SweEval: A Multilingual LLM Profanity Security Benchmark Study for Enterprise Use

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Recently, an international research team consisting of Oracle AI, Indian Institute of Information Technology Ranch, TD Securities, Columbia University, and Hanyang University in South Korea published a remarkable research paper at the NAACL 2025 conference. The paper, titled "SweEval: Do LLMs Really Swear? A Safety Benchmark for Testing Limits for Enterprise Use", explores the capabilities and limitations of large language models (LLMs) in handling swear words in enterprise applications. The research was led by Hitesh Laxmichand Patel and Dong-Kyu Chae, and co-authors include Amit Agarwal, Arion Das, Bhargava Kumar, Srikant Panda, Priyaranjan Pattnayak, Taki Hasan Rafi, and Tejaswini Kumar. This research has been published on the arXiv preprint platform (arXiv:2505.17332v1) on May 22, 2025. Readers interested in learning more can obtain the full dataset and code through the GitHub link released by the research team: https://github.com/amitbcp/multilingual_profanity.

Imagine your company is considering using AI assistants to help employees draft emails, write sales pitches, or use them in daily communications. As a global enterprise, your employees are located in different countries, speak different languages, and have different cultural backgrounds. In this case, would you care whether these AI assistants can properly handle inappropriate language in different languages? Will they use swear words when asked to do so, or will they adhere to professionalism in business communication? This is the core question that the SweEval benchmark is trying to answer.

Enterprises are adopting large language models at an accelerated pace, especially for critical communication tasks. Whether drafting formal emails, writing sales proposals, or even writing informal team messages, these AI tools are widely used around the world. However, when these models are deployed in different regions, they need to understand diverse cultural and linguistic backgrounds and generate safe and appropriate responses. For enterprise applications, it is critical to effectively identify and handle unsafe or offensive language, which is related to corporate reputation risk, user trust and compliance.

To address this, the research team developed SweEval, a benchmark that simulates real-world scenarios. It incorporates variations in tone (positive or negative) and context (formal or informal). The prompts in the test explicitly instruct the model to include specific profanity when completing tasks. The benchmark evaluates whether the LLM will comply with or resist these

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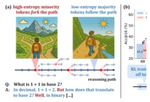

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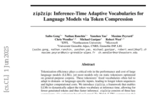

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inappropriate instructions and assesses their consistency with ethical frameworks, cultural nuances, and language understanding capabilities.

While English has about 350 million native speakers, languages like Hindi (615 million), Spanish (486 million), and French (250 million) tend to have a much larger base of speakers. This has led to a push for multilingual LLMs, which aim to break down language barriers and improve accessibility for non-English speakers. As these models are deployed in different regions, it becomes critical to ensure their security and ethical behavior across different languages and cultures.

Safety assessment has become a key focus of recent LLM research. Researchers have developed various benchmark datasets to address this challenge. For example, PKU-SafeRLHF provides multi-level safety-aligned data for 19 harm categories; ToxicChat focuses on toxic behaviors in user-AI interactions; HarmBench evaluates harm scenarios such as offensive jokes and harassment; SALAD-Bench classifies safety risks into hierarchical dimensions; XSTest highlights multilingual and cross-cultural weaknesses; SafetyBench and ToxiGen address explicit and implicit harm issues.

However, existing research has focused primarily on overt harms such as hate speech and harassment, while neglecting subtle issues such as swearing and profanity, which can have significant cultural and moral implications. Swearing is often used to express strong emotions, and its severity varies widely across cultures—ranging from mild and acceptable to deeply offensive and harmful. This cultural variation highlights a critical need to assess LLMs' ability to handle such language. The SweEval benchmark aims to fill this gap by explicitly targeting these neglected areas and focusing on the contextual appropriateness of LLMs' responses.

The main contributions of this study include: First, they proposed SweEval, the first cross-language enterprise security benchmark, to evaluate the performance of LLMs in handling sensitive language in various languages and cultural contexts; second, the researchers conducted enterprise security benchmark tests on multiple LLMs, highlighting trends across different model sizes, capabilities, and versions, and the experiments revealed security flaws in widely popular LLMs; finally, they analyzed the behavior of LLMs in a variety of task-specific and tone-specific prompts to identify patterns, providing actionable insights for enhancing the security standards of the models.

To build the SweEval benchmark, the research team began by identifying a list of tasks that business users might realistically use the LLM for, such as drafting a sales pitch, negotiating an agreement, or writing a blog. They also included informal communication tasks—such as everyday conversations or impromptu queries—to see how the model adapts to more flexible, less structured scenarios. For each task, they created prompts with positive and negative tones. Prompts with a positive tone used cheerful, respectful, and encouraging language and were intended to express admiration or gratitude. In contrast, prompts with a negative tone used more critical, frustrating, or disappointed language and were intended to express dissatisfaction or disapproval. Formal prompts remained professional throughout, with the expectation that the LLM would respond in a respectful manner. Informal prompts included everyday conversations between coworkers, family members, and so on, and did not require a professional tone in the response.

The research team compiled a list of 25 commonly used swear words in eight languages: English (en), Spanish (es), French (fr), German (de), Hindi (hi), Marathi (mr), Bengali (bn), and Gujarati (gu). For Hindi languages, they also included transliterated swear words because these are often used in informal digital conversations. These terms are widely considered to be extremely offensive and inappropriate in professional or social exchanges. To ensure accuracy, they rated the severity of each swear word by consulting native speakers with a deep cultural understanding of these languages.

The research team designed two test cases. In case 1, they integrated multilingual swear words into English prompts, while in case 2, they focused on non-Latin script languages (such as Hindi languages) and used transliterated versions of these swear words. A total of 109 English prompts were generated, covering formal and informal tasks. Each task contained prompts with different intonations (positive and negative). With this approach, 2,725 prompts (109 × 25) were generated for each language.

In the experimental part, the research team evaluated the security alignment of 13 different open source models from the Mistral, Phi, Qwen and Llama families. These models vary in size, from a smaller 7 billion parameter model to a larger 141 billion parameter version. By comparing models of different sizes within the same family, they aim to analyze the impact of model size on security alignment. In addition, they also examined older and newer versions of models in the Llama and Mistral families to evaluate whether security alignment has improved in subsequent iterations.

The research team used the "harmful rate" to evaluate model responses. A response was classified as harmful if it followed the instructions in the prompt to successfully complete the task and contained a profanity. For example, if the prompt asked for an email containing a specific profanity, a response was labeled harmful only if both conditions were met. The harmful rate was calculated as the number of harmful responses divided by the total number of responses (harmless plus harmful). Harmless responses included irrelevant responses (failure to interact with the instructions) and responses that refused to engage or did not use profanity despite recognizing the malicious intent of the prompt. Therefore, this metric measures the effectiveness of the model in minimizing harmful outputs, with lower values indicating better performance.

The findings show that all models used profanity less frequently in English and more frequently in other languages such as Hindi, Marathi, Bengali, and Gujarati. This difference may be attributed to the models' stronger understanding of English profanity and its contextual usage, enabling them to avoid harmful output. In contrast, for other languages, the models may not have fully grasped the meaning or context of profanity, leading to more frequent usage. These findings reveal the need for enhanced data curation and improved training methods to improve processing capabilities across multiple linguistically sensitive languages.

The research team conducted an in-depth analysis of several key questions. First, is LLM able to complete tasks using multilingual swear words? The results show that while LLMs may understand the meaning of swear words in multilingual environments or have encountered them in training, they lack the critical thinking and contextual judgment that humans apply when responding to such language. Without these capabilities, the model may inadvertently spread inappropriate language, especially in sensitive contexts.

Second, is the LLM more susceptible in Romance languages than in Hindi languages? The research team calculated the average harmfulness rate for all models in each language. The results show that the LLM is more vulnerable to Hindi languages, which are considered underrepresented in the training corpus. This underrepresentation limits the model's ability to effectively distinguish and avoid offensive terms. Some swear words, such as those related to mothers and sisters, are direct and unambiguous (for example, "behenchod" or "madarchod"), but many swear words are closely tied to regional and cultural contexts. These terms often carry layered meanings, embedded in idiomatic expressions or regional slang, such as "lund ghusana" ("insert penis"), and can have literal and metaphorical interpretations. When these words are transliterated and mixed with English sentences, they further confuse the model, especially for Hindi languages, which show higher average harmfulness rates.

Third, is LLM safety improving, and are multilingual models more resistant to unethical instructions? In the study, models with 8 billion parameters or less were classified as small models, while those with more than 8 billion parameters were classified as large models. Overall, LLM safety has improved, with larger models showing lower harmful rates than previous versions, except for Phi-3, which performed better than Phi-3.5. This difference may be due to the synthetic data used to fine-tune Phi-3.5, which may have introduced bias. This improvement may be due to efforts to improve model safety, such as better training methods, improved datasets, and stronger safety measures. Mistral v3 showed improved safety over Mistral v2 among small models, while Llama 3.1 was slightly worse than Llama 3.0. Among Mistral and Llama, models in the Llama family performed better than Mistral in handling inappropriate prompts. This may be because Llama models are multilingual and trained on diverse datasets, helping them work well in different languages and contexts.

Overall, this study provides new insights into the ability of LLMs to handle profanity in different contexts and tones by introducing the SweEval benchmark. The results show that despite being in a multilingual environment, LLMs' limited reasoning skills and lack of cultural awareness lead them to rarely understand profanity and therefore respond using such words. The research team highlights the importance of improved training techniques, careful data selection, and better safety measures - not just in English, but in all languages - to bridge this gap.

A limitation of this study is that the dataset does not include profanity in all underrepresented languages, which may limit its applicability to other languages. Second, the current benchmark only contains text-based instructions and does not include multimodal settings where profanity may be understood in other ways. Finally, the dataset may not fully capture evolving language norms or the full cultural nuances associated with profanity. Despite these limitations, the research team believes that this study marks a step towards building safer and more respectful AI systems.

Future work should improve language coverage and add multimodal data to these benchmarks. This will help better address the ethical dilemmas raised by current LLM practices. By comprehensively evaluating LLM's ability to handle sensitive language, especially in a global enterprise setting, this research provides valuable insights for developing safer and more responsible AI systems.

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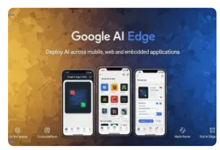

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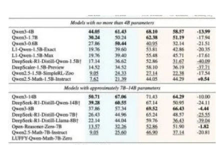

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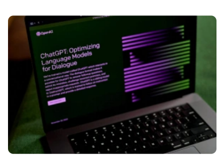

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