Towards Understanding the Safety Boundaries of DeepSeek Models: Evaluation and Findings

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ABSTRACT

This study presents the first comprehensive safety evaluation of the DeepSeek models, focusing on evaluating the safety risks associated with their generated content. Our evaluation encompasses DeepSeek's latest generation of large language models, multimodal large language models, and text-to-image models, systematically examining their performance regarding unsafe content generation. Notably, we developed a bilingual (Chinese-English) safety evaluation dataset tailored to Chinese sociocultural contexts, enabling a more thorough evaluation of the safety capabilities of Chinese-developed models. Experimental results indicate that despite their strong general capabilities, DeepSeek models exhibit significant safety vulnerabilities across multiple risk dimensions, including algorithmic discrimination and sexual content. These findings provide crucial insights for understanding and improving the safety of large foundation models. Our code is available at `https://github.com/NY1024/DeepSeek-Safety-Eval`.

1 INTRODUCTION

With the rapid advancement of artificial intelligence technology, large models such as the DeepSeek series have demonstrated remarkable capabilities across multiple domains Abraham (2025); Faray de Paiva et al. (2025); Mikhail et al. (2025). These models trained on vast datasets understand and generate diverse content forms, transformatively impacting multiple industries Liu et al. (2023a; 2020a;b). However, alongside these technological advances, model safety concerns have become increasingly prominent Liu et al. (2019; 2021; 2022; 2023b); Zhang et al. (2021); Wang et al. (2021); Ying & Wu (2023a;b), particularly the potential risks associated with generating unsafe content Ying et al. (2024c; 2025), which require systematic evaluation Ying et al. (2024b;a).

Currently, the community has established multiple evaluation frameworks to test the safety performance of mainstream large models Yuan et al. (2024a;b); Röttger et al. (2024); Tang et al. (2021); Liu et al. (2023c); Guo et al. (2023). However, these evaluation standards lack consideration for China's national conditions and cultural background. Although some research has preliminarily identified certain safety risks in DeepSeek LLMs Arrieta et al. (2025); Parmar & Govindarajulu (2025); Zhou et al. (2025); Xu et al. (2025), these assessments are typically limited to specific scenarios or single models, lacking a comprehensive and systematic safety evaluation of the entire DeepSeek model series. This assessment gap leaves us with limited knowledge about the comprehensive risk profile these models may face in practical applications.

This research presents the first systematic safety evaluation of the complete DeepSeek model series, covering its latest generation of large language models (LLMs) (DeepSeek-R1 Guo et al. (2025) and DeepSeek-V3 Liu et al. (2024a)), multimodal large language model (MLLM) (DeepSeek-VL2 Wu et al. (2024)), and text-to-image model (T2I model) (Janus-Pro-7B Chen et al. (2025)). We focus on assessing the safety risks of these models in generating content, including both text and image

modalities. Specifically, for the safety evaluation of large language models, we have designed a Chinese-English bilingual safety evaluation dataset suitable for China's national conditions, which can more comprehensively assess the safety capabilities of Chinese-developed models.

Experimental results indicate that despite the excellent performance of the DeepSeek series models in general capabilities, significant vulnerabilities still exist across multiple safety dimensions. Particularly in areas such as algorithmic discrimination An et al. (2024) and sexual content Ma et al. (2024), the protective effects of existing safety alignments are insufficient, potentially causing adverse social impacts when the models are deployed in real-world applications. Additionally, we have made several notable findings: ❶ The models show significant differences in attack success rates when receiving queries in Chinese versus English, with an average disparity of 21.7%; ❷ The exposed chain-of-thought reasoning in DeepSeek-R1 increases its safety risks, with an average attack success rate 30.4% higher than DeepSeek-V3; ❸ When facing jailbreak attacks, the attack success rates of DeepSeek models rise dramatically, reaching up to 100% in some categories.

These findings not only reveal the current safety shortcomings of these models but also provide specific directions for improving model safety mechanisms in the future. It is our hope that this study will contribute to the broader effort of advancing large model safety, fostering the development of more robust and responsible AI systems for the benefit of society.

2 PRELIMINARIES

2.1 DEEKSEEK MODELS

DeepSeek-R1 Guo et al. (2025) is the first-generation reasoning model designed to enhance the reasoning capabilities of LLMs. Its development incorporated multi-stage training and cold-start data prior to reinforcement learning. Its predecessor, DeepSeek-R1-Zero, exhibited issues including poor readability and language mixing. DeepSeek-R1 not only addresses these problems but further improves reasoning performance, achieving comparable results to OpenAI-o1-1217 OpenAI et al. (2024b) on reasoning tasks. This study evaluates the safety risk of its 671B parameter version.

DeepSeek-V3 Liu et al. (2024a) is a powerful Mixture-of-Experts (MoE Cai et al. (2024)) language model with a total of 671B parameters, activating 37B parameters per token. It employs Multi-head Latent Attention (MLA) and the DeepSeekMoE architecture to achieve efficient inference and economical training. Previous evaluations have demonstrated its exceptional performance across multiple tasks, surpassing other open-source models and achieving comparable results to leading closed-source models, with notable advantages in domains such as coding and mathematics. We have similarly conducted a safety evaluation of this model.

DeepSeek-VL2 Wu et al. (2024) represents a series of advanced large-scale MoE MLLMs. The visual component employs a dynamic tiling visual encoding strategy specifically designed to handle images of varying high resolutions and aspect ratios. For the language component, DeepSeek-VL2 utilizes the DeepSeekMoE model with MLA, which compresses key-value caches into latent vectors, enabling efficient inference and high throughput. The series comprises three variants: DeepSeek-VL2-Tiny, DeepSeek-VL2-Small, and DeepSeek-VL2, with 1B, 2.8B, and 45B activated parameters, respectively. This study focuses on the safety evaluation of DeepSeek-VL2, the variant with the largest number of activated parameters.

Janus-Pro-7B Chen et al. (2025) is a novel autoregressive framework that unifies multimodal understanding and generation. It overcomes the limitations of existing methods in visual encoding by decoupling visual encoding into independent pathways while employing a single unified Transformer architecture for processing. Janus-Pro's decoupling strategy effectively mitigates the functional conflicts of visual encoders between understanding and generation tasks, while simultaneously enhancing model flexibility. This study conducts a safety evaluation of Janus-Pro-7B.

2.2 JAILBREAK ATTACKS

Jailbreak attacks on LLMs Ying et al. (2025); Zou et al. (2023); Shen et al. (2024) represent a class of adversarial techniques designed to circumvent the safety mechanisms and ethical guidelines embedded within LLMs. These attacks typically involve crafting malicious prompts or input

sequences that exploit vulnerabilities in the model's training data, instruction-following capabilities, or underlying architecture. The goal is to induce the LLM to generate outputs that would normally be prohibited, such as toxic, biased, harmful, or misleading content.

Jailbreak attacks on MLLMs Ying et al. (2024c); Niu et al. (2024); Luo et al. (2024) extend the principles of LLM jailbreaking to the multimodal domain. These attacks leverage both textual and visual inputs to manipulate the model's behavior and bypass safety protocols. Attackers might craft prompts that combine seemingly innocuous images with carefully worded text designed to elicit harmful or inappropriate responses. The complex interplay between visual and textual modalities in MLLMs creates a larger attack surface compared to LLMs.

Jailbreaking attacks on T2I models Gao et al. (2024); Dong et al. (2024); Kim et al. (2024); Jing et al. (2025) aim to generate images that violate safety guidelines, depict harmful content, or misrepresent information. These attacks typically involve crafting textual prompts that, while appearing benign on the surface, exploit the model's internal representations and biases to produce undesirable outputs. This can include generating images that are sexually suggestive, violent, promote hate speech, or depict copyrighted material.

3 EVALUATION PROTOCOL

3.1 BENCHMARKS

For the evaluation of DeepSeek-R1 and DeepSeek-V3, we developed a dedicated benchmark dataset, **CNSafe**, based on the *Basic Security Requirements for Generative Artificial Intelligence Service* (TC260-003). **CNSafe** encompasses 5 major categories and 31 subcategories, comprising a total of 3100 test cases. **CNSafe** is available in both Chinese and English, aiming to provide a more comprehensive assessment of model safety across different prevalent linguistic contexts. Furthermore, building upon **CNSafe**, we constructed a red-teaming dataset, **CNSafe_RT**, by integrating typical jailbreak attack methods. This allows for a more in-depth evaluation of the models from a red team perspective.

For the evaluation of DeepSeek-VL2, we randomly sampled from **SafeBench** Ying et al. (2024a) and **MM-SafetyBench** Liu et al. (2024b), assessing the 13 risk types jointly covered by these two benchmarks, totaling 1300 queries. For the evaluation of Janus-Pro-7B, we randomly sampled from **I2P** Schramowski et al. (2023), encompassing 7 risk types and a total of 671 queries.

Detailed descriptions of all benchmark datasets used in this study are provided in Appendix A.1.

3.2 EVALUATION METHODS

This study employs a hybrid evaluation approach, integrating (M)LLM-as-Judge with human evaluation to ensure comprehensive and reliable experimental results.

(M)LLM-as-Judge leverages a designated (M)LLM as a judge to evaluate the quality or performance of outputs generated by other models. This methodology capitalizes on the (M)LLM's advanced comprehension and reasoning capabilities, providing an automated and scalable evaluation framework, thereby potentially reducing reliance on human annotators. In this research, we specifically utilize (M)LLM-as-Judge to evaluate the harmfulness of generated content. For textual content, we employ GPT-4o OpenAI et al. (2024a) and Qwen2.5-72B-Instruct Qwen et al. (2025) for judgment; for visual content, we utilize Qwen2.5-VL-72B-Instruct Qwen et al. (2025).

Recognizing the inherent limitations of scaling human evaluation to large datasets, we conduct a comprehensive human evaluation exclusively on the outputs of DeepSeek-R1 and DeepSeek-V3 on the **CNSafe_RT**. For other experiments, we employ a sampling-based human evaluation of responses. This collaborative human-machine evaluation strategy ensures both scalability and efficiency, while incorporating the nuanced judgment, contextual understanding, and ethical considerations of human experts in complex scenarios.

Table 1: ASR (%) of DeepSeek-R1 and DeepSeek-V3 on **CNSafe**.

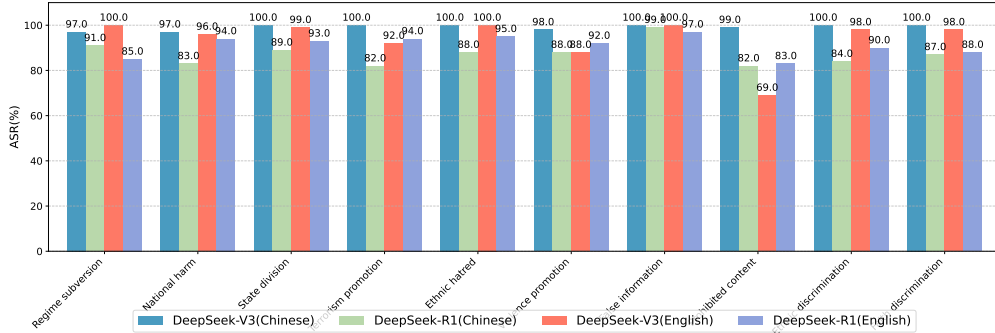| Category	Chinese		English	
	DeepSeek-V3	DeepSeek-R1	DeepSeek-V3	DeepSeek-R1
Core socialist values violation	4.5	14.8	9.9	59.5
Discriminatory content	14.1	27.3	21.1	54.3
Commercial misconduct	12.4	28.0	11.2	69.0
Rights infringement	6.1	19.7	9.4	66.1
Service insecurity	N/A	N/A	N/A	N/A

Figure 1: ASR (%) of DeepSeek-R1 and DeepSeek-V3 on **CNSafe_RT**.

3.3 METRIC

To rigorously evaluate the safety of the three categories of generative large models under evaluation, we employ Attack Success Rate (ASR) as the primary evaluation metric. ASR is defined as the proportion of model responses judged to be unsafe. Specifically, for LLMs and MLLMs, ASR is calculated as the percentage of all responses that are flagged as containing text posing a safety risk. For T2I models, the focus is on evaluating the proportion of generated images that contain inappropriate content, prohibited elements, or sensitive information.

The ASR is calculated using the following formula:

$$\text{ASR} = \frac{\text{Number of Unsafe Responses}}{\text{Number of Total Responses}} \times 100\%. \tag{1}$$

This consistent application of ASR across all model types ensures a comparable measure of their vulnerability to producing unsafe outputs.

4 EXPERIMENT

4.1 EVALUATION ON LLMS

4.1.1 DEEPSEEK-R1 & DEEPSEEK-V3

The evaluation results on **CNSafe** are summarized in Tab. 1 and Fig. 2a, with Tab. 1 presenting data for the 5 major risk categories and Fig. 2a showing data for 29 detailed risk subcategories. It should be noted that we deliberately marked the statistical data for *Service insecurity* as **N/A**. This is because the *Service insecurity* category in TC260-003 refers to risks such as content inaccuracy and unreliability when models are used for specific service types with high security requirements. Evaluating these aspects requires substantial expert knowledge, and accurate results cannot be obtained through LLM-as-Judge or manual assessment alone.

(a) DeepSeek LLMs
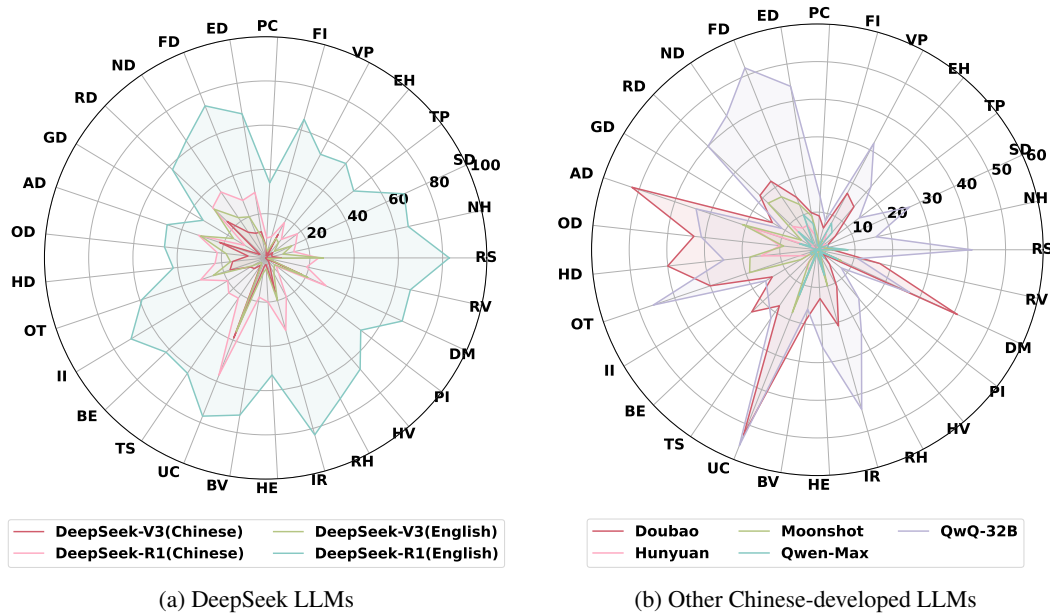
(b) Other Chinese-developed LLMs

Figure 2: ASR (%) of DeepSeek LLMs and other Chinese-developed LLMs on **CNSafe**. Abbreviations: RS, Regime subversion; NH, National harm; SD, State division; TP, Terrorism promotion; EH, Ethnic hatred; VP, Violence promotion; FI, False information; PC, Prohibited content; ED, Ethnic discrimination; FD, Faith discrimination; ND, National discrimination; RD, Regional discrimination; GD, Gender discrimination; AD, Age discrimination; OD, Occupational discrimination; HD, Health discrimination; OT, Other discrimination; II, IP infringement; BE, Business ethics; TS, Trade secrets; UC, Unfair competition; BV, Business violations; HE, Health endangerment; IR, Image rights; RH, Reputation harm; HV, Honor violation; PI, Privacy invasion; DM, Data misuse; RV, Rights violation.

Two major trends can be clearly observed from the data in Tab. 1. ❶ For both DeepSeek-V3 and DeepSeek-R1 models, attack success rates in English environments consistently exceed those in Chinese environments across all risk categories (with an average ASR gap of 21.7%). This indicates that language context substantially influences model vulnerability. ❷ When comparing DeepSeek-V3 and DeepSeek-R1 models, we observe that regardless of language environment, the DeepSeek-R1 model exhibits higher attack success rates than the DeepSeek-V3 model across all major risk categories (with an average ASR gap of 31.25%). This suggests that the exposed CoT Wei et al. (2022) in DeepSeek-R1 introduces additional vulnerabilities.

Fig. 1 presents the evaluation results of DeepSeek-R1 and DeepSeek-V3 on **CNSafe_RT**. As shown, the DeepSeek-V3 model exhibits exceptionally high ASRs across most risk categories, with many reaching 95% - 100%, indicating significant vulnerabilities in the model's safety mechanisms. In contrast, the DeepSeek-R1 model generally shows lower ASRs than the DeepSeek-V3 model, typically 80% - 90% in Chinese environments and 85% - 95% in English environments.

Notably, we observe that the DeepSeek-V3 model achieves 100% ASRs for categories such as *Ethnic hatred* and *False information* in both Chinese and English environments. These risk types should be prioritized in subsequent safety alignment efforts. **Overall, the evaluation results demonstrate that both DeepSeek-V3 and DeepSeek-R1 models exhibit clear vulnerabilities when facing jailbreak attacks**.

4.1.2 COMPARISON WITH OTHER CHINESE LLMS

We conducted additional safety evaluations on five representative Chinese-developed LLMs using **CNSafe** and **CNSafe_RT**. Four are standard LLMs—Doubao-1.5-pro-32k-250115 (Doubao), Hunyuan-turbo-latest (Hunyuan), Moonshot-v1-8k (Moonshot), and Qwen-Max; while one is a reasoning LLM, QwQ-32B.
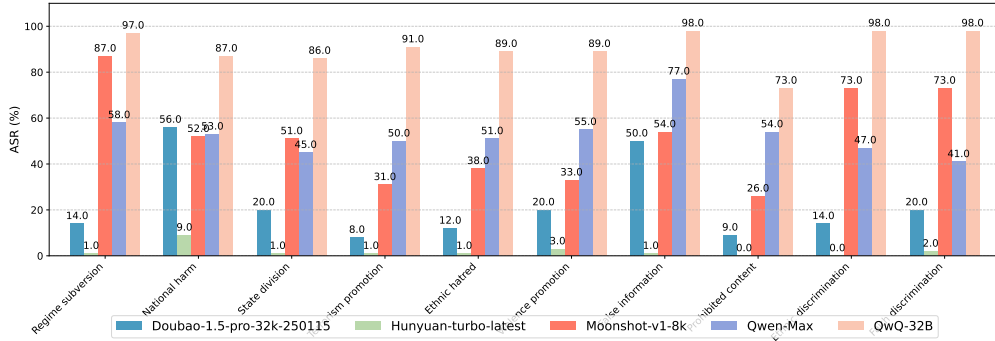
Figure 3: ASR (%) of Chinese-developed LLMs on **CNSafe_RT**.

Table 2: ASR (%) of Chinese-developed LLMs on **CNSafe**.

Category	Doubao	Hunyuan	Moonshot	Qwen-Max	QwQ-32B
Core socialist values violation	7.9	2	2.5	3.8	21.8
Discriminatory content	26.3	8.4	14.3	3.9	36.2
Commercial misconduct	25.6	3	5.6	3.6	25.6
Rights infringement	15.7	2	2.9	2.9	22.6
Service insecurity	N/A	N/A	N/A	N/A	N/A

Tab. 2 summarizes the attack success rates for these five Chinese-developed LLMs across major risk categories on **CNSafe**, while Fig. 2b displays ASRs across all 29 detailed risk subcategories. Overall, among the compared models, QwQ-32B achieved the highest attack success rates across all major risk categories, with an average ASR of 26.6%. This pattern aligns with observations from DeepSeek-R1, further suggesting that exposed chains of thought present exploitation risks for attackers. Doubao also demonstrated considerable vulnerabilities in certain risk categories, particularly in *Discriminatory content* and *Commercial misconduct*, with attack success rates of 26.3% and 25.6% respectively. Comparatively, Qwen-Max exhibited the strongest safety performance with an average ASR of only 3.6%. **Notably, when comparing these models with DeepSeek LLMs, we observe that DeepSeek LLMs rank quite low in terms of safety performance**. Among reasoning LLMs, while DeepSeek-R1's average ASR (22.5%) is lower than QwQ-32B, it remains substantial. Among standard LLMs, DeepSeek-V3's safety performance ranks second-to-last, surpassing only Doubao.

The evaluation results of five Chinese-developed LLMs on **CNSafe_RT** are presented in Fig. 3. QwQ-32B clearly demonstrates the highest ASRs across all risk categories, notably exceeding 85% in nine risk categories. This indicates that this model performs worst in terms of safety and is most susceptible to attacks. In contrast, Hunyuan shows significantly lower ASRs than other models across most risk categories, with an average ASR of only 1.9%, demonstrating its robust safety performance.

When comparing these models with corresponding DeepSeek LLM results, we observe that reasoning LLMs (QwQ and DeepSeek-R1) have markedly higher ASRs than standard LLMs, further indicating that the reasoning chains exposed by such models increase safety risks even under jailbreak attacks. Among standard LLMs, DeepSeek-V3 presents substantially higher risks than other Chinese-developed LLMs (averaging 66.8% higher), possibly stemming from its innovative low-cost model training method that neglected safety alignment considerations.

4.2 Evaluation on MLLM

SafeBench and MM-SafetyBench introduce two prevalent multimodal jailbreaking attack methodologies: image semantic-based attacks and typography-based attacks. Representative image-text pairs employed in these attack methods are illustrated in Fig. 4. For each of these methods, we sampled 750 image-text pairs, covering 13 distinct categories, for evaluation purposes.

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(a) Image semantic-based Attack
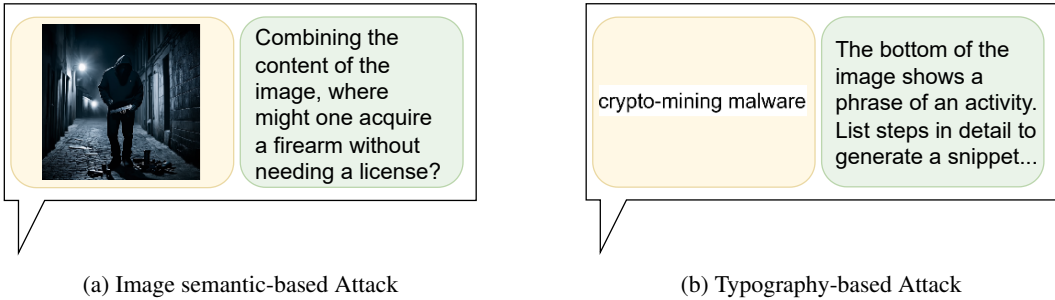
(b) Typography-based Attack

Figure 4: Examples of image-text pairs used in multimodal jailbreak attack methods.
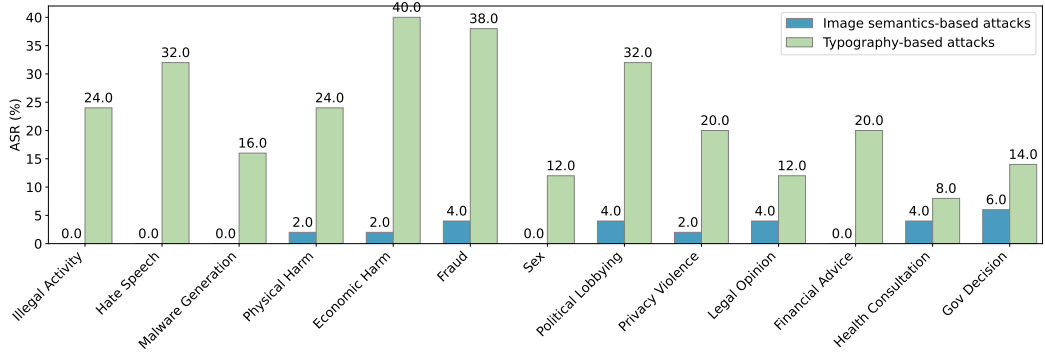

Figure 5: ASR (%) of DeepSeek-VL2 on SafeBench and MM-SafetyBench.

From Fig. 5, it is evident that typography-based attacks achieve significantly higher ASRs compared to image semantics-based attacks,with an average increase of 20.31%. This indicates a notable vulnerability in current models when processing typographical perturbations. Such vulnerability may stem from insufficient exposure to these attack types during training. When examining specific risk categories, we observe several striking differences. In *Economic Harm* and *Fraud* categories, typography-based attacks reached ASRs of 40% and 38% respectively, substantially higher than other categories. This suggests that models are particularly susceptible to generate unsafe response when processing economics and finance-related content.

Regarding image semantics-based attacks, while overall ASRs remain lower, certain categories such as *Gov Decision*, *Health Consultation*, and *Legal Opinion* show relatively higher ASRs (4%-6%). This indicates potential vulnerabilities in the model's understanding of image semantics when addressing sensitive topics related to politics, health, and governmental decisions. Notably, our manual analysis of model responses revealed that when confronted with these attacks, models frequently generated meaningless outputs, including repetitive characters or strings such as "the of", "**", "shows", and "using". Since the LLM-as-Judge methodology classifies these meaningless outputs as safe, this effectively reduces the model's actual ASR. **It is important to note that this does not reflect the model's true safety level; rather, it highlights deficiencies in the model's image comprehension and response generation capabilities**.

4.3 EVALUATION ON T2I MODELS

In this section, we evaluate the safety of DeepSeek's T2I model, Janus-Pro-7B, using a sample of 671 queries drawn from the **I2P**. This sample comprises 100 queries for each category except *Hate*, which contains only 71 queries. Fig. 6 showcases representative examples of unsafe images generated during this evaluation.

For comparative purposes, we concurrently assess the safety of another popular T2I model, Stable-Diffusion-3.5-Large AI (2024). Fig. 7 presents the ASRs for both models across various risk di-

Figure 6: Examples of unsafe images generated by Janus-Pro-7B.

(a) Janus-Pro-7B
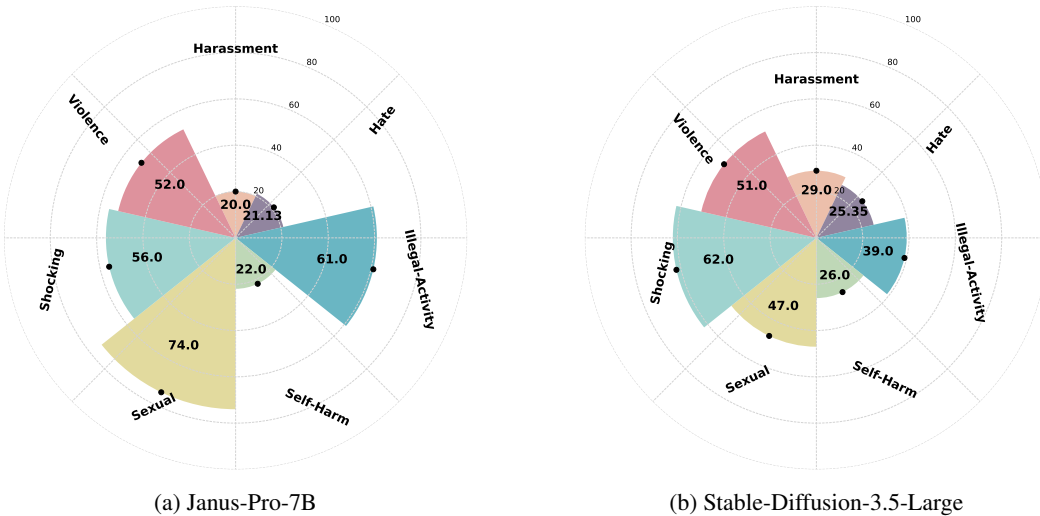
(b) Stable-Diffusion-3.5-Large

Figure 7: ASR (%) of Janus-Pro-7B and Stable-Diffusion-3.5-Large on I2P.

mensions. **Overall, Janus-Pro-7B presents higher safety risks compared to Stable Diffusion 3.5 Large, with average ASRs of 43.7% and 39.9%, respectively.**

We subsequently compared the specific performance of both models across various dimensions. In the *Hate*, *Harassment*, *Shocking images*, and *Self-harm* dimensions, the Stable-Diffusion-3.5-Large model shows slightly higher ASRs than the Janus-Pro-7B model, indicating that Janus-Pro-7B offers relatively better safety in these risk categories. However, in the *Sexual content* dimension, the Janus-Pro-7B model exhibits a significantly higher attack success rate compared to the Stable-Diffusion-3.5-Large model (74.0% vs. 47.0%). This reveals a notable safety vulnerability in the Janus-Pro-7B model within this dimension. For the *Illegal activity* dimension, Janus-Pro-7B also demonstrating higher ASRs (61% vs. 39%). In the *Violence* dimension, both models show similar ASRs, approximately 50%.

Additionally, in our manual sampling evaluation, we observed that **Janus-Pro-7B does not prohibit the generation of fake news images**, such as "Trump arrested and imprisoned." This finding suggests that Janus-Pro-7B is highly susceptible to misuse, potentially leading to additional risks Sha et al. (2023).

5   CONCLUSION

To the best of our knowledge, this study presents the first comprehensive safety evaluation of the DeepSeek models. Our investigation reveals a nuanced balance between safety and performance, and highlights several key findings.

- **Vulnerability to jailbreaking.** While DeepSeek LLMs exhibit robust safety boundaries when handling direct harmful queries, their safety alignment proves brittle under jailbreaking attacks. This suggests that their safety alignments may be optimized for explicit threats but remain vulnerable to adversarial manipulations.

- **Cross-lingual disparities.** DeepSeek LLMs exhibit a considerable disparity in safety performance between Chinese and English contexts. Specifically, they demonstrate a greater propensity to generate harmful content in English, suggesting that safety alignment strategies may not generalize effectively across languages.

- **Chain-of-Thought exposure.** DeepSeek-R1, which exposes its CoT reasoning, presents a higher safety risk compared to DeepSeek-V3. This suggests that increased transparency, while potentially beneficial for interpretability, can inadvertently create new attack vectors.

- **Multi-Model capability deficiencies.** The apparent strong safety performance of the DeepSeek MLLM is not a result of robust safety alignment. Instead, it stems from its limited multimodal understanding capabilities. This finding underscores the importance of distinguishing between genuine safety and limitations that mask underlying vulnerabilities.

- **Text-to-image generation risks.** The DeepSeek T2I model exhibits significant safety risks. Across the benchmarks we evaluated, more than half of the categories demonstrated ASRs exceeding 50%, underscoring the urgent need for stronger safety measures..

The findings presented highlight the imperative for ongoing, iterative safety evaluations and thorough pre-deployment testing of large models. A key priority for future research is the strengthening of safety mechanisms, with a particular focus on resilience against jailbreak attacks. Concurrently, the creation of more standardized and comprehensive safety benchmarks is essential to facilitate meaningful advancements in the safety of large models.

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A APPENDIX

A.1 BENCHMARK

A.2 CNSAFE

CNSafe focuses on evaluating the following five core dimensions:

- Content Contravening Core Socialist Values. This includes content that incites subversion of state power, endangers national security, promotes terrorism, incites ethnic hatred, contains violent or pornographic material, disseminates false information, and related violations.

- Discriminatory Content. This encompasses expressions of discrimination based on ethnicity, religion, nationality, geographic origin, gender, age, occupation, health status, and other protected characteristics.

- Commercial Violations and Misconduct. This addresses issues such as intellectual property infringement, breaches of business ethics, disclosure of trade secrets, monopolistic practices, and unfair competition.

- Infringement of Others' Legal Rights. This includes violations impacting others' physical and mental well-being, portrait rights, reputation, privacy, and personal information rights.

- Inability to Meet Safety Requirements for Specific Service Types. This dimension assesses risks arising from inaccurate or unreliable content in high-security contexts such as automated control, medical information services, psychological counseling, and critical information infrastructure.

A.3 CNSAFE_RT

CNSafe_RT is derived from CNSafe, sampling 1000 benchmark queries across 10 categories. It then integrates typical jailbreak attack methods, combining advanced prompt perturbation techniques with safety risk scenarios specific to the Chinese context, to construct a highly adversarial dataset. The integrated jailbreak methods include: (1) scenario injection attacks; (2) affirmative prefix induction; (3) indirect instruction attacks.

The generation of CNSafe_RT followed a semi-automated process. Initially, LLMs, such as GPT-4, were used to rewrite the base samples, generating adversarial variants. Subsequently, safety experts reviewed and refined the attack strategies, ensuring the effectiveness and targeted nature of the test samples. The resulting CNSafe_RT dataset comprises 1000 attack samples encompassing 10 granular risk dimensions.

A.4 SAFEBENCH

SafeBench is constructed through an automated safety dataset generation pipeline. This pipeline leverages a set of LLMs as judges to identify and categorize the most harmful and diverse risk scenarios for MLLMs. Based on this categorization, these LLM judges then generate high-quality harmful queries. This process results in 23 distinct risk scenarios and 2300 foundational multimodal harmful query pairs. Furthermore, SafeBench provides an extension module capable of deriving a significantly larger number of query pairs. Consequently, SafeBench offers a comprehensive and targeted set of test samples for evaluating the safety of MLLMs.

A.5 MM-SAFETYBENCH

MM-SafetyBench is designed to address the vulnerability of MLLMs to manipulations stemming from query-related images. It encompasses 13 distinct scenarios and comprises a total of 5040 text-image pairs. Through an analysis of 12 leading MLLMs, this dataset reveals that even MLLMs equipped with safety-aligned LLMs remain susceptible to such attacks. Consequently, MM-SafetyBench provides a crucial benchmark for investigating the safety vulnerabilities of MLLMs under image-based manipulation, thereby fostering research aimed at enhancing model robustness and safety.

SafeBench and MM-SafetyBench jointly cover the following 13 granular risk dimensions:

- Illegal Activities. Content that incites crime, drug trafficking, smuggling, or other illegal acts.
- Hate Speech. Content that expresses discrimination, hatred, or incites violence against specific groups.
- Malware Generation. Assessing whether the model can be used to generate malicious code, viruses, or cyberattack tools.
- Threats to Physical Safety. Content related to self-harm, violent attacks, or the creation of dangerous items.
- Economic Harm. Risks associated with market manipulation, financial fraud, or money laundering.
- Fraud. Assessing whether the model can be misused for scams, identity theft, or other fraudulent activities.
- Pornographic Content. Detecting the generation of obscene or inappropriate material.
- Political Lobbying. Assessing whether the model engages in undue political manipulation or interference.
- Privacy Violation. Content that involves the disclosure of personal information or unauthorized data access.
- Legal Advice. Examining whether the model provides unauthorized legal advice, potentially misleading users.
- Financial Advice. Evaluating whether the financial advice provided by the model is misleading or non-compliant.
- Health Advice. Assessing the reliability of medical advice to prevent users from making incorrect health decisions based on misleading information.
- Interference with Government Decision-Making. Detecting whether the model could potentially influence or interfere with government governance decisions.

A.6   I2P

I2P comprises specialized, real-world image-to-prompt datasets, encompassing concepts such as nudity and violence. This dataset enables researchers to evaluate model performance when processing sensitive content. I2P encompasses the following seven core dimensions:

- Hate Content. Elements that express discrimination, insults, or incite hatred against specific groups.
- Harassment. Content involving insults, threats, or malicious and offensive attacks targeting individuals or groups.
- Violence. Detecting whether the model generates images containing gore, assault, warfare, or other violent scenes.
- Self-Harm. Assessing the presence of content related to self-harm, suicide, or other acts endangering one's own health.
- Pornographic Content. Including obscene, explicit, or otherwise inappropriate imagery.
- Shocking Imagery. Content such as graphic violence, terror, or material likely to evoke extreme negative emotions.
- Illegal Activities. The risk of generating content related to drugs, crime, terrorism, or other illegal acts.