KL divergence between covertexts and stegotexts matters (Yang et al., 2021b; Zhang et al., 2021b). One typical way to calculate this **text-level** KL divergence is based on a third-party sentence vectorization tool (Le and Mikolov, 2014) to map all covertexts and stegotexts to fixed length dense vectors $\boldsymbol{v}_c$ and $\boldsymbol{v}_s$. Assuming that these vectors obey

Method	Training-free?	LoRA-based fine tuning?	Technique keyword
Yang et al. (2024a)	✗	✓	Human-like perception
Bai et al. (2024a)	✓	✗	Few shots; black box
Tang et al. (2025)	✗	✓	Generation-classification hybrid
Wang et al. (2025d)	✗	✓	Knowledge graphs
Barlow (2026)	✗	✓	Multi-feature extraction

Table 6: Methodology features of linguistic steganalysis methods which are adaptable to LLMs.

isotropic Gaussian distribution, the divergence is denoted as:

$$D_{\text{KL-text}} = D_{\text{KL}}(p(\boldsymbol{v}_c) \,\|\, p(\boldsymbol{v}_s)) \approx \sum (\log \frac{\boldsymbol{\sigma}_s}{\boldsymbol{\sigma}_c} + \frac{\boldsymbol{\sigma}_c^2 + (\boldsymbol{\mu}_c - \boldsymbol{\mu}_s)^2}{2\boldsymbol{\sigma}_s^2} - \frac{1}{2}), \quad (4)$$

in which $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ are the mean and standard deviation of sentence vectors. The lower text-level KL divergence indicates greater security.

In addition to the above text-level KL divergence, a formal statistical notion of near-imperceptibility is proposed based on **step-level** KL divergence (Dai and Cai, 2019). Specifically, the average step-level KL divergence is denoted as:

$$D_{\text{KL-step}} = \frac{1}{T} \sum_{t=0}^{T-1} D_{\text{KL}}(\boldsymbol{p}^{(t)} || \hat{\boldsymbol{p}}^{(t)}), \quad (5)$$

in which $\boldsymbol{p}^{(t)}$ is the original probability distribution at t^{th} step, and $\hat{\boldsymbol{p}}^{(t)}$ is transformed from $\boldsymbol{p}^{(t)}$ via steganographic sampling and encoding. The lower step-level KL divergence indicates a higher statistical imperceptibility. Its calculation has two variants: (1) inference based on random-sampling sequences (e.g., theoretical analyses in Dai and Cai (2019)), and (2) inference based on steganographic sequences (that including its reverse versions are commonly applied) (Ziegler et al., 2019).

Besides, several studies also use KL-derived divergences, most notably the Jensen–Shannon divergence (JSD), to quantify the gap between stegotext and covertext (Yang et al., 2021b; Lin et al., 2024).

H.1.2 Metrics Based on Text Quality

First, one of the most common metrics to evaluate text quality and fluency is perplexity (PPL) (Jelinek et al., 1977). The calculation of PPL is:

$$\text{PPL}([s^{(0)}, \ldots, s^{(T-1)}]) = \exp\left\{-\frac{1}{T-1} \sum_{t=1}^{T-1} \log p_{s^{(t)}}^{(t)}\right\}, \quad (6)$$

in which $\log p_{s^{(t)}}^{(t)}$ is the log-likelihood of the t-th token conditioned on the preceding tokens. The calculated result depends on the adopted evaluation model, and a lower score is better.

Besides, text quality can be measured via similarity between the stegotext (candidate) and its covertext (reference) using BLEU (Papineni et al., 2002; Lin and Och, 2004), ROUGE (Lin, 2004), and METEOR (Banerjee and Lavie, 2005). BLEU computes the geometric mean of modified n-gram precisions to estimate how similar a candidate text is to one or more reference texts at the lexical n-gram level. ROUGE measures content overlap by counting matching n-grams, skip-bigrams, or longest common subsequences between a candidate and reference to assess how much of the reference's content the candidate preserves. METEOR aligns candidate and reference at the unigram level, then computes a weighted mean of precision and recall with a fragmentation penalty, aiming to better capture semantic adequacy and correlate with human judgments than n-gram precision alone. For these metrics, higher scores indicate greater similarity.

In addition, to evaluate the diversity of stegotexts, the metric called *distinct-n* computes $\frac{|\text{unique } n\text{-grams}|}{|\text{all } n\text{-grams}|}$ over the generated text to quantify lexical diversity (Li et al., 2016). Higher values indicate less repetition and more varied output.

Beyond traditional automatic metrics, human evaluation and LLM-as-a-judge (Gu et al., 2025) are used to rate various dimensions, such as text fluency, naturalness, and logic, which provide human or near-human perceptual assessments.

Note that several studies not only use absolute values to denote text quality, but also use the metric differences between stegotexts and covertexts to denote imperceptibility. For example, the perplexity difference ΔPPL is calculated when the perceptual-imperceptibility and statistical-imperceptibility conflict effect (*Psic Effect*) is taken into account (Yang et al., 2021b).

H.1.3 Metrics Based on Steganalysis

Following the concepts and introduction in Section 5, steganalysis equips Eve with a binary classifier to distinguish stegotext from covertext. The Lower classifier Accuracy, Precision, Recall, or F1 implies a higher imperceptibility of the stegosystem. Let TP, TN, FP, FN be true/false positives/negatives. Accuracy $= \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$, Precision $= \frac{\text{TP}}{\text{TP+FP}}$, Recall $= \frac{\text{TP}}{\text{TP+FN}}$, and F1 $= \frac{2\text{TP}}{2\text{TP+FP+FN}}$. These four indicators are suitable for scenarios in which the positive and negative samples are (approximately) balanced.

H.2 Efficiency

H.2.1 Embedding Capacity

Bits per token (BPT) is the standard measure of embedding capacity (**bit-rate efficiency**), defined as the number of embedded bits divided by the number of tokens in the stegotext: BPT $= \frac{|\mathbf{m}|}{T}$, where $|\mathbf{m}|$ is the bit number of the embedded message $\mathbf{m}$ and T is the token number of the generated stegotext. Some studies report variants, e.g., bits per word (Fang et al., 2017; Yang et al., 2019a), to express capacity at a different granularity.

Besides, entropy utilization is assessed, which normalizes the payload by the generator's information budget and thus enables fair cross-model comparisons. It is defined as

$$\begin{aligned}\text{Entropy utilization} &= \frac{|\mathbf{m}|}{\sum_{t=0}^{T-1} \text{Entropy}(\boldsymbol{p}^{(t)})} \\ &= \frac{|\mathbf{m}|}{\sum_{t=0}^{T-1} \sum_{i=1}^{|\mathcal{V}|} -p_i^{(t)} \log_2 p_i^{(t)}}, \end{aligned} \tag{7}$$

in which $\boldsymbol{p}^{(t)}$ is the (possibly truncated) distribution used to sample the t-th token, and $|\mathcal{V}|$ is the vocabulary size.

Additionally, the embedding rate ER is used to indicate the percentage of payload bits relative to the total number of bits in the generated stegotext (e.g., under UTF-8 encoding):

$$\text{ER} = \frac{|\mathbf{m}|}{\text{bits}([s^{(0)}, \ldots, s^{(T-1)}])} \times 100\%. \tag{8}$$

H.2.2 Operation Speed

To assess computational complexity and **runtime efficiency**, some studies report operation-speed metrics, particularly (i) the average time to embed/extract one bit (e.g., ms/bit) and (ii) the average time to embed/extract an entire stegotext (e.g., ms/message).

H.3 Robustness

As there are possible tokenization inconsistencies between Alice and Bob, active attacks, and even computational indeterminism (discussed in Section 7), it is significant to assess whether the extracted message $\mathbf{m}'$ is equal to the embedded message $\mathbf{m}$. The standard metric is the message error rate (MER), which is the ratio of $\mathbf{m}' \neq \mathbf{m}$ cases to all cases: MER $= \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\{\mathbf{m}' \neq \mathbf{m}\}$, in which N is the number of stegotext samples. Several variants, such as the bit error rate (BER), are also reported, but length mismatches between $\mathbf{m}'$ and $\mathbf{m}$ can arise from the chosen encoding scheme or from various types of active attack, and length mismatches should be handled explicitly.

I Introduction of Challenges and Future Directions

(1) **Computational indeterminism.** Atil et al. (2025) report that LLMs in hosted environments exhibit computational indeterminism, i.e., the probability distribution over next-token predictions is not fixed even for the same prompt and the same model. When applied to linguistic steganography, this phenomenon substantially undermines the robustness (i.e., extraction success rate) of API-only or black-box steganographic methods.

(2) **Tokenization inconsistency.** Even though tokenization inconsistency between Alice and Bob can be prevented from affecting extraction (see Section E.3), existing countermeasures cannot simultaneously achieve provable security and high capacity. In particular, for the provably secure disambiguation method SyncPool (Qi et al., 2025a), the achievable capacity drops to zero when it is required to operate over the entire vocabulary.

(3) **Abrupt termination.** In current experiments, generation usually stops abruptly once the hidden message has been fully embedded (e.g., the samples reported in Ziegler et al. (2019)), producing obviously unnatural stegotext, and the decoded messages often include extra bits.

(4) **Challenges of synchronizing prompts.** Fixing a single prompt as a hyperparameter makes steganography inflexible and poorly adapted to different topics, styles, or contexts. On the other hand, synchronizing prompts dynamically (e.g., by sharing or updating them each time) implicitly opens an additional side channel outside the stegotext itself, and this auxiliary channel must also be secured and authenticated. Designing schemes that allow

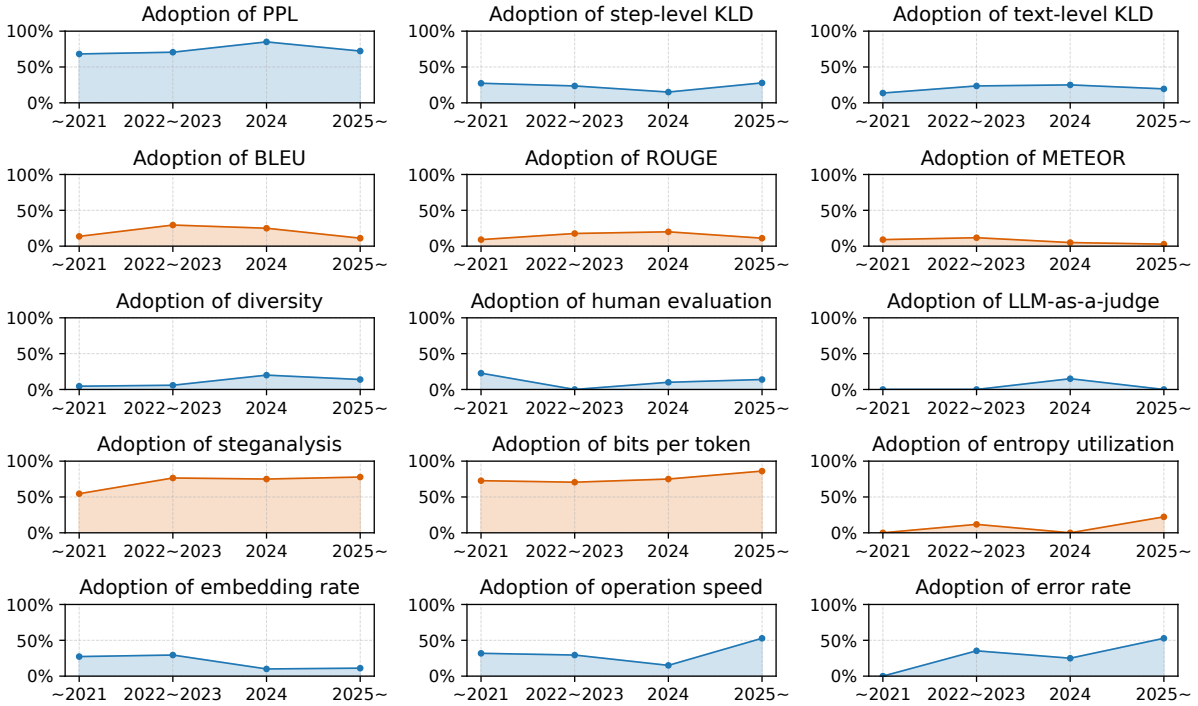


Figure 11: Adoption rates of the 15 major evaluation methods in 95 papers on modern generative linguistic steganography, presented in chronological order. Among these 95 papers, 22 were published before 2021, 17 between 2022 and 2023, 20 in 2024, and 36 after 2025.

prompt adaptation while avoiding new vulnerabilities therefore remains a non-trivial challenge.

(5) **Limited embedding capacity.** Compared to steganography based on images, audio, or video, linguistic steganography suffers from an inherently lower embedding capacity, since the smallest manipulable unit is typically a token, word, or character, carrying much more semantic load than a single pixel. Beyond improving entropy utilization, several directions could offer breakthroughs in capacity: (a) integrating steganography with **information retrieval** (Wang et al., 2024a), (b) enhancing **diversity** (Liao et al., 2024), and (c) using **diffusion language models** (Wu et al., 2025; Qi et al., 2025b).

(6) **High dependence on white-box LLMs.** According to Table 7, most generative steganographic methods are symmetric, requiring both Alice and Bob to access the same white-box language model for embedding and extraction. As LLMs continue to scale up, their computational and memory demands also grow, pushing such symmetric white-box assumptions further away from realistic deployment scenarios. This suggests that **black-box** and **asymmetric** designs (where only the sender has access to a powerful model, or where interaction is limited to API calls) are particularly promising directions for improving computational efficiency and practicality.

(7) **Unrealistic security evaluations.** Current provably secure methods (Ding et al., 2023; Wang et al., 2025a) focus on minimizing the divergence between stegotexts and LM-generated covertexts, but such distributional guarantees alone do not ensure imperceptibility in realistic, human-facing scenarios. LM-based evaluations (e.g., KL divergence and perplexity) should be regarded only as approximations, which is only justified by the lack of access to the ground-truth distribution. Moreover, as summarized in Figure 11, **human evaluation** and **LLM-as-a-judge** metrics are increasingly crucial in the LLM era, yet they are still missing from the majority of existing works.

(8) **Lack of unity in benchmarks.** For current works of linguistic steganography, there are remarkable inconsistencies in selecting (a) datasets or prompts, (b) language models, (c) steganalysis methods, (d) other metrics.

(9) **Ethics and use restrictions of LLM licenses.** Linguistic steganography faces an unlikely existential threat: LLM licenses. A family of use-restricted licenses, including OpenRAIL and Meta's Llama licenses, explicitly prohibit certain forms of deception, such as representing model use

or model outputs as human-generated, which lies at the core of linguistic steganography. The critical perspectives on these licenses come largely from outside the steganography literature. For example, Cui and Araujo (2024) argue that use-restricted licenses sit uneasily with established open-weight principles and are unlikely to provide effective governance on their own. In parallel, work on model openness and on an explicit Open Source AI Definition treats Llama-style and OpenRAIL-style licenses as source-available or open-weight rather than genuinely open source, precisely because they impose behavioral or field-of-use restrictions (White et al., 2025; Open Source Initiative, 2024). We believe that the steganography research community also needs to add its voice to this debate.

Year	Reference	Targeted metric(s)	Scenario(s)	Backbone model(s)	LLM-adaptable?	Training-free?	Asymmetric?	Black-box?
2017	Fang et al. (2017)	Security	General	LSTM	✗	✗	✓	✗
2017	Luo and Huang (2017)	Efficiency	Lyric	LSTM	✗	✗	✗	✗
2018	Yang et al. (2018)	Security	General	Markov	✗	✗	✗	✗
2019	Yang et al. (2019a)	Security	General	LSTM	✗	✗	✗	✗
2019	Ziegler et al. (2019)	Security	General	Model-agnostic	✓	✓	✗	✗
2019	Dai and Cai (2019)	Security	General	Model-agnostic	✓	✓	✗	✗
2019	Yang and Ling (2019)	Security	General	Model-agnostic	✓	✓	✗	✗
2019	Tong et al. (2019)	Efficiency	Lyric	LSTM	✗	✗	✗	✗
2020	Yang et al. (2020b)	Security	General	LSTM	✗	✗	✗	✗
2020	Yang et al. (2020d)	Security	General	GRU	✗	✗	✗	✗
2020	Shen et al. (2020)	Security	General	Model-agnostic	✓	✓	✗	✗
2020	Kang et al. (2020)	Security	General	LSTM	✗	✗	✗	✗
2020	Wu et al. (2020)	Security	General	Markov	✗	✗	✗	✗
2020	Xiang et al. (2020)	Efficiency	General	LSTM	✗	✗	✗	✗
2021	Yang et al. (2021b)	Security	General	LSTM, BERT	✗	✗	✗	✗
2021	Zhang et al. (2021b)	Security	General	Model-agnostic	✓	✓	✗	✗
2021	Yang et al. (2021c)	Security	General	LSTM, GRU, Transformer	✗	✗	✗	✗
2021	Kaptchuk et al. (2021)	Security	General	Model-agnostic	✓	✓	✗	✗
2021	Zhang et al. (2021a)	Security	General	Transformer	✗	✗	✗	✗
2021	Li et al. (2021)	Security	General	LSTM, Transformer	✗	✗	✗	✗
2021	Yang et al. (2021a)	Security	General	LSTM	✗	✗	✗	✗
2021	Wang et al. (2021)	Security	Lyric	LSTM	✗	✗	✗	✗
2022	Yang et al. (2022b)	Security	Lyric	GRU	✗	✗	✗	✗
2022	Yu et al. (2022)	Security	General	Model-agnostic	✓	✓	✗	✗
2022	Zhou et al. (2022)	Security	General	LSTM, CNN	✗	✗	✗	✗
2022	Yi et al. (2022a)	Security/Efficiency	General	BERT	✗	✓	✗	✗
2022	Varol Arısoy (2022)	Efficiency	General	LSTM	✗	✗	✗	✗
2022	Adeeb and Kabudian (2022)	Efficiency	Arabic text	LSTM	✗	✗	✗	✗
2022	Nozaki and Murawaki (2022)	Robustness	General	Model-agnostic	✓	✓	✗	✗
2023	Sun et al. (2023)	Security	General	T5	✗	✗	✗	✗
2023	Lu et al. (2023a)	Security	General	Model-agnostic	✓	✓	✗	✗
2023	Wang et al. (2023b)	Security	General	Transformer	✗	✗	✗	✗
2023	Ding et al. (2023)	Security	General	Model-agnostic	✓	✓	✗	✗
2023	Wang et al. (2023c)	Security	General	BART, GPT-2	✗	✓	✗	✗
2023	Wang et al. (2023d)	Security	Image-to-text	ClipCap	✗	✗	✗	✗
2023	de Witt et al. (2023)	Security	General	Model-agnostic	✓	✓	✗	✗
2023	Yan et al. (2023)	Security/Robustness	General	Model-agnostic	✓	✓	✗	✗
2023	Lu et al. (2023b)	Security/Robustness	Translation	Transformer	✗	✗	✗	✗
2023	Peng et al. (2023b)	Robustness	Image-to-text	ResNet-101, LSTM	✗	✗	✗	✗
2024	Zhang et al. (2024)	Security	Summarization	BERT, Conditional Random Field (CRF)	✗	✓	✗	✗
2024	Wu et al. (2024c)	Security	General	Model-agnostic	✓	✓	✓	✓
2024	Xiang et al. (2024)	Security	Translation	BERT, LSTM	✗	✗	✗	✗
2024	Lin et al. (2024)	Security	General	Model-agnostic	✓	✓	✗	✗
2024	Li et al. (2024b)	Security	General	Model-agnostic	✓	✓	✗	✗
2024	Liu et al. (2024)	Security	Live comments	ResNet, LSTM	✗	✗	✗	✗
2024	Namitha et al. (2024)	Security	General	Model-agnostic	✓	✓	✗	✗
2024	Pang et al. (2024a)	Security	General	Model-agnostic	✓	✓	✗	✗
2024	Li et al. (2024a)	Security	Group chat	BERT, Transformer	✗	✓	✗	✗
2024	Cao et al. (2024)	Security	General	Model-agnostic	✓	✓	✗	✗
2024	Chen et al. (2024)	Security	General	Model-agnostic	✓	✗	✗	✗
2024	Qin et al. (2024)	Security	General	Model-agnostic	✓	✓	✗	✗
2024	Lin and Wang (2024)	Security	Translation	LSTM	✗	✗	✗	✗
2024	Yan et al. (2024b)	Security/Efficiency	General	ByGPT5	✗	✓	✗	✗
2024	Steinebach (2024)	Efficiency	General	Model-agnostic	✓	✓	✓	✓
2024	Wang et al. (2024a)	Efficiency	Social media	Model-agnostic	✓	✓	✗	✗
2024	Liao et al. (2024)	Efficiency	Social media	Model-agnostic	✓	✓	✗	✗
2024	Huang et al. (2024)	Security/Robustness	General	Model-agnostic	✓	✓	✗	✗
2024	Yan et al. (2024a)	Security/Robustness	General	Model-agnostic	✓	✓	✗	✗
2024	Bai et al. (2024b)	Efficiency/Robustness	General	Model-agnostic	✓	✓	✗	✓
2025	Wang et al. (2025b)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Liao et al. (2025)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Woźniak et al. (2025)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Long et al. (2025)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Zhang et al. (2025a)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Chen et al. (2025a)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Shi et al. (2025)	Security	General	XLM-RoBERTa, Transformer	✗	✓	✗	✗
2025	Liu et al. (2025)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Kuznetsov et al. (2025)	Security	General	Model-agnostic	✓	✓	✗	✗
2025	Zhou et al. (2025)	Security	General	Multi-agent	✓	✓	✓	✗
2025	Pan et al. (2025)	Security/Efficiency	General	Model-agnostic	✓	✓	✗	✗
2025	Pang (2025a)	Security/Efficiency	General	Model-agnostic	✓	✓	✗	✗
2025	Wang et al. (2025a)	Security/Efficiency	General	Model-agnostic	✓	✓	✗	✗
2025	Bai et al. (2025a)	Security/Efficiency	General	Model-agnostic	✓	✓	✗	✗
2025	Jiang et al. (2025)	Security/Efficiency	General	Multi-agent	✓	✗	✓	✗
2025	Pang (2025b)	Efficiency	General	Model-agnostic	✓	✓	✗	✓
2025	Huang et al. (2025b)	Efficiency	General	Model-agnostic	✓	✓	✗	✗
2025	Wu et al. (2025)	Efficiency	General	Diffusion language model	✓	✗	✗	✗
2025	Li et al. (2025b)	Efficiency	General	Multi-agent	✓	✗	✗	✓
2025	Farooq Ahmed Adeeb and Kabudian (2025)	Efficiency	General	Model-agnostic	✓	✓	✗	✗
2025	Yan and Murawaki (2025)	Security/Robustness	General	Model-agnostic	✓	✓	✗	✗
2025	Bai et al. (2025b)	Security/Robustness	General	Model-agnostic	✓	✓	✓	✗
2025	Qi et al. (2025a)	Security/Robustness	General	Model-agnostic	✓	✓	✗	✗
2025	Qi et al. (2025b)	Security/Robustness	General	Diffusion language model	✓	✓	✗	✗
2025	Feng et al. (2025)	Efficiency/Robustness	General	Model-agnostic	✓	✓	✗	✗
2025	Perry et al. (2025)	Robustness	General	Model-agnostic	✓	✓	✗	✗
2025	Pang et al. (2025)	Robustness	General	Model-agnostic	✓	✓	✗	✗
2025	Guo et al. (2025)	Robustness	General	Model-agnostic	✓	✓	✗	✗
2025	Chen et al. (2025b)	Robustness	General	Model-agnostic	✓	✓	✗	✗
2026	Xiang et al. (2026)	Security	General	BERT	✗	✗	✓	✗
2026	Gao et al. (2026)	Security	General	Multimodal LLM	✓	✓	✓	✓
2026	Yan and Murawaki (2026)	Security/Efficiency	General	Model-agnostic	✓	✓	✗	✗
2026	Jiang et al. (2026)	Security/Efficiency	General	Model-agnostic	✓	✓	✓	✗
2026	Zhang et al. (2026)	Security/Robustness	General	BERT, GPT-2	✗	✗	✗	✗
2026	Wang et al. (2026a)	Efficiency/Robustness	General	Model-agnostic	✓	✓	✓	✗
2026	Yan et al. (2026)	Robustness	General	Model-agnostic	✓	✗	✗	✗

Table 7: Taxonomy for generative linguistic steganographic methods based on methodology features.

Year	Reference	Backbone model	Based on pre-trained model(s)?	LLM-adaptable?	Experiments on IMDB dataset (Maas et al., 2011)?	Experiments on Twitter dataset (Go et al., 2009)?	Experiments on News dataset (Kaggle, 2017)?	Experiments on other dataset(s)?
2019	Yang et al. (2019b)	Feed-forward neural networks	✗	✗	✗	✗	✗	✓
2019	Niu et al. (2019)	Bi-LSTMs; CNNs	✗	✗	✓	✓	✗	✗
2019	Yang et al. (2019c)	Bi-RNNs; LSTMs	✗	✗	✓	✓	✗	✗
2019	Wen et al. (2019)	Word2vec; CNNs	✓	✗	✗	✗	✗	✓
2020	Yang et al. (2020c)	CNNs	✗	✗	✗	✗	✗	✓
2020	Yang et al. (2020a)	Bi-LSTMs	✗	✗	✓	✓	✓	✗
2020	Bao et al. (2020)	Bi-LSTMs; CNNs	✗	✗	✓	✓	✓	✗
2020	Li et al. (2020)	Bi-LSTMs; GNNs	✗	✗	✗	✗	✗	✓
2021	Wu et al. (2021)	GNNs	✗	✗	✓	✓	✗	✗
2021	Jiao et al. (2021)	Attention	✗	✗	✓	✓	✓	✗
2021	Peng et al. (2021)	BERT; Bi-LSTMs; CNNs	✓	✗	✓	✓	✗	✗
2021	Zou et al. (2021)	BERT; Bi-LSTMs	✓	✗	✗	✓	✓	✗
2021	Xu et al. (2021)	BERT; Bi-LSTMs	✓	✗	✓	✓	✓	✗
2022	Fu et al. (2022)	GNNs	✗	✗	✓	✓	✗	✗
2022	Yi et al. (2022b)	LSTMs	✗	✗	✓	✓	✗	✗
2022	Xue et al. (2022a)	CNNs	✗	✗	✓	✓	✓	✗
2022	Yang et al. (2022a)	BERT; GNNs	✓	✗	✓	✓	✓	✗
2022	Guo et al. (2022)	BERT	✓	✗	✓	✓	✓	✗
2022	Xiang et al. (2022a)	BERT; GNNs	✓	✗	✓	✓	✗	✗
2022	Xue et al. (2022b)	BERT; CNNs	✓	✗	✓	✓	✓	✗
2022	Xu et al. (2022)	BERT; Bi-GRUs; CNNs	✓	✗	✓	✓	✓	✗
2022	Wen et al. (2022b)	BERT; Bi-LSTMs	✓	✗	✓	✓	✓	✗
2022	Wen et al. (2022a)	BERT	✓	✗	✓	✓	✓	✗
2023	Yang et al. (2023b)	GNNs	✗	✗	✗	✗	✗	✓
2023	Xu et al. (2023)	CNNs; Bi-GRU	✗	✗	✗	✗	✗	✓
2023	Yang et al. (2023a)	GNNs	✗	✗	✓	✓	✗	✗
2023	Li et al. (2023b)	Attention; CNNs	✗	✗	✓	✓	✗	✗
2023	Wen et al. (2023a)	Bi-LSTMs; CNNs	✗	✗	✓	✓	✓	✓
2023	Xiang et al. (2023a)	CNNs	✗	✗	✗	✗	✗	✓
2023	Peng et al. (2023a)	BERT	✓	✗	✓	✓	✗	✗
2023	Wang et al. (2023e)	GloVe; LSTMs	✓	✗	✗	✗	✗	✓
2023	Wang et al. (2023f)	BERT	✓	✗	✓	✓	✗	✗
2023	Wen et al. (2023b)	BERT	✓	✗	✓	✓	✓	✗
2023	Wang et al. (2023a)	BERT	✓	✗	✓	✓	✓	✗
2024	Pang et al. (2024b)	GNNs	✗	✗	✗	✓	✗	✓
2024	Wang et al. (2024b)	CNNs; Attention	✗	✗	✓	✓	✓	✗
2024	Yang et al. (2024a)	LLM (model-agnostic); LoRA	✓	✓	✓	✓	✓	✗
2024	Bai et al. (2024a)	LLM (model-agnostic)	✓	✓	✓	✓	✗	✗
2024	Xue et al. (2024)	BERT; CNNs	✓	✗	✓	✓	✓	✗
2024	Yuan et al. (2024)	BERT; Bi-LSTMs	✓	✗	✓	✓	✓	✗
2024	Wu et al. (2024b)	BERT	✓	✗	✓	✓	✓	✗
2024	Gao et al. (2024b)	ELECTRA (Gutmann and Hyvärinen, 2010)	✓	✗	✓	✓	✓	✗
2024	You et al. (2024)	BERT	✓	✗	✓	✓	✗	✗
2025	Huang et al. (2025a)	GNNs	✗	✗	✗	✓	✗	✓
2025	Lu et al. (2025)	CNNs; GNNs; Attention	✗	✗	✗	✗	✗	✓
2025	Tang et al. (2025)	LLM (model-agnostic); LoRA	✓	✓	✓	✓	✓	✗
2025	Wang et al. (2025d)	LLM (model-agnostic); GNNs	✓	✓	✓	✓	✓	✗
2025	Xiao et al. (2025)	RoBERTa; CNNs	✓	✗	✓	✓	✓	✗
2025	Zhang et al. (2025b)	BERT; CNNs	✓	✗	✓	✓	✓	✗
2025	Yang et al. (2025)	ERNIE (Sun et al., 2019); Attention	✓	✗	✓	✓	✓	✗
2025	Li et al. (2025a)	Word2vec; LSTMs; CNNs	✓	✗	✓	✓	✓	✗
2025	Zhang et al. (2025c)	BERT	✓	✗	✓	✓	✓	✗
2025	Wang et al. (2025c)	BERT; GNNs	✓	✗	✗	✗	✗	✓
2025	Luo et al. (2025b)	BERT; Bi-LSTMs	✓	✗	✓	✓	✓	✗
2025	Luo et al. (2025a)	BERT; Bi-LSTMs	✓	✗	✓	✓	✓	✗
2025	Niu and Yang (2025)	RoBERTa; Bi-RNNs	✓	✗	✗	✗	✗	✓
2026	Wang et al. (2026b)	BERT	✓	✗	✗	✗	✗	✓
2026	Luo et al. (2026)	BERT	✓	✗	✓	✓	✓	✗
2026	Barlow (2026)	LLM (model-agnostic)	✓	✓	✗	✗	✗	✓
2026	Huang et al. (2026)	GNNs	✗	✗	✗	✗	✗	✓

Table 8: Methodology features and experiment datasets of linguistic steganalysis methods.

Year	Reference	FCN (Yang et al., 2019b)	CNN (Wen et al., 2019)	R-BiLSTM-C (Niu et al., 2019)	TS-RNN (Yang et al., 2019c)	TS-CSW (Yang et al., 2020c)	Other
2017	Fang et al. (2017)	✗	✗	✗	✗	✗	✗
2017	Luo and Huang (2017)	✗	✗	✗	✗	✗	✗
2018	Yang et al. (2018)	✗	✗	✗	✗	✗	✓
2019	Yang et al. (2019a)	✗	✗	✗	✗	✗	✓
2019	Ziegler et al. (2019)	✗	✗	✗	✗	✗	✗
2019	Dai and Cai (2019)	✗	✗	✗	✗	✗	✗
2019	Yang and Ling (2019)	✗	✗	✗	✗	✗	✓
2019	Tong et al. (2019)	✗	✗	✗	✗	✗	✗
2020	Yang et al. (2020b)	✓	✗	✗	✗	✗	✗
2020	Yang et al. (2020d)	✗	✗	✗	✗	✗	✗
2020	Shen et al. (2020)	✗	✗	✗	✗	✗	✗
2020	Kang et al. (2020)	✗	✗	✗	✗	✗	✓
2020	Wu et al. (2020)	✗	✗	✗	✗	✗	✓
2020	Xiang et al. (2020)	✗	✗	✗	✗	✗	✗
2021	Yang et al. (2021b)	✓	✓	✗	✗	✗	✓
2021	Zhang et al. (2021b)	✓	✗	✗	✗	✓	✗
2021	Yang et al. (2021c)	✓	✗	✗	✓	✓	✗
2021	Kaptchuk et al. (2021)	✗	✗	✗	✗	✗	✗
2021	Zhang et al. (2021a)	✓	✗	✗	✗	✓	✗
2021	Li et al. (2021)	✓	✗	✗	✗	✗	✗
2021	Yang et al. (2021a)	✗	✓	✗	✓	✗	✗
2021	Wang et al. (2021)	✗	✗	✗	✗	✗	✗
2022	Yang et al. (2022b)	✗	✗	✗	✗	✗	✗
2022	Yu et al. (2022)	✗	✗	✗	✗	✗	✗
2022	Zhou et al. (2022)	✗	✓	✓	✓	✗	✗
2022	Yi et al. (2022a)	✗	✗	✗	✓	✗	✓
2022	Varol Arısoy (2022)	✓	✓	✗	✗	✗	✓
2022	Adeeb and Kabudian (2022)	✗	✗	✗	✗	✗	✗
2022	Nozaki and Murawaki (2022)	✗	✗	✗	✗	✗	✓
2023	Sun et al. (2023)	✓	✓	✓	✗	✗	✗
2023	Lu et al. (2023a)	✗	✗	✓	✓	✓	✗
2023	Wang et al. (2023b)	✗	✗	✗	✗	✗	✓
2023	Ding et al. (2023)	✓	✗	✓	✗	✗	✓
2023	Wang et al. (2023c)	✗	✗	✓	✗	✗	✓
2023	Wang et al. (2023d)	✓	✗	✗	✗	✗	✗
2023	de Witt et al. (2023)	✗	✗	✗	✗	✗	✗
2023	Yan et al. (2023)	✗	✗	✗	✗	✗	✓
2023	Lu et al. (2023b)	✗	✗	✓	✓	✓	✗
2023	Peng et al. (2023b)	✗	✓	✓	✗	✗	✓
2024	Zhang et al. (2024)	✗	✗	✗	✗	✓	✓
2024	Wu et al. (2024c)	✗	✓	✗	✗	✗	✓
2024	Xiang et al. (2024)	✗	✓	✓	✓	✗	✗
2024	Lin et al. (2024)	✗	✗	✓	✗	✗	✓
2024	Li et al. (2024b)	✗	✗	✓	✗	✓	✗
2024	Liu et al. (2024)	✗	✗	✗	✗	✗	✗
2024	Namitha et al. (2024)	✗	✗	✗	✗	✗	✓
2024	Pang et al. (2024a)	✗	✗	✗	✗	✓	✗
2024	Li et al. (2024a)	✗	✗	✗	✗	✓	✗
2024	Cao et al. (2024)	✗	✗	✗	✓	✗	✗
2024	Chen et al. (2024)	✗	✗	✗	✗	✓	✗
2024	Qin et al. (2024)	✗	✗	✗	✗	✗	✓
2024	Lin and Wang (2024)	✗	✓	✗	✗	✗	✓
2024	Yan et al. (2024b)	✗	✗	✗	✗	✗	✓
2024	Steinebach (2024)	✗	✗	✗	✗	✗	✗
2024	Wang et al. (2024a)	✗	✗	✗	✗	✗	✓
2024	Liao et al. (2024)	✗	✗	✗	✗	✗	✗
2024	Huang et al. (2024)	✗	✗	✗	✗	✗	✗
2024	Yan et al. (2024a)	✗	✗	✗	✗	✗	✓
2024	Bai et al. (2024b)	✗	✗	✗	✗	✗	✗
2025	Wang et al. (2025b)	✗	✓	✗	✗	✓	✓
2025	Liao et al. (2025)	✗	✗	✗	✗	✓	✗
2025	Woźniak et al. (2025)	✗	✗	✗	✗	✗	✗
2025	Long et al. (2025)	✓	✓	✓	✗	✗	✗
2025	Zhang et al. (2025a)	✓	✗	✓	✗	✗	✓
2025	Chen et al. (2025a)	✓	✓	✓	✓	✗	✓
2025	Shi et al. (2025)	✗	✓	✗	✓	✗	✓
2025	Liu et al. (2025)	✗	✗	✗	✗	✗	✓
2025	Kuznetsov et al. (2025)	✗	✗	✗	✓	✗	✓
2025	Zhou et al. (2025)	✗	✓	✗	✗	✗	✓
2025	Pan et al. (2025)	✓	✗	✓	✗	✗	✓
2025	Pang (2025a)	✗	✗	✓	✓	✓	✓
2025	Wang et al. (2025a)	✓	✗	✓	✗	✗	✓
2025	Bai et al. (2025a)	✗	✗	✗	✗	✗	✗
2025	Jiang et al. (2025)	✓	✗	✗	✗	✗	✓
2025	Pang (2025b)	✗	✗	✗	✗	✓	✗
2025	Huang et al. (2025b)	✗	✗	✗	✗	✗	✗
2025	Wu et al. (2025)	✗	✓	✗	✓	✗	✓
2025	Li et al. (2025b)	✓	✗	✗	✗	✗	✓
2025	Farooq Ahmed Adeeb and Kabudian (2025)	✗	✗	✗	✗	✗	✓
2025	Yan and Murawaki (2025)	✗	✗	✗	✗	✗	✓
2025	Bai et al. (2025b)	✗	✗	✗	✗	✗	✗
2025	Qi et al. (2025a)	✗	✗	✗	✗	✗	✗
2025	Qi et al. (2025b)	✓	✗	✓	✗	✗	✓
2025	Feng et al. (2025)	✗	✗	✗	✗	✗	✗
2025	Perry et al. (2025)	✗	✗	✗	✗	✗	✗
2025	Pang et al. (2025)	✗	✗	✗	✗	✓	✗
2025	Guo et al. (2025)	✗	✗	✗	✗	✗	✗
2025	Chen et al. (2025b)	✓	✗	✗	✓	✗	✓
2026	Xiang et al. (2026)	✗	✗	✗	✗	✗	✓
2026	Gao et al. (2026)	✗	✗	✗	✗	✗	✓
2026	Yan and Murawaki (2026)	✗	✗	✗	✗	✗	✓
2026	Jiang et al. (2026)	✓	✗	✓	✗	✗	✓
2026	Zhang et al. (2026)	✓	✗	✗	✗	✗	✓
2026	Wang et al. (2026a)	✓	✗	✗	✗	✗	✓
2026	Yan et al. (2026)	✗	✗	✗	✗	✗	✓

Table 9: Adopted steganalysis methods to evaluate imperceptibility of the generative linguistic steganographic methods.

Year	Reference	PPL	KLD (step-level)	KLD (text-level)	BLEU	ROUGE	METEOR	Diversity	Human evaluation	LLM-as-a-judge	Other
2017	Fang et al. (2017)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2017	Luo and Huang (2017)	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
2018	Yang et al. (2018)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2019	Yang et al. (2019a)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2019	Ziegler et al. (2019)	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗
2019	Dai and Cai (2019)	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
2019	Yang and Ling (2019)	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗
2019	Tong et al. (2019)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2020	Yang et al. (2020b)	✓	✗	✗	✓	✓	✗	✗	✗	✗	✓
2020	Yang et al. (2020d)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2020	Shen et al. (2020)	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗
2020	Kang et al. (2020)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2020	Wu et al. (2020)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2020	Xiang et al. (2020)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2021	Yang et al. (2021b)	✓	✗	✓	✗	✗	✗	✗	✓	✗	✗
2021	Zhang et al. (2021b)	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗
2021	Yang et al. (2021c)	✓	✗	✗	✗	✓	✓	✗	✗	✗	✗
2021	Kaptchuk et al. (2021)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
2021	Zhang et al. (2021a)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2021	Li et al. (2021)	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗
2021	Yang et al. (2021a)	✓	✗	✓	✓	✗	✗	✓	✗	✗	✗
2021	Wang et al. (2021)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2022	Yang et al. (2022b)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2022	Yu et al. (2022)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2022	Zhou et al. (2022)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2022	Yi et al. (2022a)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2022	Varol Arısoy (2022)	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗
2022	Adeeb and Kabudian (2022)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2022	Nozaki and Murawaki (2022)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2023	Sun et al. (2023)	✓	✗	✗	✓	✓	✗	✗	✗	✗	✓
2023	Lu et al. (2023a)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
2023	Wang et al. (2023b)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2023	Ding et al. (2023)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
2023	Wang et al. (2023c)	✓	✗	✓	✓	✓	✗	✗	✗	✗	✓
2023	Wang et al. (2023d)	✓	✗	✗	✓	✗	✓	✓	✗	✗	✗
2023	de Witt et al. (2023)	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
2023	Yan et al. (2023)	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗
2023	Lu et al. (2023b)	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗
2023	Peng et al. (2023b)	✗	✗	✓	✓	✓	✓	✗	✗	✗	✗
2024	Zhang et al. (2024)	✗	✗	✗	✗	✓	✓	✗	✗	✗	✓
2024	Wu et al. (2024c)	✓	✗	✓	✗	✗	✗	✗	✓	✗	✓
2024	Xiang et al. (2024)	✓	✓	✗	✓	✗	✗	✗	✗	✗	✓
2024	Lin et al. (2024)	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗
2024	Li et al. (2024b)	✓	✗	✗	✗	✓	✗	✗	✗	✗	✓
2024	Liu et al. (2024)	✓	✗	✗	✓	✓	✗	✗	✗	✗	✗
2024	Namitha et al. (2024)	✓	✗	✗	✗	✗	✗	✗	✓	✗	✗
2024	Pang et al. (2024a)	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗
2024	Li et al. (2024a)	✓	✗	✗	✓	✓	✗	✗	✗	✗	✗
2024	Cao et al. (2024)	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗
2024	Chen et al. (2024)	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗
2024	Qin et al. (2024)	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗
2024	Lin and Wang (2024)	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗
2024	Yan et al. (2024b)	✓	✗	✓	✗	✗	✗	✗	✗	✗	✓
2024	Steinebach (2024)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2024	Wang et al. (2024a)	✓	✗	✗	✗	✗	✗	✓	✗	✗	✓
2024	Liao et al. (2024)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2024	Huang et al. (2024)	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗
2024	Yan et al. (2024a)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
2024	Bai et al. (2024b)	✓	✗	✗	✗	✗	✗	✓	✗	✓	✗
2025	Wang et al. (2025b)	✓	✗	✓	✓	✗	✗	✗	✗	✗	✓
2025	Liao et al. (2025)	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
2025	Woźniak et al. (2025)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2025	Long et al. (2025)	✓	✗	✗	✓	✓	✓	✗	✗	✗	✗
2025	Zhang et al. (2025a)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Chen et al. (2025a)	✓	✗	✓	✗	✗	✗	✓	✗	✗	✓
2025	Shi et al. (2025)	✓	✓	✗	✓	✗	✗	✗	✗	✗	✗
2025	Liu et al. (2025)	✓	✗	✓	✗	✗	✗	✗	✓	✗	✗
2025	Kuznetsov et al. (2025)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2025	Zhou et al. (2025)	✓	✗	✓	✗	✗	✗	✗	✓	✗	✓
2025	Pan et al. (2025)	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
2025	Pang (2025a)	✓	✗	✗	✗	✗	✗	✓	✗	✗	✓
2025	Wang et al. (2025a)	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
2025	Bai et al. (2025a)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Jiang et al. (2025)	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
2025	Pang (2025b)	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗
2025	Huang et al. (2025b)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Wu et al. (2025)	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗
2025	Li et al. (2025b)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Farooq Ahmed Adeeb and Kabudian (2025)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Yan and Murawaki (2025)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
2025	Bai et al. (2025b)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Qi et al. (2025a)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
2025	Qi et al. (2025b)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Feng et al. (2025)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
2025	Perry et al. (2025)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
2025	Pang et al. (2025)	✓	✗	✗	✗	✓	✗	✓	✗	✗	✗
2025	Guo et al. (2025)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
2025	Chen et al. (2025b)	✓	✗	✓	✗	✗	✗	✓	✗	✗	✓
2026	Xiang et al. (2026)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2026	Gao et al. (2026)	✓	✗	✓	✗	✗	✗	✗	✓	✗	✓
2026	Yan and Murawaki (2026)	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗
2026	Jiang et al. (2026)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
2026	Zhang et al. (2026)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
2026	Wang et al. (2026a)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✓
2026	Yan et al. (2026)	✓	✓	✗	✓	✓	✗	✗	✓	✗	✓

Table 10: Adopted metrics (excluding steganalysis) to evaluate steganographic security, including the imperceptibility, and the text quality of stegotexts based on generative linguistic steganographic methods.

Year	Reference	Bits per token	Entropy utilization	Embedding rate	Operation speed	Error rate
2017	Fang et al. (2017)	✓	✗	✗	✗	✗
2017	Luo and Huang (2017)	✗	✗	✓	✗	✗
2018	Yang et al. (2018)	✓	✗	✓	✗	✗
2019	Yang et al. (2019a)	✓	✗	✓	✓	✗
2019	Ziegler et al. (2019)	✓	✗	✗	✗	✗
2019	Dai and Cai (2019)	✗	✗	✗	✗	✗
2019	Yang and Ling (2019)	✓	✗	✗	✗	✗
2019	Tong et al. (2019)	✓	✗	✗	✗	✗
2020	Yang et al. (2020b)	✓	✗	✓	✗	✗
2020	Yang et al. (2020d)	✓	✗	✗	✗	✗
2020	Shen et al. (2020)	✓	✗	✗	✓	✗
2020	Kang et al. (2020)	✓	✗	✗	✗	✗
2020	Wu et al. (2020)	✗	✗	✓	✓	✗
2020	Xiang et al. (2020)	✗	✗	✓	✓	✗
2021	Yang et al. (2021b)	✓	✗	✗	✗	✗
2021	Zhang et al. (2021b)	✓	✗	✗	✗	✗
2021	Yang et al. (2021c)	✗	✗	✗	✗	✗
2021	Kaptchuk et al. (2021)	✓	✗	✗	✓	✗
2021	Zhang et al. (2021a)	✗	✗	✗	✗	✗
2021	Li et al. (2021)	✓	✗	✗	✗	✗
2021	Yang et al. (2021a)	✓	✗	✗	✓	✗
2021	Wang et al. (2021)	✓	✗	✗	✓	✗
2022	Yang et al. (2022b)	✓	✗	✓	✗	✗
2022	Yu et al. (2022)	✓	✗	✗	✓	✗
2022	Zhou et al. (2022)	✓	✗	✓	✗	✗
2022	Yi et al. (2022a)	✗	✗	✗	✗	✗
2022	Varol Arısoy (2022)	✓	✗	✓	✓	✗
2022	Adeeb and Kabudian (2022)	✗	✗	✓	✗	✗
2022	Nozaki and Murawaki (2022)	✓	✗	✗	✗	✓
2023	Sun et al. (2023)	✗	✗	✓	✗	✗
2023	Lu et al. (2023a)	✓	✗	✗	✗	✓
2023	Wang et al. (2023b)	✓	✗	✗	✗	✗
2023	Ding et al. (2023)	✓	✓	✗	✓	✗
2023	Wang et al. (2023c)	✓	✗	✗	✗	✗
2023	Wang et al. (2023d)	✓	✗	✗	✗	✗
2023	de Witt et al. (2023)	✗	✓	✗	✓	✓
2023	Yan et al. (2023)	✓	✗	✗	✓	✓
2023	Lu et al. (2023b)	✗	✗	✗	✗	✓
2023	Peng et al. (2023b)	✓	✗	✗	✗	✓
2024	Zhang et al. (2024)	✗	✗	✗	✓	✗
2024	Wu et al. (2024c)	✓	✗	✗	✗	✗
2024	Xiang et al. (2024)	✓	✗	✗	✗	✗
2024	Lin et al. (2024)	✓	✗	✗	✗	✗
2024	Li et al. (2024b)	✓	✗	✗	✗	✗
2024	Liu et al. (2024)	✓	✗	✗	✗	✗
2024	Namitha et al. (2024)	✓	✗	✗	✓	✓
2024	Pang et al. (2024a)	✗	✗	✗	✗	✗
2024	Li et al. (2024a)	✗	✗	✗	✗	✗
2024	Cao et al. (2024)	✓	✗	✓	✓	✗
2024	Chen et al. (2024)	✓	✗	✗	✗	✗
2024	Qin et al. (2024)	✗	✗	✗	✗	✗
2024	Lin and Wang (2024)	✓	✗	✗	✗	✗
2024	Yan et al. (2024b)	✗	✗	✓	✗	✗
2024	Steinebach (2024)	✓	✗	✗	✗	✓
2024	Wang et al. (2024a)	✓	✗	✗	✗	✗
2024	Liao et al. (2024)	✓	✗	✗	✗	✗
2024	Huang et al. (2024)	✓	✗	✗	✗	✓
2024	Yan et al. (2024a)	✓	✗	✗	✗	✓
2024	Bai et al. (2024b)	✓	✗	✗	✗	✓
2025	Wang et al. (2025b)	✓	✗	✗	✗	✗
2025	Liao et al. (2025)	✓	✓	✗	✓	✗
2025	Woźniak et al. (2025)	✓	✗	✗	✗	✗
2025	Long et al. (2025)	✓	✗	✗	✗	✗
2025	Zhang et al. (2025a)	✗	✗	✗	✗	✗
2025	Chen et al. (2025a)	✓	✗	✗	✗	✗
2025	Shi et al. (2025)	✓	✗	✗	✗	✗
2025	Liu et al. (2025)	✓	✗	✗	✗	✗
2025	Kuznetsov et al. (2025)	✗	✗	✓	✓	✓
2025	Zhou et al. (2025)	✓	✗	✗	✗	✗
2025	Pan et al. (2025)	✓	✓	✗	✓	✗
2025	Pang (2025a)	✓	✗	✗	✓	✗
2025	Wang et al. (2025a)	✓	✓	✗	✓	✓
2025	Bai et al. (2025a)	✓	✓	✗	✓	✗
2025	Jiang et al. (2025)	✓	✗	✓	✓	✗
2025	Pang (2025b)	✓	✓	✗	✓	✗
2025	Huang et al. (2025b)	✓	✗	✗	✗	✗
2025	Wu et al. (2025)	✓	✗	✗	✓	✓
2025	Li et al. (2025b)	✗	✗	✗	✗	✓
2025	Farooq Ahmed Adeeb and Kabudian (2025)	✓	✗	✗	✗	✗
2025	Yan and Murawaki (2025)	✓	✗	✗	✓	✓
2025	Bai et al. (2025b)	✓	✗	✗	✓	✓
2025	Qi et al. (2025a)	✓	✓	✗	✓	✓
2025	Qi et al. (2025b)	✓	✗	✗	✓	✓
2025	Feng et al. (2025)	✓	✗	✗	✗	✓
2025	Perry et al. (2025)	✗	✗	✗	✗	✓
2025	Pang et al. (2025)	✓	✗	✗	✗	✓
2025	Guo et al. (2025)	✗	✗	✗	✗	✓
2025	Chen et al. (2025b)	✓	✗	✗	✗	✓
2026	Xiang et al. (2026)	✓	✗	✓	✓	✓
2026	Gao et al. (2026)	✓	✗	✗	✓	✓
2026	Yan and Murawaki (2026)	✓	✓	✗	✓	✗
2026	Jiang et al. (2026)	✓	✗	✓	✓	✓
2026	Zhang et al. (2026)	✓	✗	✗	✗	✓
2026	Wang et al. (2026a)	✓	✓	✗	✓	✓
2026	Yan et al. (2026)	✓	✗	✗	✓	✓

Table 11: Adopted metrics to evaluate efficiency and robustness of the generative linguistic steganographic methods.