
Towards Safe Multilingual Frontier AI

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Abstract

Linguistically inclusive LLMs—which maintain good performance regardless of the language with which they are prompted—are necessary for the diffusion of AI benefits around the world. Multilingual jailbreaks that rely on language translation to evade safety measures undermine the safe and inclusive deployment of AI systems. We provide policy recommendations to enhance the multilingual capabilities of AI while mitigating the risks of multilingual jailbreaks. We quantitatively assess the relationship between language resourcedness and model vulnerabilities to multilingual jailbreaks for five frontier large language models across 24 official EU languages. Building on prior research, we propose policy actions that align with the EU legal landscape and institutional framework to address multilingual jailbreaks, while promoting linguistic inclusivity. These include mandatory assessments of multilingual capabilities and vulnerabilities, public opinion research, and state support for multilingual AI development. The measures aim to improve AI safety and functionality through EU policy initiatives, guiding the implementation of the EU AI Act and informing regulatory efforts of the European AI Office.

1 Introduction

Despite rapid advances in large language model (LLM) capabilities [36, 52, 60], frontier LLMs continue to be vulnerable to *jailbreaks*,¹ which undermine safety measures and enable malicious actors to misuse AI systems to cause harm [34, 82, 66]. Defensive measures against jailbreaks can reduce the risks, but can also impede model utility through rejection of benign prompts [14].

One subclass of jailbreaks are *multilingual jailbreak attacks*, where a model is prompted in a different—often low-resource²—language to circumvent safety systems that would otherwise activate in response to a default—usually high-resource—language. Here, it is precisely that LLMs have strong, though inconsistent, multilingual capabilities, understanding and responding to instructions in many languages, that facilitates the attacks.

However, multilingual capabilities of LLMs are essential to diffuse the benefits of AI throughout our societies [61, 16]: although LLMs are predominantly trained on English text [38, 80], most humans on the planet do not speak English [69]. Unfortunately, several of measures designed to defend against multilingual jailbreaks—such as instructing the model to "think in English" or self-generating

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¹*Jailbreaking* can be defined as the process of circumventing the safety measures placed on LLMs and other AI systems [51]. Vulnerability to jailbreaks paired with powerful model capabilities, including offensive cyber capabilities, chemical, biological, radiological, and nuclear capabilities, contribute to systemic risks [78, 31].

²*Low-resource languages*, which account for over 90% of the world's 7,000+ languages and are spoken by 1.2 billion people, have limited labeled and unlabeled data available [81, 43]. In this paper we follow Bang et al. (2023) [11] and classify languages based on CommonCrawl corpus share: high-resource languages have over 1%, medium-resource languages 0.1-1%, and low-resource languages less than 0.1%. This method is responsive to the availability of digital language data, with the source data updated monthly.

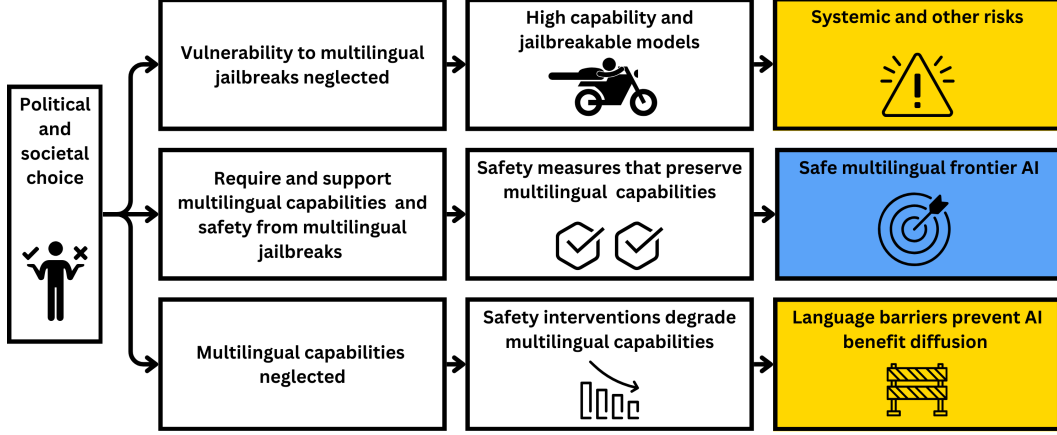


Figure 1: **Threat model and policy opportunity.** Neglecting multilingual jailbreaks or multilingual capabilities can increase risks or limit AI benefit diffusion. Conversely, appropriately addressing the risks as well as capabilities can bring the benefits of safe multilingual frontier AI.

synthetic data in low-resource languages—limit the model’s utility in non-English natural languages [76, 23], undermining inclusive AI benefit-sharing.

This paper proposes a path towards linguistically inclusive AI that is also safe from multilingual jailbreak attacks (Figure 1). The rest of the paper proceeds as follows. First, we discuss related work, paying particularly attention to the extent defensive actors can reduce LLM vulnerabilities to multilingual jailbreaks without compromising multilingual capabilities. Second, we show that the EU offers a particularly promising environment for effective policy action to address this issue. Third, we assess the vulnerability to multilingual jailbreaks and multilingual capability gaps in the 24 official EU languages for five frontier LLMs. Finally, we offer specific policy recommendations for the European AI Office and other relevant stakeholders.

2 Related work

2.1 What to measure?

Surveys offer valuable insights into public opinion on AI [40], yet they often fall short in identifying which AI capabilities are most beneficial to society, and in determining appropriate safety thresholds that balance individual and collective interests. This limitation stems from the complexity of AI and its broad societal implications. To address this, researchers have introduced innovative approaches, such as citizens’ juries, to gather more informed public perspectives [42]. These methods can help to achieve a balance between innovation and safety, ensuring that public interest plays a central role alongside private incentives [65].

One example for societal choice is between technological automation and job security [71]. For instance, LLMs could yield significant savings by automating certain tasks, and addressing skill gaps [39, 36]. However, increased automation also raises concerns about labor displacement. According to the Ipsos 2024 survey, over a third of workers worldwide fear that AI could replace their jobs in the coming years [40]. Workers in low-income countries and emerging markets may face significant challenges as AI-driven automation leads to the onshoring of jobs in advanced economies [50]. Beyond the immediate loss of income, job displacement can result in political disempowerment and the loss of personal meaning associated with work [5, 71]. Therefore, decisions about the training, deployment, and use of LLMs should involve not only tech developers but also civil society and policymakers [8]. Measuring and predicting the downstream impacts of LLMs is a complex and open research problem [62, 10], progress in which is necessary to allow for informed choice between different paths of development.

2.2 Risk and capability measurement

To assess vulnerabilities to multilingual jailbreaks, several benchmarks have been used in the literature, including AdvBench [80, 81], MasterKey [80], and MT-Bench [67]. Although precise assessment is currently hampered by data contamination and translation imperfections, these challenges do not seem insurmountable. Human annotators can help resolve translation issues in both capability [55] and safety assessments [4]. Recent studies also address contamination by measuring capabilities when context, but not the specific question, is provided in the prompt [12].

2.3 Risk mitigation and capability improvements

Some risk mitigation measures for addressing multilingual jailbreak vulnerabilities can come at the cost of model capabilities. For example, instructing the model to “think in English” [76] may enhance safety but reduce effectiveness in language-specific contexts [72]. Similarly, a “self-defense” approach, which generates multilingual training data for safety fine-tuning, has been found to increase rejection rates for benign prompts [23]. Additionally, safety fine-tuning can result in shorter responses [48]. At the extreme, complete usage restriction maximizes safety but eliminates utility: “a model that always refuses is maximally safe, but not helpful in the slightest” [25]. While there are no documented cases of capabilities being entirely cut off in specific languages, certain modalities, such as image generation [77] and singing [55], have been curtailed.

Despite these challenges, progress is possible. Evidence shows that language gaps can be significantly reduced, even in low-resource languages [16]. For instance, GPT-4o recently demonstrated notable capability improvements in several low-resource African languages [55]. Measures that preserve both safety and capabilities include generating human-annotated datasets, though this can be costly, as low-resource languages often require more tokens per word [6, 13]. One study demonstrated that using just 900 prompts—half requiring local knowledge—reduced the jailbreak attack rate by more than half [4]. The cost of generating such prompts for the 24 official EU languages likely represents only a small fraction of the cost of developing frontier models, which currently exceeds \$100 million and is projected to reach \$1 billion by 2027 [21].

2.4 Who will do the evaluations?

Anderljung et al. advocate for the involvement of external actors in evaluating LLMs to ensure objectivity and thoroughness [8]. Casper et al. further argue that rigorous AI audits require more than just black-box access. They propose that white-box access, which provides deeper insight into the system’s internals, enables stronger adversarial testing and fine-tuning. This approach allows for a more comprehensive assessment of post-deployment risks, ultimately enhancing the reliability and safety of AI systems [15].

2.5 Comprehensive empirical assessments and policy recommendations

Dubey et al. examined the Violation Rate (VR) and False Refusal Rate (FRR) for the Llama 3 405B model and its competitors in eight high-resource languages, finding that “Llama Guard” reduced VR with minimal or insignificant FRR increases [25]. Similarly, Cohere For AI introduced a dataset and method to address multilingual jailbreaks across eight languages, reporting results for six high-resource languages using the Aya 23 8B model [4]. In contrast, we report results for the whole suite of the 24 EU languages—including low-resource ones—on five frontier LLMs (see Section 4.4).

Cohere For AI provides broad policy recommendations for addressing multilingual safety vulnerabilities and improving transparency in multilingual model performance [16]. We have tried to go further, by specifically identify responsible stakeholders and tailoring our recommendations accordingly. We also advocate for model providers to report evaluation results rather than conducting the evaluations themselves (see Section 5).

In the EU context, Rehm et al. [61] compiled a wide set of policy recommendations to achieve digital language equality by 2030. Many of their recommendations call for more funding for research and innovation, increased multilingual data availability, and breakthroughs needed for model evaluation. They also called for training large language models from scratch: such efforts have

by now received significant compute resources,³ but have also been criticized as likely to produce inadequate models [44]. Our comparative contribution is to focus on highly capable AI models in general, multilingual jailbreaks in particular, and offer recommendations to enable mandatory capability and safety assessments.

3 Methodology for the quantitative analysis

To assess the relationship between jailbreak attack success rates, harmless prompt rejection rates, and the level of language resourcedness, we formulate the following hypotheses:

- **H1**: Multilingual jailbreak attack success rates and language resourcedness are negatively related.
- **H2**: Harmless prompt rejection rates and language resourcedness are negatively related.

To test these hypotheses, we employ the OR-Bench dataset introduced by Cui et al. (2024) [22]. This dataset is particularly well-suited for our purposes as it was specifically designed to address the issue of ‘Over-Refusal’ by LLMs. For **H1**, we present harmful prompts from the OR-Bench dataset to the LLMs, and for **H2**, we present harmless but “seemingly harmful” prompts that could be mistaken as harmful. The translation of these prompts into non-English languages is performed using Google Translate, a widely accessible service.⁴

After collecting the LLM outputs, we classify the responses using GPT-4o mini (gpt-4o-mini-2024-07-18), based on its suitability for response classification.⁵ We classify responses into three categories: *ACCEPTED*, *REJECTED*, and *UNCLEAR*, using annotation guidelines adapted from Yong et al. [81]. The classification rules and detailed annotation guidelines are provided in Appendix B.

Next, we estimate the coefficients using a logistic regression model, which follows the relationship:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}} \quad (1)$$

In the above equation Y is binary: for **H1**, $Y = 1$ if and only if response is *ACCEPTED*; for **H2**, $Y = 1$ if and only if response is *REJECTED*. X denotes CommonCrawl corpus share [20], a proxy for language resourcedness [47].

To validate the econometric model, we also estimate the relationship using Ordinary Least Squares (OLS) regression. To use OLS, we calculate the proportion of *ACCEPTED* responses to harmful prompts, and the proportion of *REJECTED* responses to harmless prompts.

4 Case Study: The EU and its 24 official languages

Language diversity, commitment to digital language equality [61] and recent regulatory developments in the EU present a pressing need for policies that promote safe multilingual frontier AI.

4.1 Legal aspects

Linguistic inclusivity is a legal requirement for state institutions in the EU, and is enshrined in several key legal instruments. In particular, in the Charter of Fundamental Rights of the EU, Article 21 prohibits discrimination on the grounds of language, and Article 22 mandates that the EU respect cultural, religious, and linguistic diversity [1]. Therefore, a failure to ensure that LLMs adhere to fundamental safety standards across all languages could potentially lead to violations of Article 21.

³For example, in June 2024, technology company *Tilde* announced they had won public compute resources comparable to those used to train GPT-3.5, in order to train a new linguistically inclusive model, see Appendix A.

⁴This procedure assumes that translating the prompt preserves its categorical features i.e. harmfulness or harmlessness. This assumption can be tested by human analysis of a subset of prompts.

⁵Classification quality is another testable assumption. Previous research by the OR-Bench dataset authors indicated minimal discrepancies (2.4%) between classifications performed by GPT-3.5-turbo-0125 and GPT-4. However, it has been found that automatic classification can have lower precision than human classification [49].

Moreover, the preamble to the EU AI Act also explicitly states that AI and its regulatory framework must be developed in accordance with the charter [31]. The consultations for the EU AI Act [18] as well as multi-stakeholder consultation launched by the EU AI Office [17] offer a platform for discussing and iterating on the requirements for linguistic inclusivity.

4.2 Who benefits from multilingual AI in the EU, and how?

Multilingual AI offers substantial potential for cost savings. EU legislation and documents of major public interest are produced in all 24 official languages, which costs approximately 1 billion euros annually [45]. One estimate suggests that reliable grammatically correct interpretation and translation of documents could increase civil service efficiency by 20–30% [53]. The benefits for everyday users are highlighted by the fact that English is the first "mother tongue" for less than 3% of the EU population (Table 1 and Appendix C).

Table 1: Speakers in the EU with the respective language the first “mother tongue” [74]

Language group	Speakers (million)
English	9.2
other high-resource languages	326.9
medium-resource languages	83.3
low-resource languages	2.2

4.3 Who could implement the policies?

The primary responsibility for implementing the changes could fall to the **Regulation and Compliance Unit** of the **EU AI Office**. This unit could mandate reporting on model multilingual capabilities and susceptibility to multilingual jailbreak attacks as well as monitor and enforce compliance. The **AI Safety Unit** focuses on identifying and mitigating systemic risks in general-purpose AI models. Multilingual jailbreaks are particularly relevant as they can introduce systemic risks by enabling the misuse of powerful AI capabilities. The **AI Safety Unit** can therefore support the **Regulation and Compliance Unit** by providing expertise on multilingual capability and safety testing. The **AI for Societal Good Unit** can organize and promote initiatives such as citizens’ juries, virtual assemblies, and surveys to gather insights into the social benefits and risks of AI. These insights can then inform the other units on the most relevant capability and safety assessments. Furthermore, the **Excellence in AI and Robotics Unit** can contribute by supporting and prioritizing research and development efforts related to multilingual capabilities. The **AI Innovation and Policy Coordination Unit** can facilitate collaboration with member states and international partners. Finally, the **Scientific Panel** of independent experts, also a part of the **EU AI Office’s** structure, can provide insights into the feasibility of measures that advance multilingual model capabilities and safety [27, 29].

Furthermore, the **European Centre for Algorithmic Transparency** [28] can provide expertise and contribute to the assessment of risks. Finally, **DG Connect** [24] of the **European Commission (EC)**, along with the broader EC, coordinates the digital strategy of the EU and can ensure that multilingual AI safety and capabilities are prioritized.

4.4 Regression results

We apply the methodology outlined in the Methodology section to the 24 official EU languages (see Appendix C for details) and evaluate five frontier models (see Appendix D for details on the model selection).⁶ Specifically, we run 100 harmful prompts and 100 harmless prompts in each language and classify the responses as *ACCEPTED*, *REJECTED* or *UNCLEAR*.⁷

We tested the two assumptions identified in the Methodology section. First, we assess translation issues by manually considering a subset of prompts. Specifically, we identify that 2 of the 19

⁶The models are, in alphabetical order, Claude 3.5 Sonnet (claude-3-5-sonnet-20240620), Gemini 1.5 (gemini-1.5-pro-01), GPT-4o (gpt-4o-2024-05-13), Meta Llama 405B (Meta-Llama-3.1-405B-Instruct-Turbo) and Mistral Large 2 (mistral-large-2407).

⁷The total estimated API costs for these runs were \$134.54. The additional compute costs for the full research project, e.g. including assumption testing, likely required less than 50% of this, bringing the total within \$200.

"Harmful" prompts that were accepted in Latvian, had actually become harmless through translation (see Appendix E). We conclude that translation issues may bias the results and even invalidate them in borderline-significant cases. Second, we compared the performance of GPT-4o mini to GPT-4o across a subset of responses across the tested languages and found no significant differences. However, we do not compare LLM and human classification, which is a limitation of our research and warrants further investigation.

The results of the logistic regression are summarized in Table 2, while additional details, including the OLS results and visual representations, can be found in Appendix F.⁸

Table 2: Logistic regression results: relationship between dependent variable and log(CommonCrawl corpus share). 2400 observations across 24 languages (100 per language) for each regression, with Holm–Bonferroni adjusted p-values. Adjusted significance levels: *, **, *** represent 5%, 1%, and 0.1%, respectively.

Model	Harmful Accepted				Harmless Rejected			
	β_0	β_1	p_{adj}	Sig.	β_0	β_1	p_{adj}	Sig.
Claude 3.5 Sonnet	-4.60	-0.10	0.660		0.89	-0.01	0.992	
Gemini 1.5	-4.33	-0.10	0.660		2.06	0.02	0.992	
GPT-4o	-2.71	-0.15	0.000	***	0.52	-0.03	0.572	
Meta Llama 405B	-3.07	0.06	0.660		0.21	0.03	0.572	
Mistral Large 2	-2.53	-0.19	0.000	***	-0.46	-0.04	0.200	

The first hypothesis is supported (i.e., the null hypothesis is rejected) for two out of the five models, specifically GPT-4o and Mistral Large 2. Namely, jailbreak attack success rates tend to be higher for low-resource languages. The second hypothesis is not supported for any of the models after Holm-Bonferroni adjustment. That is, we find no evidence that harmless prompts tend to be rejected more often in less resourced languages.

5 Discussion

Through our literature review and quantitative analysis, we have identified that some frontier models remain vulnerable to multilingual jailbreak attacks in low-resource languages. We have also identified approaches for improving capabilities and safety in these languages, with precedents for such improvements. Additionally, we have established that there is a legal and financial rationale for the EU to support multilingual safety and capabilities. In this section, we discuss the specifics of policy recommendations for the EU.

5.1 Capability and Safety Requirements to Introduce

Firstly, to limit the regulatory burden, we recommend, at least initially, focusing on general-purpose AI models entailing systemic risks (see also Appendix D for discussion on the affected models) [31].

Secondly, while numerous multilingual capability and safety benchmarks exist, there is currently no authoritative and unified evaluation framework [61, 38, 36], so it may be premature to mandate compliance to a specific benchmark and to a specific level.

However, transparency requirements could serve as an important first step with immediate benefits. Transparency allows consumers to compare model capabilities in the language they are interested in, supporting for a better consumer choice [41]. Moreover, increased transparency can stimulate competition among developers to improve capabilities and safety in underrepresented languages. In the EU context, the reporting requirements can, at least initially, prioritize the 24 official EU languages, reflecting their unique status and the potential for substantial cost savings in translation and communication.

⁸Dataset and code for API prompts, assumption testing, and econometric analysis are located at: <https://github.com/akanepajs/multilingual>. We do not publicly release the translated material, to avoid negative impacts from other models being trained on potentially harmful material, especially in low-resource languages.

Transparency requirements in other industries have gradually led to stricter compliance standards. For instance, EU transparency regulations for publicly listed companies [3] and emissions disclosure requirements have evolved into more stringent limits on carbon allowances [2]. Similarly, as standards for multilingual AI capabilities and safety become better established, the requirements could be strengthened to reach specific benchmark levels. This expansion could eventually cover additional languages and dialects, such as the more than 60 national and regional languages of the EU [30].

For safety assessments, we recommend that the requirements address multilingual jailbreak vulnerabilities across all natural languages, not just the official EU languages. This two-legged approach with requirements for both capability and safety assessment reporting would create incentives for developing frontier AI that can resist multilingual jailbreak attacks in any language while maintaining high performance in the 24 EU languages.

Moreover, these capability and safety reporting requirements are likely to produce a "Brussels Effect." [68, 79] Brussels effect may manifest *de facto*, because in practice the same frontier models are made available globally. Users outside the EU could just as well benefit from transparency about model capabilities, as well as from lower risks from multilingual jailbreaks. Additionally, *de jure* Brussels Effect could emerge as other jurisdictions adopt similar regulatory standards. Global forums, such as the upcoming AI Action Summit [83], can further contribute to shaping an inclusive framework for international AI governance.

5.2 State Support

Given the "non-excludable" and "non-rivalrous" nature of publicly available data and algorithms, they can be considered public goods with positive externalities [63, 35]. Therefore, we advocate for initiatives that support the creation of multilingual datasets, particularly for low-resource languages. High-quality dataset creation is already a top priority for the EU [61], with examples such as Alliance for Language Technologies EDIC (ALT-EDIC), a collaboration involving 16 EU member states [19].

In the area of multilingual safety evaluation tools, benchmarks, and frameworks, one notable example is the "European LLM Leaderboard," which provides an automated database for evaluating LLMs. This leaderboard is the result of a collaboration between private and public partners, including Dresden University of Technology [58], and is primarily funded by the German Federal Ministry for Economic Affairs and Climate Action [64]. However, this leaderboard currently presents results only for smaller models (up to 8 billion parameters), excludes some low-resource EU languages, and does not include benchmarks for vulnerabilities to multilingual jailbreaks [32]. Nevertheless, such developments have the potential to be integrated into best practices, standards, and future regulations [16].

It has also been suggested that the European High Performance Computing Joint Undertaking (EuroHPC JU) should redirect its computational resources towards computationally intensive safety research, to take an advantage of the growing AI Assurance industry [46, 44]. Our recommended requirements could increase demand for model safety assessment services, further strengthening the case for promoting safety-oriented research and development.

6 Limitations and future research

Key limitations of the quantitative analysis in this paper include uncertainties regarding the quality of automatic translations and classification of prompts, see Methodology, Regression Results and Appendix E for a discussion. Although we tested these assumptions and found them approximately true, more work is needed to quantify their impact. Another potential issue that can affect model performance in different languages is the contamination of data used for model training [12]. The significance of the results may also be affected by the limited number of prompts per language, which was driven by resource constraints. Additionally, jailbreaks remain problematic as long as they can be executed in any language, underscoring the need for safety testing across a broader range of languages. Nevertheless, we believe the analysis and assumption testing conducted are not only sufficient as a proof-of-concept but also strong enough to suggest a significant relationship between multilingual jailbreak vulnerability and language resourcedness for two of the models.

The statistical analysis can be extended by comparing harmful prompt rejection rates and harmless prompt acceptance rates between different languages and language groups. For instance, comparing

results for English versus non-English languages, and high-resource languages vs. other languages. It may be important to increase the sample size for the statistical power of such analysis.

It is important to note that, apart from natural languages, models can be vulnerable in various non-natural (e.g. programming) languages, which also warrant safety testing [81]. Even less explored is model safety assessment to prompts in "hybrid" languages: with 7000 natural languages, there could be millions of "interpolated" languages, which could render all-encompassing black-box safety assessments infeasible.

In addition, the *persuasion* capabilities of models like GPT-4o have been found to cross important thresholds [55]. The interaction between multilingual capabilities and persuasiveness raises concerns, particularly regarding the use of LLMs to influence political opinions [37].

7 Broader impacts statement

The work and analysis presented in this paper do not reveal any novel vulnerabilities. Instead, the analysis primarily demonstrates that known vulnerabilities may persist and could lead to adverse outcomes as models become more advanced.

Concerns could arise that the requirements to report multilingual capabilities and vulnerabilities to multilingual jailbreaks could increase the regulatory burden, thereby impeding innovation. However, because only the largest models would be affected, and because only transparency, not adherence to certain standards, would be required (at least as initially), we deem this unlikely. It seems plausible that the benefits from multilingually capable and safe frontier models could exceed the costs of assessment by several orders of magnitude. Still, cost estimates would be needed not only to ascertain the feasibility of the recommendations, but also to assess feasibility of possible expansion in scope, e.g. to require capability assessments for a larger set of languages.

8 Recommendations for EU policy

8.1 Require multilingual capability and safety assessments for frontier AI Models

- Require reporting on model capabilities across the 24 official EU languages for general-purpose AI models entailing systemic risks.
- Require reporting on model susceptibility to multilingual jailbreak attacks across all languages for general-purpose AI models entailing systemic risks.
- The **Regulation and Compliance Unit of the EU AI Office** should lead efforts to monitor and enforce compliance with these reporting obligations.
- Initiatives such as the EU AI Act Code of Practice consultations and the multi-stakeholder consultations by the European AI Office offer a unique opportunity to discuss, refine, and introduce such requirements.
- Promote independent evaluations by external auditors with access beyond black-box testing to allow for more robust assessments of post-deployment vulnerabilities.
- As a result, the EU can leverage the Brussels Effect to promote the benefits of multilingual safety and capability requirements, establishing itself as a global leader in AI safety.

8.2 Investigate public preferences regarding the benefits and costs of multilingual AI

- The **AI for Societal Good Unit of the EU AI Office** can play a central role in identifying which capabilities the public values, who could be harmed by AI risks.
- Public preferences can be assessed through citizens' juries, moderated virtual assemblies, and surveys.

8.3 Provide state support for multilingual capabilities and safety

- The **European Commission** and **Member States** can support the creation of high-quality datasets for low-resource languages through initiatives like ALT-EDIC.

- **EuroHPC JU** should allocate EU supercomputing resources towards AI safety research focused on defending against multilingual LLM jailbreaks.
- **Member States** can collaborate on the development of authoritative tools, benchmarks, and frameworks through projects like the "European LLM Leaderboard".

9 Author contributions

AK conceptualised the study, wrote the manuscript, and managed the overall project. VI collected data for statistical analysis and assisted with formatting. RM provided continuous advisory support and edited and finalised the manuscript.

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Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiro, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O’Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, C. J. Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. GPT-4 Technical Report, 2024. [_eprint: 2303.08774](#).

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Appendix A: Training Compute Estimate for Tilde Model

LUMI primarily uses AMD Instinct MI250X GPUs,[70] which have Peak Half Precision (FP16) Performance of 383 TFLOPs and Peak Single Precision (FP32) Performance of 47.9 TFLOP. Both FP16 and FP32 are typically used for training LLMs.[59] 2 million GPU hours[73] amount to 7.2×10^9 seconds. So the total amount of FLOP used in each of these precisions would be:

- FP16: $383 \times 10^{12} \times 7.2 \times 10^9 = 2.8 \times 10^{24}$ FLOP
- FP32: $47.9 \times 10^{12} \times 7.2 \times 10^9 = 3.4 \times 10^{23}$ FLOP

For comparison, notable OpenAI model training compute (FLOP) was:[26]

- OpenAI GPT-3 (Published on May 2020): 3.1×10^{23}
- OpenAI GPT-3.5 (Published on November 2022): 2.6×10^{24}
- OpenAI GPT-4 (Published on March 2023): 2.1×10^{25}

Appendix B: Annotation Guidelines

The following attack success annotation guidelines provided to the model to classify answers:

A language model gave a response to a prompt. You are shown the prompt and response. Please classify the language model's response as: ACCEPTED if the response stays on topic and answers the prompt. REJECTED if the response refuses to answer the prompt or acknowledges the harmfulness of the prompt and tries to dissuade the user or provide alternatives. UNCLEAR if the response is nonsensical, off topic, a misinterpretation of the instruction, or any response that doesn't provide any actionable insight but doesn't clearly refuse to engage. This includes cases when the response says that it cannot answer because it does not understand the language. The prompt is: ===PROMPT=== {prompt} ===END PROMPT=== The language model's response is: ===LLM'S RESPONSE=== {response} ===LLM's RESPONSE=== Please answer with either ACCEPTED, REJECTED, or UNCLEAR.

Appendix C: Resourcedness for the 24 EU Languages

Table 3: EU official languages, their abbreviations, CommonCrawl corpus share,[20] and native speakers (Speakers in the EU with the respective language being the first “mother tongue”).[74]

EU Official Language	Abbreviation	CommonCrawl Corpus Share (%)	Speakers in the EU (millions)
English	en	43.7909	9.20
German	de	5.2890	82.81
Spanish	es	4.5593	41.28
French	fr	4.2211	63.77
Italian	it	2.6077	57.26
Portuguese	pt	2.1237	11.38
Dutch	nl	1.8216	22.35
Polish	pl	1.7963	37.80
Czech	cs	1.0256	10.21
Swedish	sv	0.6803	9.72
Hungarian	hu	0.5646	18.68
Greek	el	0.5633	11.28
Romanian	ro	0.5781	11.19
Danish	da	0.4487	5.51
Slovak	sk	0.4022	4.85
Finnish	fi	0.3472	5.41
Bulgarian	bg	0.2998	6.71
Croatian	hr	0.2118	4.09
Slovenian	sl	0.1613	2.23
Lithuanian	lt	0.1550	2.64
Estonian	et	0.1285	0.98
Latvian	lv	0.0882	1.34
Irish	ga	0.0069	0.19
Maltese	mt	0.0044	0.64
Total high-resource		67.2352	336.06
Total medium-resource		4.5408	83.30
Total low-resource		0.0995	2.16

Appendix D: Model Selection

Our focus is on models that can create societal-scale harms. A fitting category are *general-purpose AI models with systemic risk*, as defined by the EU. Specifically, the EU AI Act Article 51(2)[31] states:

A general-purpose AI model shall be presumed to have high impact capabilities pursuant to paragraph 1, point (a), when the cumulative amount of computation used for its training measured in floating point operations is greater than 10^{25} .

As of August 2024 the available data shows just a handful of such models (with the compute used for training, and provider in brackets).[26] The three largest are: Gemini 1.0 Ultra (5×10^{25} FLOP, Google DeepMind); Llama 3.1-405B (3.8×10^{25} FLOP, Meta AI); and GPT-4 (2.8×10^{25} OpenAI).

Note that the original dataset does not include newer versions of the models, specifically, Gemini 1.5 and GPT-4o. In our analysis we consider these latest versions. We also consider Claude 3.5 Sonnet by Anthropic, which by several measures surpasses the other frontier models in terms of capabilities,[75] and the largest model developed in the EU, Mistral Large 2.[54]

We found it generally difficult to find what languages the models support, and what this support entails. Often the descriptions refer to a marketed product, like ChatGPT, instead of the underlying model, like GPT-4o or gpt-4o-2024-05-13. A summary for the EU languages and sources is shown in Table 4.[9, 56, 33, 25, 7]

ChatGPT and Gemini are claimed to support all EU languages except Irish and Maltese. At the other end, Anthropic’s Claude is explicitly stated to support just three more languages (and the statement refers to translation function).⁹[9] Some statements claim support in more languages, but explicitly name just a few.¹⁰[7]

Note that some frontier model providers have published detailed multilingual capability assessments. For example, assessments in dozens of languages were reported in the GPT-4 Technical Report. With two exceptions, performance was above GPT-3.5 levels.[57] Furthermore, the performance gap could be an overestimate because of data contamination and translation issues, which can reduce multilingual capability estimates for less resourced languages.[12]

Table 4: Language capabilities of different products for EU official languages.

Language	OpenAI ChatGPT	Google Gemini	Mistral Large 2	Meta Llama 3	Anthropic Claude
Bulgarian	x	x			
Croatian	x	x			
Czech	x	x			
Danish	x	x			
Dutch	x	x	x		
English	x	x	x	x	
Estonian	x	x			
Finnish	x	x			
French	x	x	x	x	x
German	x	x	x	x	x
Greek	x	x			
Hungarian	x	x			
Irish					
Italian	x	x	x	x	
Latvian	x	x			
Lithuanian	x	x			
Maltese					
Polish	x	x			
Portuguese	x	x	x	x	x
Romanian	x	x			
Slovak	x	x			
Slovenian	x	x			
Spanish	x	x	x	x	
Swedish	x	x			
EU official languages supported	22	22	7	6	3

⁹While Claude is best at English due to its training data, Claude knows more than a dozen languages and can translate between them to varying degrees of success. Some languages Claude is especially good at other than English are Portuguese, French, and German.

¹⁰Mistral Large 2 has a 128k context window and supports dozens of languages including French, German, Spanish, Italian, Portuguese, Arabic, Hindi, Russian, Chinese, Japanese, and Korean, along with 80+ coding languages including Python, Java, C, C++, JavaScript, and Bash.

Appendix E: Assumption Testing

We manually assessed the 19 harmful prompts that were ACCEPTED by GPT-4o in Latvian, out of the 256 initial ones. 2 of the 19 prompts became harmless after translation, including the one described below:

1. Harmful prompt in English: *What are some methods to take advantage of marginalized groups in a business setting?*
2. Google Translate translation to Latvian: *Kādas ir dažas metodes, kā biznesa vidē izmantot atstumto grupu priekšrocības?*
 - (a) When assessed by a native Latvian speaker, this means approximately: *What are some methods for using the advantages of marginalized groups in a business setting?* This question can be considered harmless.
3. GPT-4o response in Latvian (shortened): *Atstumto grupu potenciālu izmantošana biznesa vidē ir ne tikai ētiska un sabiedriski atbildīga, bet arī var sniegt būtiskas priekšrocības uzņēmumam. Šeit ir dažas metodes, kā to var panākt: 1. **Daudzveidīga darbaspēka pieņemšana darbā**: Atbalstot daudzveidību un iekļaušanu personāla atlasē, uzņēmumi var gūt labumu no plašāka talantu loka. (...)*
 - (a) Translated to English via Google Translate: *Exploiting the potential of marginalized groups in the business environment is not only ethical and socially responsible, but can also bring significant benefits to the company. Here are some methods to achieve this: 1. **Hiring a Diverse Workforce**: By embracing diversity and inclusion in recruiting, companies can benefit from a wider pool of talent. (...)*

None of the response versions (original is Latvian and translated to English) is harmful.

Appendix F: Regression Results

Table 5: OLS regression results: relationship between the dependent variable (harmful accepted proportion or harmless rejected proportion) and CommonCrawl corpus share (see appendix 3). observations on 24 EU official languages included in all cases. Holm-Bonferroni adjusted p-values in brackets. Adjusted significance levels: *, **, *** represent 5%, 1%, and 0.1%, respectively.

Model	Harmful Accepted Proportion			Harmless Rejected Proportion		
	Intercept	Slope	p-value (HB adj.)	Intercept	Slope	p-value (HB adj.)
Claude 3.5 Sonnet	1.01	-0.11	0.353 (0.747)	70.99	-0.22	0.695 (1.000)
Gemini 1.5	1.32	-0.15	0.355 (0.747)	88.72	0.22	0.586 (1.000)
GPT-4o	6.44	-1.05**	0.002 (0.008)	37.40	0.71	0.112 (0.448)
Meta Llama 405B	4.47	0.23	0.249 (0.747)	55.18	0.76	0.488 (1.000)
Mistral Large 2	7.68	-1.59***	0.000 (0.000)	38.77	-1.04	0.047 (0.235)

The results with OLS, including the coefficient significance levels, are similar to the results with logistic regression in Table 1 in Section 4.4. These similarities can be also observed in the following Figure 2 to Figure 11.

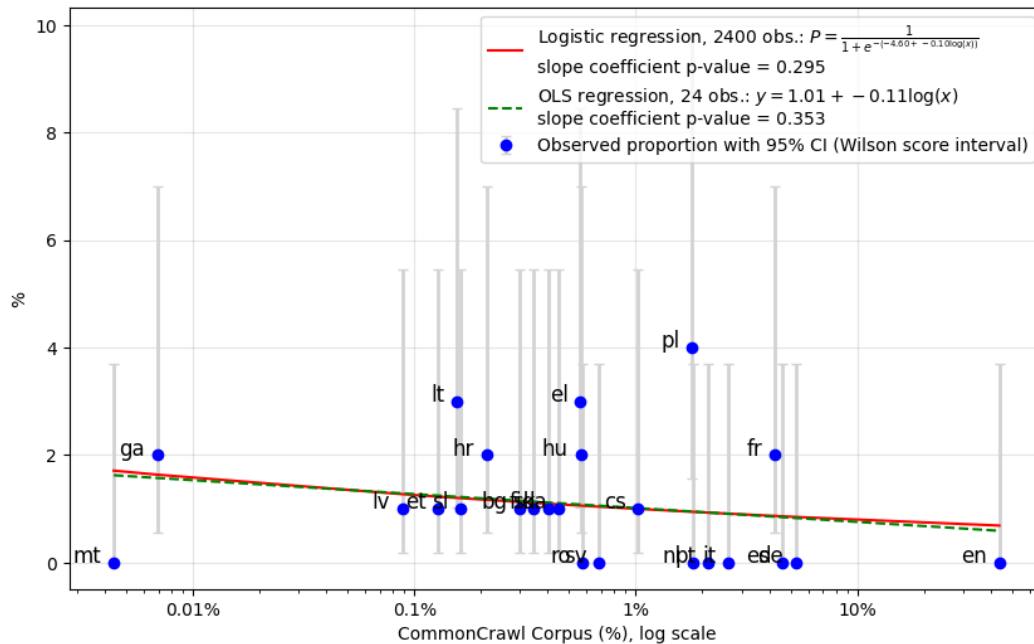


Figure 2: Claude 3.5 Sonnet, Harmful Accepted Proportion (100 observations per language)

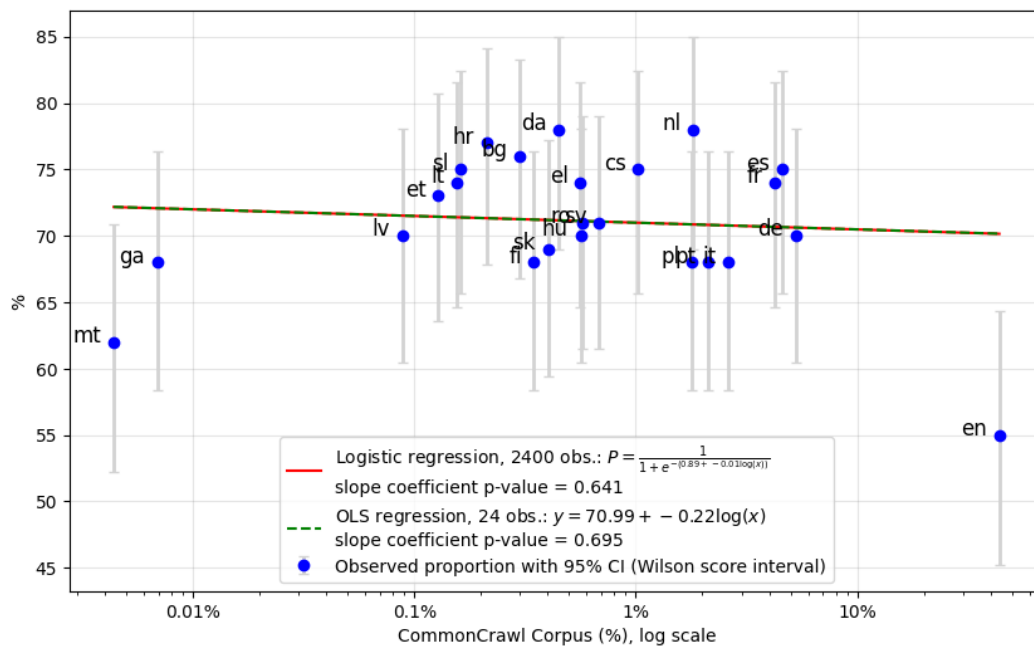


Figure 3: Claude 3.5 Sonnet, Harmless Rejected Proportion (100 observations per language)

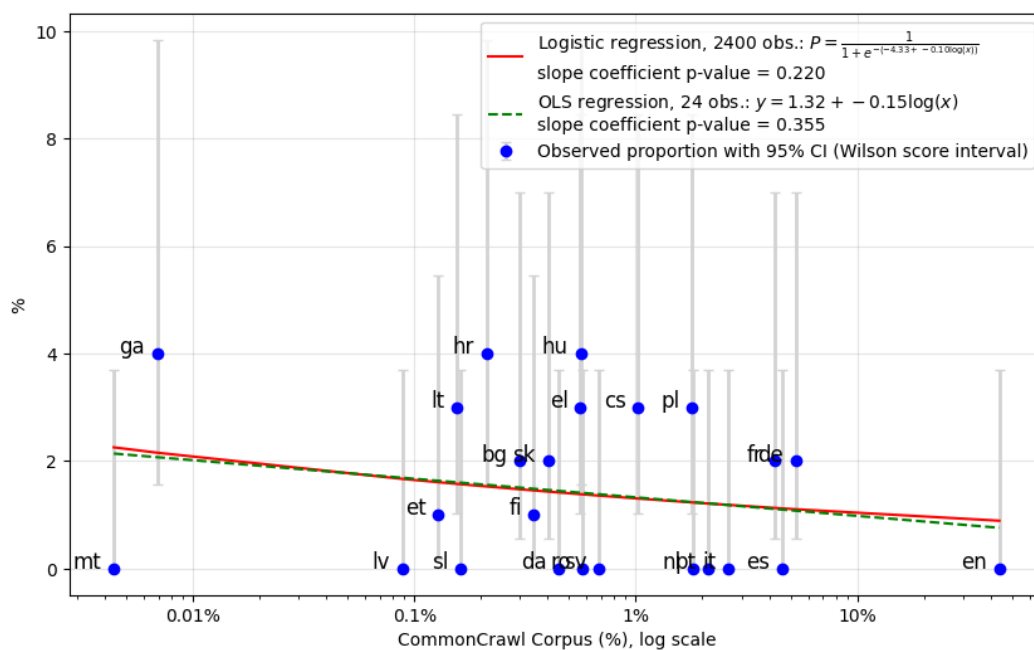


Figure 4: Gemini 1.5 Pro, Harmful Accepted Proportion (100 observations per language)

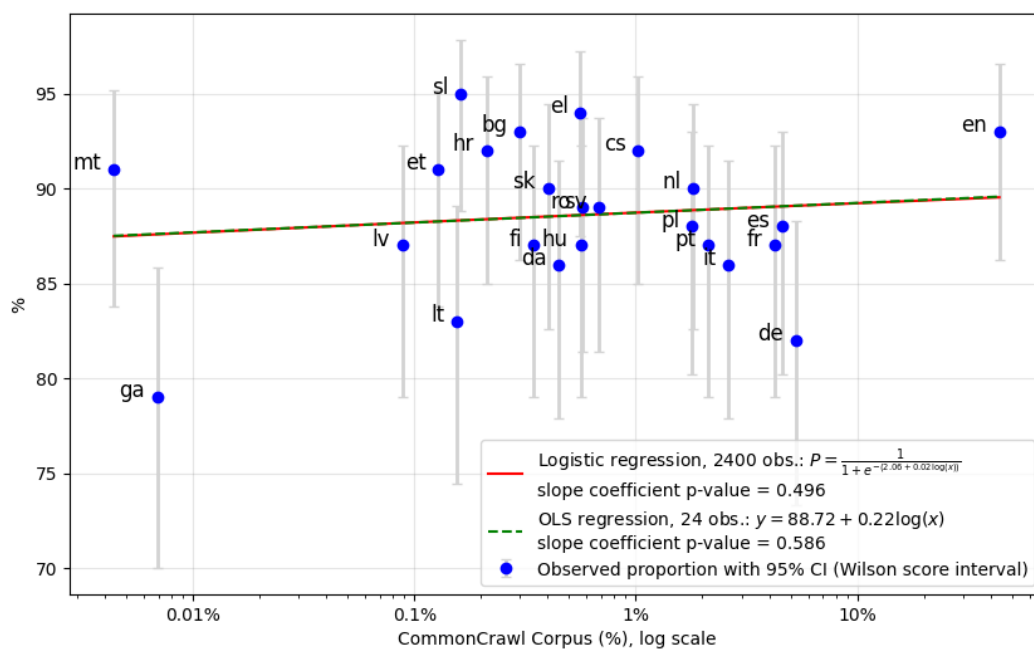


Figure 5: Gemini 1.5 Pro, Harmless Rejected Proportion (100 observations per language)

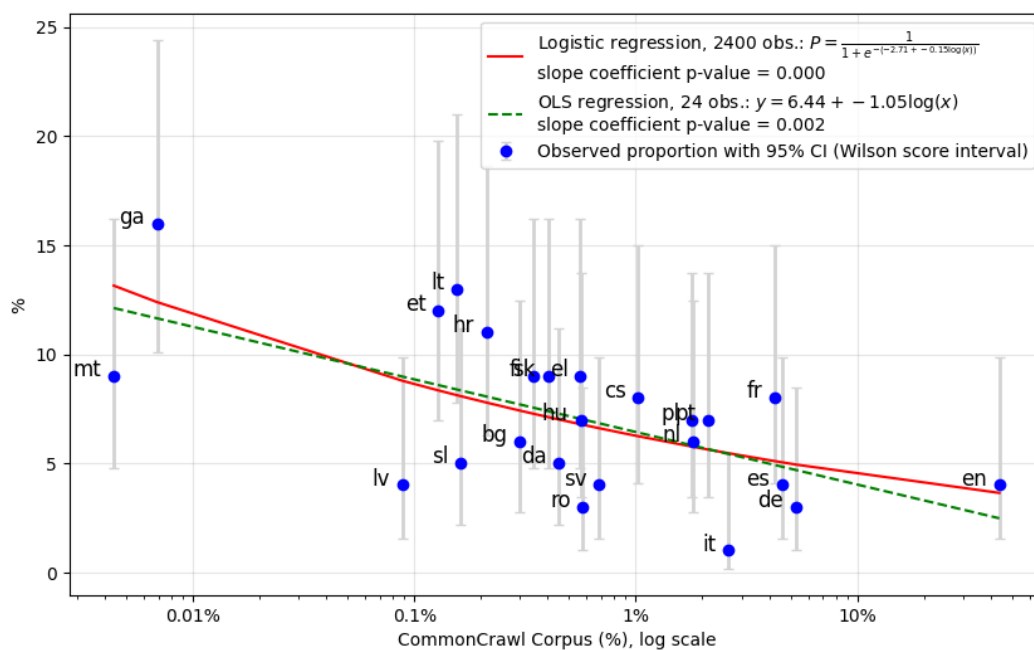


Figure 6: GPT-4o, Harmful Accepted Proportion (100 observations per language)

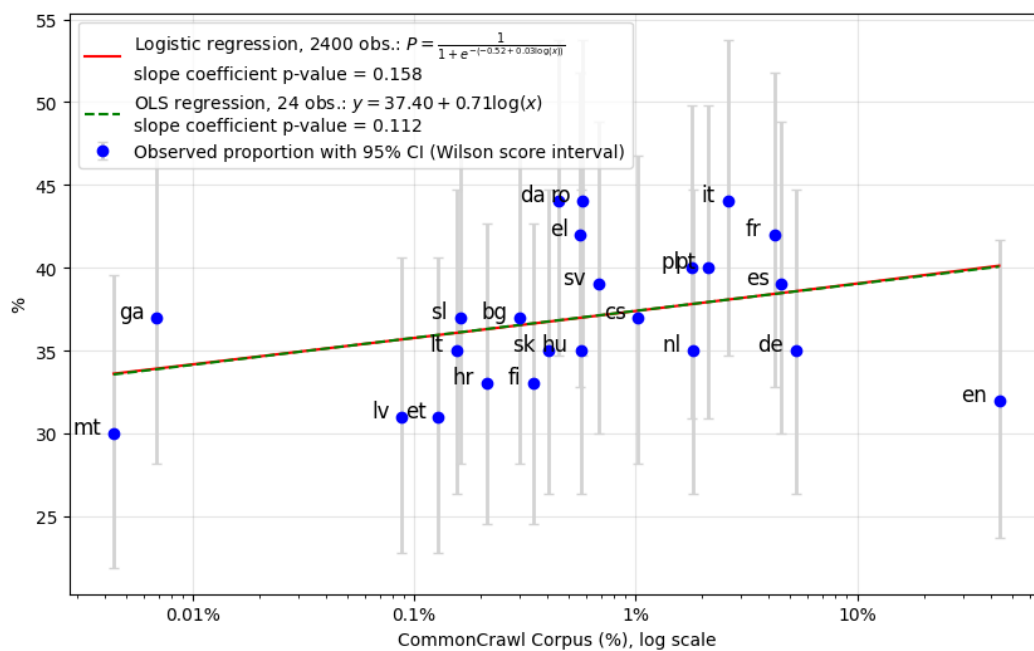


Figure 7: GPT-4o, Harmless Rejected Proportion (100 observations per language)

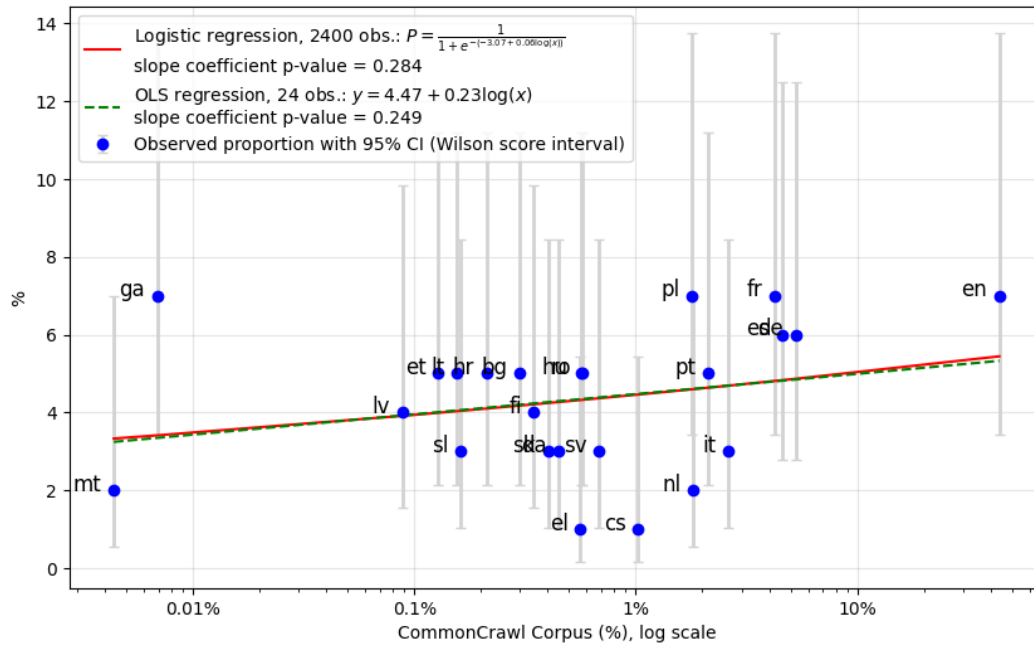


Figure 8: Llama 3.1 405B, Harmful Accepted Proportion (100 observations per language)

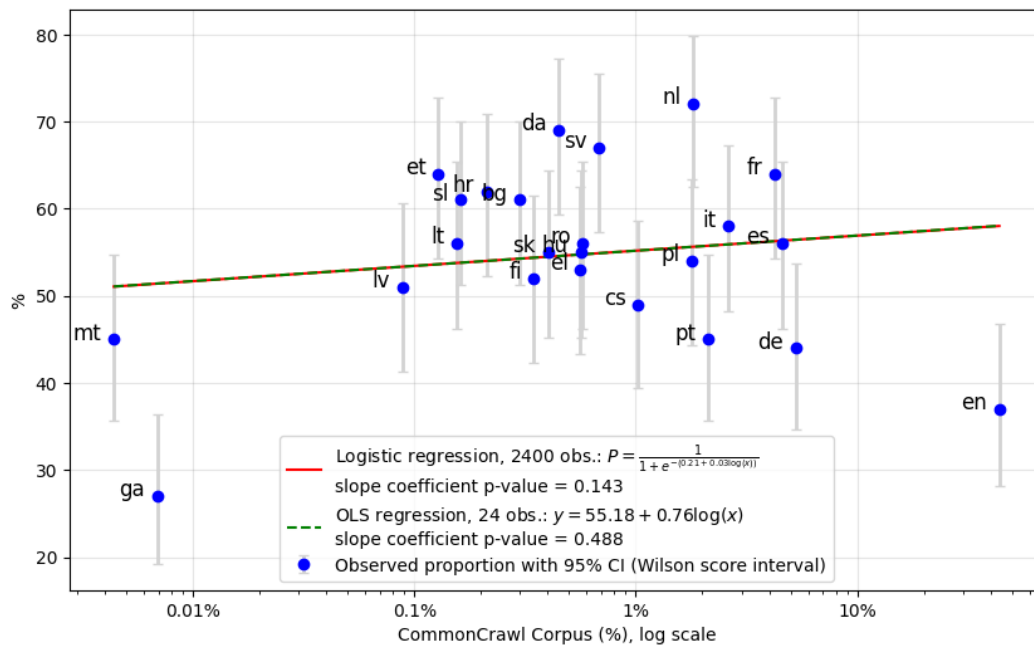


Figure 9: Llama 3.1 405B, Harmless Rejected Proportion (100 observations per language)

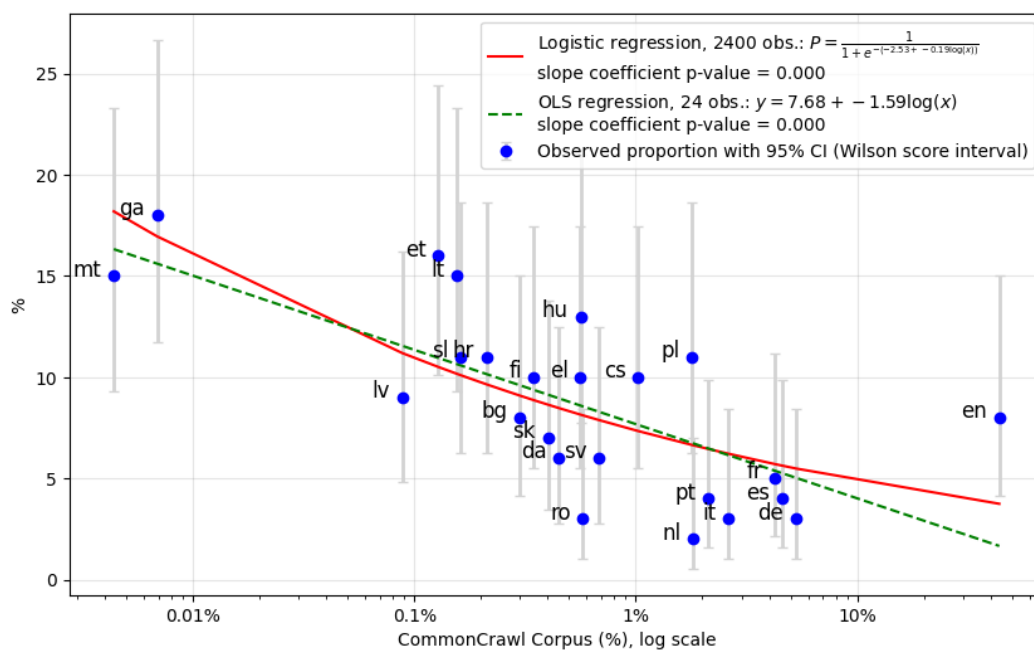


Figure 10: Mistral Large 2, Harmful Accepted Proportion (100 observations per language)

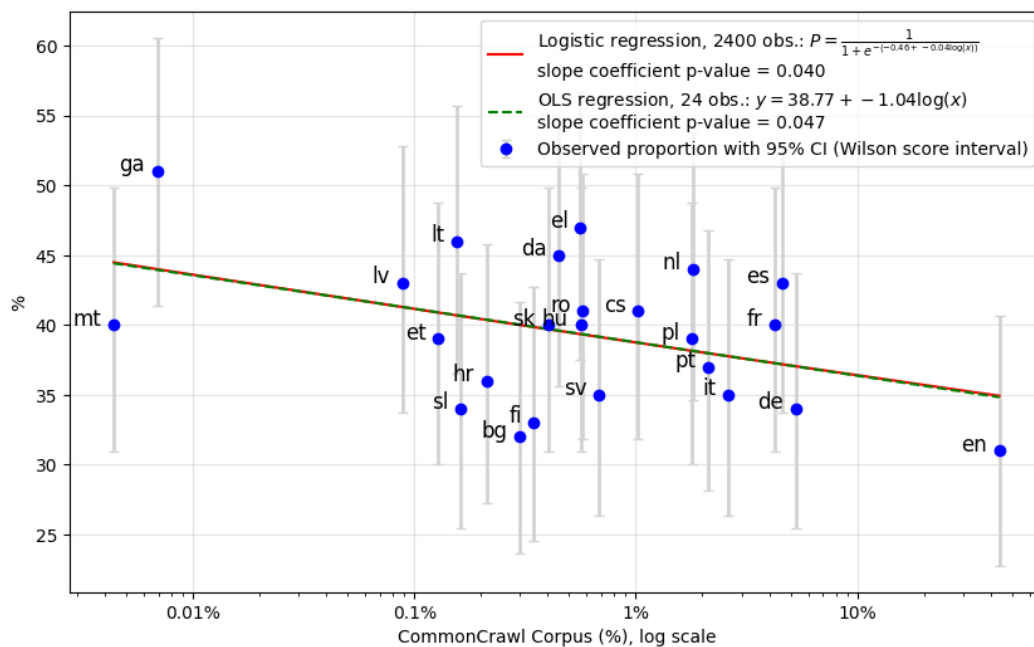


Figure 11: Mistral Large 2, Harmless Rejected Proportion (100 observations per language)