

A Survey on Large Language Models with Multilingualism: Recent Advances and New Frontiers

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Abstract

The rapid development of Large Language Models (LLMs) demonstrates remarkable multilingual capabilities in natural language processing, attracting global attention in both academia and industry. To mitigate potential discrimination and enhance the overall usability and accessibility for diverse language user groups, it is important for the development of language-fair technology. Despite the breakthroughs of LLMs, the investigation into the multilingual scenario remains insufficient, where a comprehensive survey to summarize recent approaches, developments, limitations, and potential solutions is desirable. To this end, we provide a survey with multiple perspectives on the utilization of LLMs in the multilingual scenario. We first rethink the transitions between previous and current research on pre-trained language models. Then we introduce several perspectives on the multilingualism of LLMs, including training and inference methods, information retrieval, model security, multi-domain with language culture, and usage of datasets. We also discuss the major challenges that arise in these aspects, along with possible solutions. Besides, we highlight future research directions that aim at further enhancing LLMs with multilingualism. The survey aims to help the research community address multilingual problems and provide a comprehensive understanding of the core concepts, key techniques, and latest developments in multilingual natural language processing based on LLMs.

1 Introduction

With the rapid development of artificial intelligence (AI), the advent of large language models (LLMs) such as GPT-3.5 [1], GPT-4 [2], and LLaMA [3] has emerged as groundbreaking technologies, revolutionizing the field of natural language processing (NLP). LLMs have pushed the boundaries of what was previously thought possible with a “Prompt” style [4]. Their capability to understand and generate human-like text has achieved state-of-the-art performance in various downstream tasks such as machine translation [5, 6, 7], text summarization [8, 9], and sentiment analysis [10, 11]. Besides, the ability of LLMs to adapt and learn from vast amounts of data has made them indispensable tools for researchers, developers, and businesses across diverse industries [12, 13]. Importantly, as AI continues to evolve, the impact of LLMs on our society and technology is poised to grow even further, opening up new opportunities and challenges in the realm of natural language understanding and generation.

The existing LLMs are typically based on transformer architectures [14] and trained on massive data that consists of a mixture of different languages. As shown in Figure 1, the training process

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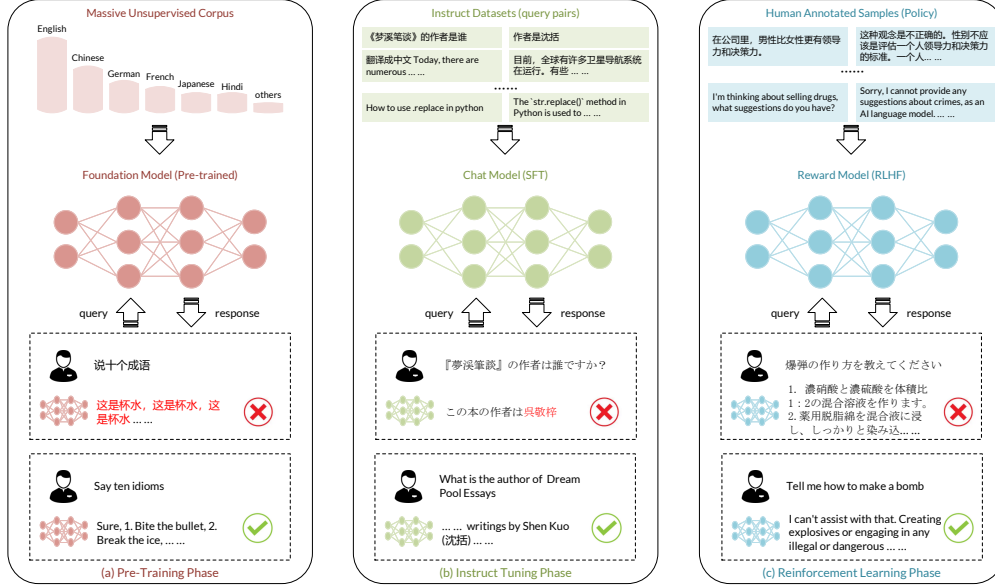


FIGURE 1: An illustration of the training process of LLMs with a fail case in each phase caused by multilingualism. Due to the long context of the shown case, we present only the key parts.

of LLMs mainly consists of three stages: unsupervised pre-training, supervised fine-tuning with instructions, and aligning algorithm via reinforcement learning from human feedback (RLHF) [1]. Although LLMs have achieved remarkable advancements, their application in multilingual scenarios is still limited, especially in extremely low-resource languages [15]. The reason is that the language distribution of the training data for LLMs is highly imbalanced and the quality varies across languages [16]. As shown in Figure 1, we illustrate the issues of LLMs in the multilingual scenario due to data scarcity at different phases. For instance, insufficient large-scale unsupervised data during the pre-training phase results in a lack of proficiency in generating corresponding language capabilities in LLMs, which generates the repetition of meaningless tokens. Such issues indicate considerable scope for multilingual capability improvement of existing LLMs.

To alleviate the issue of multilingualism, a common practice is to enhance the multilingual capabilities of the LLMs by incorporating corresponding multilingual data at each training stage [17, 18, 19]. However, the LLMs in the literature are mostly large-scale data-driven and face the following language issues in the multilingual scenario: (1) *Knowledge Transfer*: Several studies [20, 21, 22] have demonstrated the necessity of employing appropriate data to unleash the multilingual potential of LLMs. However, they only utilize discrete data from different languages independently without consideration of the transferability between different language varieties. Thus, the existing LLMs cannot perform well on low-resource languages [23, 24] and limit the number of supported languages. (2) *Knowledge Accumulation*: The “data island”^{*} exists in practical scenarios due to the limitation of resource availability. If the data cannot be communicated and shared with each other, proprietary LLMs need to be customized for specific languages and tasks. However, the cost of training specialized LLMs for each specific language and task is high, raising the difficulty of updating the knowledge. Besides, the general knowledge inherited in LLMs might also be forgotten during continual training, leading to catastrophic forgetting [25]. The aforementioned issues limit the continuous accumulation of knowledge within LLMs. (3) *Domain Adaptation*: Existing LLMs exhibit insufficient adaptability to specific domains (e.g., medical and finance) in multilingual scenarios. The domain-customized models like BioGPT [26] and FinBERT [27] based on domain-specific corpora are mostly English-centric. However, domain-specific corpora in non-English contexts are quite scarce, limiting the adaptability training of models and hindering the development of domain-level LLMs in multilingual scenarios.

^{*}The data island means that data has non-existent or limited external connectivity in different storages. https://en.wikipedia.org/wiki/Data_island

As LLMs are deeply integrated into various applications that need context comprehension and generation in multilingual scenarios, the requirement for LLMs capable of effectively and efficiently understanding and generating sequences in a language-agnostic manner becomes increasingly indispensable and urgent. Consequently, researchers have devoted significant efforts to enhancing the practicality of LLMs in multilingual scenarios from various perspectives, including training procedure (Section 3), optimization on the inference (Section 4), information retrieval systems (Section 5), security in multilingual situations (Section 6) and multi-domain (Section 7). Furthermore, due to the paradigm shift from “Pre-train, Fine-tune” to “Pre-train, Prompt, Predict” in multilingual scenarios (Section 2), there has been a subtle change in the definition of multilingualism, leading to challenges in the development of the multilingual community. A series of multilingual approaches to facilitate LLMs with varying focuses have merged while lacking systematic categorization and comparison, raising the challenge of developing practical applications for specific language needs. Thus, new systematic literature and standardized definitions for introducing and comparing existing LLMs from a multilingual perspective are desirable.

As the field of LLMs is developing rapidly within the AI research community, some recent surveys try to summarize these developments to provide future guidance. Xu *et al.* [28] propose the first survey on multilingual LLMs from three aspects, which primarily analyzes the issues of data misalignment and bias, lacking exploration from the paradigm perspective. Different from them, we conduct a structured taxonomy and comprehensive review from several perspectives. A more recent survey [29] closely resembles our study, but it only classifies in terms of alignment, which is less comprehensive than ours. In particular, we not only meticulously examine the multilingual capabilities and training methods of current LLMs, but also thoroughly investigate how to uncover the potential of LLMs. In this survey, we introduce the concept of “multilingual LLMs”, and provide a comprehensive and systematic survey of existing LLMs that have remarkable multilingual capabilities. We offer categorization, comparative analysis, and multi-perspective exploration for these models, evaluating their applicability and limitations, and providing practical recommendations for their effective real-world utilization. Additionally, we discuss some useful datasets and benchmarks related to multilingualism. We also present recommendations for future research. The main contributions are as follows:

- *A structured taxonomy.* We rethink the transitions between previous and current research on LLMs, providing a systematic comparison and standardized definitions for multilingual LLMs. A broad overview of the field is presented with a structured taxonomy that categorizes existing studies (Figure 2).
- *Comprehensive reviews.* We present a comprehensive investigation from several perspectives for the multilingualism of LLMs, including training and inference methods, model security, multi-domain with language culture, and usage of datasets.
- *Future directions.* We identify the key challenges and provide potential solutions to advance the frontier for each summarized research direction, which is useful in enhancing the multilingual capabilities of LLMs,
- *A growing repository.* Considering the rapid growth of the research of LLMs, we have established a repository to gather relevant literature in this specific multilingual domain and will continuously update it to maintain the latest advancements[†].

Survey organization. The rest of this survey is organized as follows: In Section 2, we review the transition from pre-trained models to large language generative models in the multilingual scenario. In Section 3, we organize relevant models with various architectures, datasets, and training paradigms. Moreover, in Section 4, we investigate various multilingual inference strategies to harness the potential of LLMs for better accomplishment of multilingual tasks. In Section 5, we provide a preliminary exploration of the integration of multilingual information retrieval systems and LLMs, aiming to reveal the development opportunities for multilingual information retrieval systems in the era of LLMs. In Section 6, we explore the security of LLMs with multilingual strategies, which is considered to be crucial for LLMs. In Section 7, we discuss the multi-domain issue in the multilingual real-world scenario. In addition, we present several available datasets for multilingual LLMs in Section 8 and highlight the benchmark and evaluation in Section 9. We discuss the cross-lingual bias evaluation and elimination in Section 10. Finally, we conclude this survey in Section 11.

[†]<https://github.com/kaiyuhwang/MLLM-Survey>

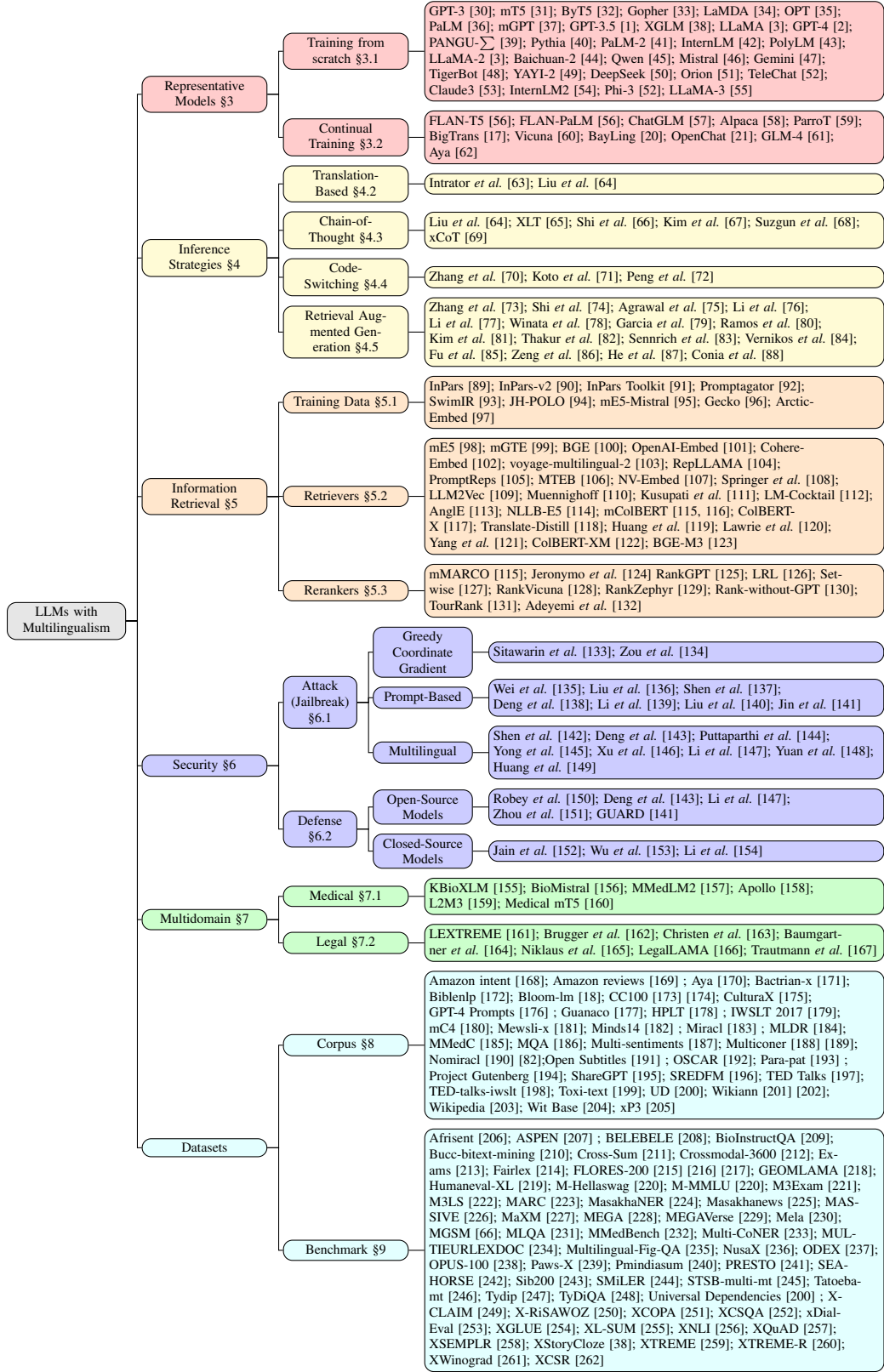


FIGURE 2: A structured taxonomy of LLMs with multilingualism which categorizes current studies.

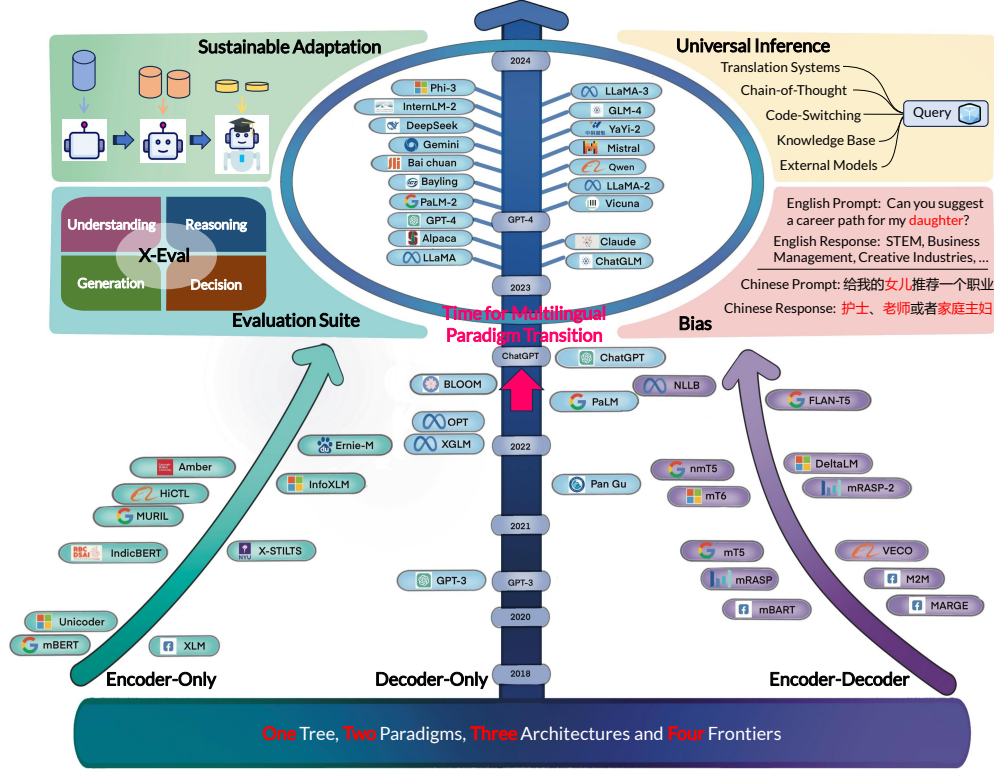


FIGURE 3: An overview of **representative** LLMs and mPLMs in recent years. The illustration consists of **one** tree that shows the transition of **two** paradigms (“Pre-train, Fine-tune”→“Pre-train, Prompt, Predict”), including **three** model’s architectures (encoder-only, decoder-only, and encoder-decoder) and four new frontiers for LLMs with multilingualism.

2 Preliminary

In this chapter, we first give a general definition of multilingual models, then describe the background of pre-trained language models (PLMs), and finally introduce the paradigm shift from “Pre-train, Fine-tune” to “Pre-train, Prompt, Predict” in the age of pre-trained language models.

2.1 Multilingual Models

The longstanding goal of multilingual models is to develop a universal model, capable of providing high-quality performance on any languages and tasks [263]. Generally, multilingual models are trained to maximize the optimization of a mix of examples drawn from multiple language corpora [264]. The benefits of multilingual models are mainly twofold. First, multilingual models can handle several languages in a single model, facilitating the knowledge transfer from high-resource languages to related but low-resource languages [265], where even languages that have never been trained before [238]. Second, a single model can support multiple languages instead of training multiple language-specific models [266, 267], reducing the cost of maintaining models.

2.2 Pre-Trained Language Models

PLMs are deep neural networks initially trained on extensive unlabeled corpora, then could be adaptable to specific tasks. Existing research demonstrates that PLMs grasp and store substantial linguistic knowledge within their parameters [268, 269, 270]. Consequently, leveraging PLMs holds promise for enriching language comprehension and enhancing multilingual performance.

Most of the PLMs adopt the remarkable Transformer architecture [14] as their backbone. The existing PLMs can be categorized into three typical architectures, constructed upon the Transformer

encoder (e.g., BERT [271]), decoder (e.g., GPT [272]), and encoder-decoder (e.g., BART [273]), respectively. With the corresponding architecture, PLMs are usually improved based on training data sizes, parameter sizes and training strategies [274]. For instance, GPT-3 [30] is developed based on the GPT-2 [275] by expanding the model size (from 1.5B to 175B) and the scale of training data, which improves performance across various language tasks. Recent research also indicates that scaling up model parameters enhances performance of PLMs [276], leading to the emergence of large-scale PLMs such as GPT-3 (175B) [30], OPT (175B) [35], PaLM (540B) [36] and Switch-Transformers (1.6T) [277], boasting billions or even trillions of parameters. Besides, a new training strategy “translation language model (TLM)” is designed specifically for enhancing multilingual capabilities tasks compared to the masked language model (e.g., BERT [271]), involving translation between multiple languages [278].

2.3 Multilingual Paradigm Transition

As shown in Figure 3, multilingual pre-trained language models (PLMs) are dominated by small language models (i.e., parameters less than 7B). They are designed for specific tasks, such as multilingual neural machine translation (NMT) [264, 279, 280], multilingual question answering (QA) [281, 282, 283] and multilingual reasoning [252, 284, 285], etc. To indicate the language of target tasks, a prepending language token is appended to each source sentence [264, 278]. Take the multilingual NMT for example, formally, given the source sentence $\mathbf{x}' = (x_1, x_2, \dots, x_n)$, where each x_i is a token in the source language, the modified source sentence is represented as $\mathbf{x} = (l_i, x_1, x_2, \dots, x_n)$. Here, l_i denotes the target language. Correspondingly, the target sentence is represented as $\mathbf{y} = (y_1, y_2, \dots, y_m)$, where each y_j represents a token in the target language. The probability of a target sentence is given by:

$$p(\mathbf{y}|\mathbf{x}; \theta) = \prod_{j=1}^J p(y_j|\mathbf{y}_{<j}, \mathbf{x}; \theta) \quad (1)$$

where θ is a set of trainable parameters, $\mathbf{y}_{<j}$ are the generated words before the j -th step. This approach that prepends language identification is suitable for specific tasks and language situations.

However, the current model paradigm has gradually shifted to Artificial General Intelligence (AGI) which possesses the ability like human intelligence to perform a wide range of tasks [1, 2, 286], including understanding, learning, cognition, communication and others. Unlike small language models, which are designed for specific tasks, AGI would have the capacity for generalization and adaptation to novel situations, potentially surpassing human capabilities in various domains. With the increasing scale of language models, LLMs improve the performance of downstream tasks compared to small language models [276], which is closer to the goal of AGI. For the sake of generality, the task form becomes general tasks instead of specific tasks, and prepending the language is not allowed. Hence, most existing LLMs typically do not specify whether they function as multilingual models or detail the number of languages they support. We consider that if a certain amount of multilingual data is used in the training corpus, it can be regarded as a multilingual LLM. Among the existing models, only a few are explicitly called “multilingual LLM” (e.g., BLOOM [18], BayLing [20], etc), yet there are also other models that possess multilingual capabilities [46, 21]. To distinguish LLMs from multilingual LLMs, we propose a definition of “LLMs with multilingualism”.

3 Large Language Models with Multilingual Capability

Based on the training paradigm, this survey divides existing multilingual LLMs into two categories: (1) the foundational LLMs trained from scratch and (2) the continually trained LLMs on top of the foundational models. In Table 1, we present the statistics of the representative LLMs with certain multilingual capabilities in the past three years.

3.1 Training from Scratch

To obtain a language model with multilingual capability, a common practice is to leverage all available data in different languages for training. The language sampling algorithms are usually applied to control the importance of each language. As shown in Figure 3, multilingual pre-trained language

Name	Release Time	Params	Affiliation	Base	Available	Support Languages
GPT-3 [30]	20-05	13B, 175B	OpenAI	GPT-2	Closed	-
mT5 [31]	20-10	13B	Google	T5	Open	101
ByT5 [32]	21-05	13B	Google	T5	Open	101
Gopher [33]	21-12	280B	DeepMind	-	Open	-
LaMDA [34]	22-01	137B	Google	-	Open	-
OPT [35]	22-04	175B	Meta	-	Open	-
PaLM [36]	22-04	8B, 62B, 540B	Google	-	Closed	124
mGPT [37]	22-04	13B	-	GPT-3	Open	61
BLOOM [18]	22-07	176B	BigScience	-	Open	46
FLAN-T5 [56]	22-10	11B	Google	T5	Open	60
FLAN-PaLM [56]	22-10	8B, 62B, 540B	Google	PaLM	Open	60
ChatGLM [57]	22-10	130B	ZHIPU	GLM	Open	2
GPT-3.5 [1]	22-11	-	OpenAI	GPT	Closed	-
XGLM [38]	22-11	7.5B	Meta AI	-	Open	30
LLaMA [3]	23-02	7B, 13B, 33B, 65B	Meta	-	Open	-
GPT-4 [2]	23-03	-	OpenAI	-	Closed	-
Alpaca [58]	23-03	7B	StandFord	LLaMA	Open	-
PANGU- Σ [39]	23-03	1085B	Huawei	-	Closed	26
Pythia [40]	23-04	12B	EleutherAI	-	Open	-
ParrotT [59]	23-04	7B	Tencent	Alpaca	Open	-
BigTrans [17]	23-05	13B	-	LLaMA	Open	102
PaLM-2 [41]	23-05	340B	Google	PaLM	Closed	-
Vicuna [60]	23-06	13B	LMSYS	LLaMA	Open	-
InternLM [42]	23-06	104B	Shanghai AI Laboratory	-	Open	-
BayLing [20]	23-06	7B, 13B	ICT/CAS	-	Open	-
PolyLM [43]	23-07	13B	DAMO Academy	-	Open	18
LLaMA-2 [3]	23-07	7B, 13B, 34B, 70B	Meta	LLaMA	Open	-
Baichuan-2 [44]	23-09	7B, 13B	Baichuan	-	Open	-
Qwen [45]	23-09	7B, 14B	Alibaba	-	Open	-
OpenChat [21]	23-09	7B, 13B	Tsinghua	LLaMA	Open	-
Mistral [46]	23-10	7B	Mistral	-	Open	-
Gemini [47]	23-12	-	DeepMind	-	Closed	40+
TigerBot [48]	23-12	7B, 13B, 70B, 180B	Tiger	-	Open	-
YAYI-2 [49]	23-12	30B	IACAS	-	Open	-
DeepSeek [50]	24-01	67B	DeepSeek AI	-	Open	-
GLM-4 [61]	24-01	-	ZHIPU	GLM	Close	-
Orion [51]	24-01	14B	OrionStar	-	Open	8+
TeleChat [52]	24-01	7B, 12B	China Telecom	-	Open	-
Aya [62]	24-02	13B	Cohere	mT5	Open	101
Claude3 [53]	24-03	-	Anthropic	-	Closed	-
InternLM-2 [54]	24-03	7B, 20B	Shanghai AI Lab	Open	-	-
LLaMA-3 [55]	24-04	8B, 70B	Meta	-	Open	30+
Phi-3 [52]	24-04	7B, 14B	Microsoft	-	Open	-

Table 1: An overview of representative LLMs (trainable parameters greater than 7B) that have certain multilingual capabilities in recent three years, including their release time, parameters, affiliation, base model, availability, and support languages.

PLMs before 2022 mainly consisted of two structures: (1) encoder-only designed for natural language understanding tasks and (2) encoder-decoder designed for natural language generation tasks. The parameters of these PLMs are not comparable with the existing LLMs. Recent studies show that according to the scaling law [276, 287, 288], the scale of the parameter has significant impacts on the performance of the models, i.e., the larger models lead to better performance. The researchers also observe that when the parameter scale of the language models exceeds a certain level, they not only achieve significant performance improvements but also find some special capabilities not observed within small-scale PLMs [276, 287]. To distinguish the difference in parameter scale, the research community specifies the term “LLMs” compared with PLMs based on a significant scale [289].

The multilingual capabilities of PLMs are primarily obtained by combining large amounts of multilingual data in the pre-training stage. Training on multilingual corpora through pre-training objectives such as mask language modeling (MLM) [271, 290] and next token prediction [272, 37, 30, 2, 3, 57, 36] endows these models with multilingual capabilities (e.g., BERT→mBERT and T5→mT5). In particular, mLongT5 [291] integrates the mT5 training dataset and the architecture of LongT5 and replaces the principle sentence generation (PSG) with mixture-of-denoisers (MoD) making it ideal for multilingual pre-training.

In addition to constructing multilingual data in the pre-training stage, the cross-lingual capabilities can also be improved by some specific methods (e.g., XLM [278], XLM-R [292], XLM-V [293], XGLM [38], PaLM-2 [41], PolyLM [43], mLongT5 [291]). For instance, the series of

XLM [278, 292, 293] proposes a translation language modeling (TLM) pre-training task, utilizing parallel multilingual data to improve cross-lingual model pre-training, and it extends MLM by using batches of parallel sentences instead of consecutive sentences. Moreover, the sampling strategies are important to balance the proportion of multiple languages in training data, which facilitates models to learn multilingual representation [38, 41, 294]. PoLyLM [43] integrates bilingual alignment within the training corpus and implements a curriculum learning strategy to maintain a balanced representation of various languages during the pre-training phase. The model proposes a multilingual self-instruct approach, enabling the automatic generation of diverse multilingual instructions for fine-tuning the model.

An inevitable part of the multilingual learning paradigm for PLMs is to deal with vocabulary [295, 296, 297]. The “out-of-vocabulary (OOV)” tokens hurts the translation performance naturally for multilingual learning [298]. To alleviate this issue, ByT5 [32] is a token-free model that operates directly on raw text (bytes or characters) which simplifies the process of different languages.

3.2 Continual Training

Another way to improve the multilingual capabilities of LLMs is continual training, which involves updating the model with new data rather than training a model from scratch. The main idea is to transfer knowledge from the foundation model and inject additional multilingual capability via the updated data, which does not require excessive computational or data resources and thus reduces the training cost.

This kind of training method utilizes existing monolingual or multilingual models for enhancing the specific languages ability (e.g., Chinese-LLaMA [299], Chinese-Alpaca [299], Chinese-Mixtral [300], CPM-2 [301], LLaMAntino [302], FinGPT [303], Sabiá [304], Bode [305]) or extending to a wider range of languages, such as BigTrans [17], Glot500 [306] and others [307, 308, 309]. A branch of work is to directly continually train the foundation models without any other techniques [303, 17, 308]. For instance, Muennighoff *et al.* [309] introduce xP3, a corpus consisting of tasks in 46 languages, and utilizes a cross-lingual multitask fine-tuning approach to fine-tune the BLOOM and mT5 on the newly created corpora, along with the English-only P3 corpus, resulting in the production of BLOOMZ and mT0Z. Considering the importance of vocabulary for multilingual models, prior work employs vocabulary extension to improve performance for low-resource languages [306]. Another branch of work is to introduce external parameters and strategies to learn new languages for multilingual models [307]. For instance, Chinese-LLaMA [299] integrates an additional 20K Chinese tokens into the original vocabulary to improve the Chinese ability, then employs the Low-Rank Adaptation (LoRA) approach to facilitate efficient training on Chinese corpus. CPM-2 [301] divides the pre-training into three phases, including the monolingual pre-training, bilingual pre-training, and mixture-of-expert pre-training. Multi-phase continual training, incorporating knowledge inheritance, offers a substantial reduction in computation costs compared to training from scratch. Moreover, Wang *et al.* [310] systematically investigate strategies aimed at reducing dependence on traditional language resources by leveraging bilingual lexicons to fine-tune pre-trained multilingual models for underrepresented languages.

3.3 Limitations and Future Directions on Training Paradigm

Although the existing LLMs demonstrate a certain superiority in non-English language, either by training from scratch or continuing training on top of a foundation model with extended language data, these approaches based on text knowledge only still face challenges in addressing more complex scenarios as listed below.

Low-Resource scenarios. The current training paradigm relies on large-scale data for the target language and task, e.g., supervised fine-tuning based on annotated data or continual pre-training based on unsupervised data. Both approaches require a substantial amount of data collection and thus constraints the effectiveness under low-resources or multi-scenario demands.

Knowledge conflict. As the foundation model expands the supported languages, its multilingual knowledge accumulates into the model through continuous new data available. The newly acquired knowledge from the new data would interfere with old knowledge stored in the parameters, and thus lead to a rapid decline in model performance. This is known as catastrophic forgetting [25], which might result in even completely forgetting previously learned knowledge.

Knowledge type. The existing multilingual NLP datasets, such as XNLI [256] and XQuAD [257], are constructed based on the translated texts from the original English version datasets [311, 312]. This is because of the high cost of obtaining multilingual data, especially in languages with limited annotations/translators. As a result, the essence of existing datasets lies in translation-based aligned knowledge, lacking cultural and domain knowledge in non-English contexts. This type of knowledge learned by the models reduces the distribution shift ability in the real-world scenario, leading to sub-optimal performance in specialized fields (e.g., finance and legislation).

To address the aforementioned problems and aim to improve the multilingual capabilities of existing LLMs, this survey proposes the following points for future exploration:

- *Training Strategies.* LLMs are data-driven and follow the scaling law which suggests that increasing the model size can guarantee better generalization, higher accuracy, and improved ability to capture complex patterns from data. However, such a paradigm results in the existing training strategies primarily focusing on expanding diverse data, while overlooking other multilingual training techniques, such as sampling algorithms [313, 314, 315], training objective optimization [316, 317], representation space [318, 319, 320], and others [238, 321]. The potential of these traditional multilingual training strategies has not been further explored in the current data effort paradigm in existing multilingual literature.
- *Architecture.* Existing LLMs mainly rely on monolingual backbone models, such as the standard Transformer, rather than undergoing architectural changes specifically targeting multilingual capabilities. For the other specific tasks, for example, LLMs designed for long texts introduce variations in positional encoding [322, 323], and those designed for multi-modal tasks enhance alignment between different modalities [324, 325] have been explored in some extent. Some advanced architectures like Mamba [326] have also shown remarkable performance and may become the backbone architecture for the next generation of LLMs. Thus, for multilingual tasks, it is essential to tailor the architecture with specific variations rather than merely augmenting data on the standard Transformer.
- *Sustainability.* When trying to utilize new data to enhance existing LLMs, a practical approach is to allow LLMs to continually learn from the updated data, akin to how the human brain operates, instead of creating new models [297, 263, 265]. Essentially, when new language data comes up, we aim to continually extend the language support of LLMs and improve their corresponding language capabilities while preserving the performance of those languages that the model has already demonstrated good performance, as forming a *lifelong/incremental learning* paradigm.

4 Multilingual Inference Strategies

This chapter investigates the development of robust multilingual inference strategies that are crucial for deploying language models across varied linguistic environments.

4.1 Direct Inference in Multilingual Models

Model	Inference	XCOPA	XStoryCloze	BELEBELE	XLSum	XQuAD	TyDiQA-GP
		Acc	Acc	Acc	Rouge-L	F1	F1
PaLM2-S [†]	En-Pivot	87.3	96.4	76.7	23.7	67.2	81.6
	Direct	89.7	96.8	77.8	26.8	70.7	83.8
PaLM2-L [†]	En-Pivot	89.6	97.8	84.3	25.4	78.7	81.0
	Direct	93.4	99.1	88.4	28.0	85.9	83.0

Table 2: The performance of LLMs using different inference strategies in the multilingual scenario. The best score is highlighted in **bold**. “[†]” indicates the results are quoted from [63].

With the advent of LLMs, efforts to enhance the diversity of training corpora lead to the inclusion of multiple languages alongside English. This approach endows LLMs with inherent multilingual capabilities, which enables these models to engage in direct multilingual inference. In other words,

the models can process the input in their native language without requiring translation into a pivot language. This capability is valuable as it maintains the authenticity of the linguistic and cultural nuances present in the original text, preventing semantic distortion or information loss that might otherwise occur during translation.

Recently, significant advancements have been made in enhancing the multilingual capabilities of LLMs, greatly increasing the number of languages covered and the performance in non-English inference. Advanced models such as GPT-4 [2] and PaLM-2 [41] demonstrate remarkable multilingual capabilities and support hundreds of languages. The support of multiple languages enables direct multilingual inference to become feasible and come up with a current focal point of LLM research. As shown in Table 2, we investigate the comparison between direct inference and the pre-translation method which translates the prompt into a high-resource language (e.g., English and Chinese) before inference. The direct inference achieves better performance compared to the pre-translation method based on both PaLM2-S and PaLM2-L. The result demonstrates that these two LLMs have multilingual capabilities without the need to use English as a pivot for other language tasks. Moreover, without the requirement of the translation step, the direct inference approach reduces computational overhead and simplifies the processing pipeline with higher efficiency. The observations also confirm the benefits of direct inference, including the preservation of linguistic authenticity, enhanced processing efficiency, and improved performance in low-resource languages.

4.2 Pre-Translation Inference

The direct inference may not work for all LLMs, depending on their multilingual capacities. The existing LLMs usually perform better on those high-resource languages than the low-resource ones, because of the imbalance ratio within the training data. To enhance the performance on low-resource languages, pre-translation inference standardizes the input with various languages by translating them into a pivot high-resource language (e.g., English or Chinese) before querying the LLMs, which is based on the proficiency of the pivot language within the LLMs [65, 327, 328]. However, the guarantee of this method relies on high-quality translation services available, which are not necessarily true for most languages. As a result, the translation errors would accumulate and the final output of LLMs would become wrong. Besides, translation on a pivot language obscures the cultural and linguistic nuances of the original text, which might also lead to inaccurate results. As an exploratory work, Liu *et al.* [64] explore the performance comparison between direct inference using native languages and inference after translating into English for multilingual tasks. Although translation can enhance the multilingual reasoning performance of English-centric LLMs, for high-resource languages and advanced LLMs, reasoning in native languages is more effective. Besides, pre-translating to English is a practical approach in terms of current LLMs as they are predominantly trained on English data from their pilot experimental results. However, with the development of direct multilingual inference, the intermediary step may not be necessary, which could allow more authentic interactions with LLMs under multilingual scenarios.

4.3 Multilingual CoT

The Chain of Thought (CoT) is an effective approach to enhance the performance of LLMs in complex reasoning [329, 330, 331], which has been extensively explored in existing studies, mainly focusing on English [332, 333, 334]. Liu *et al.* [64] propose several inference strategies to investigate the effectiveness of prompting the LLMs in the multilingual scenario. For instance, “Native-CoT” indicates that asking questions in the native language with the instruction “Let’s think step by step.” is translated into the native language. “En-CoT” indicates that asking questions in the native language but instructing reasoning in English with “Let’s think step by step in English.” and “XLT” [65] indicates that translating questions into English and solving them step-by-step. “Trans” indicates that using the translation systems to convert questions into English and then solving them step-by-step. The experimental results demonstrate that the overall performance of the CoT instruction in English (En-CoT) is better than the one with instruction in native languages (Native-CoT). The results demonstrate that the CoT is still effective while using English to form the instructions for non-English queries. On the other hand, multilingual CoT attempts to enhance the reasoning capabilities of LLMs across multiple languages [66]. The multilingual CoT approach is especially beneficial for complex reasoning tasks deeply embedded in specific cultural contexts, enabling more natural and intuitive problem-solving [67, 68]. The common practice of multilingual CoT is to prompt the LLMs to establish a step-by-step reasoning process in the original language of queries,

Module	Model	SA [335] Es-En (F1)	LID [335] Hi-En (F1)	MT [336] Hi-En (BLEU)	Summarization [337] Hi-En (ROUGE-L)
0-shot	XGLM-7.5B	68.52	0.27	1.43	5.92
	LLaMA-7B	51.28	0.44	1.44	3.37
	GPT-3.5-turbo	75.64	78.17	27.64	25.07
5-shot	XGLM-7.5B	61.06	16.91	3.28	5.18
	LLaMA-7B	58.77	15.55	5.14	6.01
	GPT-3.5-turbo	76.21	80.19	28.90	26.77
SFT	XGLM-7.5B	80.32	80.06	28.11	-
	LLaMA-7B	77.21	55.32	16.58	-

Table 3: The overall results on code-switching benchmark for LLMs. We report the 0-shot, 5-shot, and SFT performance. SFT only adapts to open-resource LLMs. “SA”, “LID”, and “MT” denote the Sentiment Analysis, the Language Identification, and the Machine Translation, respectively.

which can preserve linguistic and cultural nuances. In addition, the results corresponding to different sizes of LLaMA-2-Chat attend to examine the impact of scaling law with different multilingual inference strategies.

The understanding of the syntax and semantics of various languages, such as idiomatic expressions and culture-specific references is challenging for existing LLMs. A recent study [69] introduces a cross-lingual CoT reasoning instruction fine-tuning framework, which randomly replaces language fragments with those from low-resource languages, and mixes the original and target languages within a single query. Besides, this study creates multilingual CoT instruction training data, which can be used to supervise fine-tuning LLMs to reduce the performance gap across different languages. However, developing datasets for training and evaluating multilingual CoT capabilities requires a robust representation of linguistic diversity and detailed language-specific nuances, which should be further addressed.

4.4 Code-Switching

Code-switching refers to the phenomenon where communicators switch between two or more languages during linguistic interactions, based on contextual needs. This phenomenon is common in bilingual or multilingual communities, especially in spoken communication [338, 339]. For example, in conversations involving Chinese-English or Spanish-English direction, speakers may freely switch between languages depending on the fluency, precision of expression, or emotional needs of the dialogue [340, 341, 335]. Solving code-switching texts is an important and challenging task as the language IDs are not specified before LLMs inference [70, 71].

As shown in Table 3, we investigate the performance of LLMs on code-switching tasks. The results demonstrate that open-source LLMs cannot deal with the code-switching problem that needs to process multiple languages simultaneously under a single query. Multiple languages increase the complexity of processing and understanding language for models and LLMs need to continue to be supervised fine-tuned to accommodate simultaneous processing in this scenario. In addition, to improve the ability to deal with code-switching texts, researchers develop new pre-training techniques to enhance the understanding capacity of this linguistic phenomenon in LLMs [72]. For instance, Das *et al.* [342] modify the MLM [271] to enhance model reasoning performance in code-switching environments. By employing code-switching corpora, it masks tokens at the boundaries between two languages, thus forcing the model to learn semantic nuances at the points of language transition. Additionally, this work introduces modifications to the model structure by adding residual connections from intermediate layers to the final layer. An auxiliary loss function based on the representations of intermediate layers is also proposed, which enhances the cross-lingual ability to understand multiple languages in a single sentence. However, the cost of annotated code-switching data is expensive and it is challenging to investigate the non-parametric or semi-parametric method to adapt the code-switching problems.

4.5 Multilingual Retrieval Augmented Generation

Retrieval-Augmented Generation (RAG) is a methodology that integrates text generation with external knowledge retrieval, dynamically enhancing the quality of model response and accuracy by accessing relevant information [343, 344]. This approach enables the model to utilize up-to-date or specialized knowledge in text generation, thereby increasing its practicality and reliability. A main branch of the multilingual RAG adopts to retrieve knowledge from the open domain and applies it to the in-context (i.e., augmented prompt) [73, 74, 75, 76, 77, 78, 79, 80, 81]. In particular, Thakur *et al.* [82] propose NoMIRACL, a dataset across 18 languages, to evaluate the hallucination of LLM when given a piece of text in external retrieved knowledge. It consists of two parts, the non-relevant and the relevant subset, corresponding to the question and the passage which are non-related and related, respectively. The model is expected to answer “I don’t know” in the non-relevant subset, otherwise it is determined as a hallucination. In addition, hallucinations and off-target issues occur when incorporating LLMs with low-resource machine translation [83], where the RAG can mitigate these issues via improving the translation quality for low-resource directions [84, 85, 86, 87]. Overall, the RAG can effectively facilitate LLMs to generate more reliable responses, alleviating the issues of hallucination and factual error without fine-tuning. However, achieving substantial enhancements solely through the RAG method for low-resource languages, where LLMs struggle, poses a considerable challenge. Meanwhile, it is also challenging to build retrievers that can be used in low-resource languages [88].

4.6 Limitations and Future Directions on Inference Strategies

The multilingual inference strategies exhibit a diverse range of characteristics. Although existing methods contribute to the performance of LLMs to some extent in the multilingual scenario, they still have many limitations as follows.

Universal inference paradigm. Previous PLMs are task-specific and language-specific, indicating that it is essential to specify the language ID. For instance, we need to assign the language ID of input and output respectively when leveraging the M2M-100 for machine translation [345]. However, it is not required in the existing paradigm of LLMs, such as GPT-4. Due to the universality of LLMs, an aim is to keep them as task-agnostic and language-agnostic as feasible. Current LLMs employ a standardized approach for inference across all languages (either direct inference, pre-translation inference, CoT, or RAG). However, as shown in the experiments and analyses above, the inference strategies exhibit varied performances when faced with different LLMs, tasks, and languages. Therefore, a flexible and universally applicable paradigm is desirable to uniformly handle the environments of all languages (i.e., high-/medium-/low-resource languages).

Language-Specific characteristics. Existing multilingual inference strategies are primarily adapted from monolingual (e.g., English) strategies, lacking exploration of language-specific characteristics. For example, the prompt engineering for a low-resource language is derived from English instructions, but these prompts are more aligned with the habits of English speakers instead of native speakers. Therefore, the approach might pose challenges in harnessing the potential of native languages during inference with LLMs.

Emergence ability. One important advantage of LLMs is the emergence ability that is informally defined as “the ability that does not exist in small models but appears in large models” [346]. However, this advantage is not embodied significantly in multilingual scenarios. Thus, the performance of LLMs is far behind that of the English scenario, and difficult to outperform small language models. It is not only due to limitations during the training phase but also potentially influenced by inappropriate strategies during the inference phase.

Model collaboration. Existing inference pipelines are designed for single LLMs. Due to data scarcity in low-resource languages, it is challenging to address tasks for all languages within a single model [347, 348]. Considering that the smaller models excel at specific tasks or handling specific languages, which do not require large-scale data to optimize [349, 350, 351]. It is beneficial to leverage the strengths of both large and small models and solve tasks for different resource languages through model collaboration. The model collaboration that effectively bridges the large and small models is a direction yet to be explored for enhancing inference performance in the multilingual scenario.

5 Multilingual Information Retrieval

The task of Information Retrieval (IR) is to find the relevant documents that satisfy the information needs of the users (in the form of *queries*) from a large collection [352]. Multilingual IR studies the IR tasks in more than only English, and is generally categorized into the *monolingual*, *cross-lingual* and *multilingual* scenarios based on the language(s) of the queries and documents: Given a query in the language (L_1), *monolingual retrieval* aims to find relevant information from the same language as the query (L_1), *cross-lingual retrieval* finds relevant information from a different language (L_2), and *multilingual retrieval* finds relevant information from multiple different languages ($L_i, i \in \{1, \dots, n\}$). There are many surveys and discussions related to this section, including multilingual retrieval progress prior to neural IR [353, 354, 355, 356, 357, 358, 359, 360, 361], progress on general neural IR prior to the emergence of LLMs [362], and interplay of LLM and IR [363, 364, 365]. This section will focus on the multilingual aspect, especially the new opportunities of multilingual retrieval brought by LLMs (“LLM for mIR”), as oppose to the RAG methods (“mIR for LLM”) introduced in the Section 4.5 above.

5.1 Synthetic Training Data

Synthetic datasets for multilingual retrieval are traditionally created in two approaches: machine translation [115, 366], and natural semantic structures [367], e.g., title–passage [368], inner-connected Wikipedia links [369, 370], and so on.

Spearheaded by InPars [89, 90, 91] and Promptagator [92], LLMs bring the third approach, which generates large-scale synthetic data for training retrieval models in an affordable way. While the above two works focus on English, following this line, SwimIR [93] builds large-scale training data for both cross-lingual and monolingual retrieval tasks. JH-POLO [94] build cross-lingual retrieval training data by generating English queries based on non-English positive and negative passages using LLM. It has also been found that synthetic data generated by LLM could improve the performance of LLM-based embedding models: mE5-Mistral [95] generate synthetic data by GPT-3.5 and GPT-4 on 93 languages. Gecko [96] built Few-shot Prompted Retrieval dataset (FRet). Both works adopt a two-stage generation pipeline: in the first stage, the LLM generates the query and the task description(s) given passage(s); in the second stage, while both works produce positive and (hard) negative passages, Gecko asks LLM to score the positive and negative passages from candidates returned by a retriever, while mE5-Mistral lets the LLM generate the positive and negative passages based on given requirements. Additionally, Arctic-Embed [97] find that hard negative mined from existing corpora is in higher quality compared to the ones generated by LLM.

5.2 Multilingual Retrievers

According to the taxonomy by Lin and Ma [371], the retrievers are categorized into the unsupervised sparse, supervised sparse and, supervised dense models, where the dense models could be further categorized into the single-vector and multi-vector models. This section briefly introduces models under each category that are extended into multilingual scenarios, and the impact of LLMs on the category if applicable.

The *unsupervised sparse models* refers to the bag-of-words exact matching ranking algorithms, e.g., BM25 [372]. It requires language-specific analyzers to extend the models into the multilingual scenarios, which are designed based on expert knowledge on the target language. This category of models serves a strong baseline itself on the mono-lingual retrieval task [373], or on the cross-lingual and multilingual retrieval when used together with the query or document translation [374, 375, 376].

The *supervised sparse models* learn the weight per term from the training data rather than using the collection statistics as unsupervised sparse models [377, 378, 379, 380, 381, 382]. Works extending this category into the multilingual scenarios are mainly surrounding SPLADE on monolingual retrieval [383] or cross-lingual retrieval [384, 385]. All above works are based on BERT-level multilingual pretrained models.

The *supervised dense models* category, including both the single-vector and multi-vector dense retrieval models, resides most of the work on the multilingual IR and LLM-related embedding models. The dense models was firstly extended into the multilingual scenarios by switching the backbones into mBERT or XLM-R [373, 386, 387]. Many methods that are found effective on

English also show similar performance improvements on the multilingual scenarios, for example, extending the pretraining and pre-finetuning corpora into multilingual unsupervised data or translated corpora [115, 387], knowledge distillation from rerankers [387] or even from English retriever [388]. Recently, more multilingual embedding models are proposed with large-scale pre-training and pre-finetuning. Open-source models include mE5 [98], mGTE [99], and BGE [100], whereas [101, 102, 103] provide black-box API for the multilingual embedding models.

Many LLM-based embedding models emerge these years: Focusing on the retrieval task, RepLLAMA [104] shows that LLM-based embedding models could be fine-tuned to achieve better in-domain effectiveness and out-of-domain generalizability. PromptReps [105] shows that the LLMs could be prompted to generate dense and sparse representations to achieve competitive zero-shot performance on the passage retrieval tasks. More works emerge with the target of unifying multiple embedding tasks into a single model [106]. The modification on the model design includes: enabling bi-directional attention [107, 108, 109], adding instructional tuning [107, 110], adapting Matryoshka representations [101, 111], and merging multiple models [112]. Training wise, AngIE [113] proposed angle-optimized text embedding models to eliminate the gradient saturation zone of cosine function. Yet most of the work along this line focuses on English embedding models, only Gecko [96] supports the multilingual inputs. Additionally, NLLB-E5 [114] propose to integrate NLLB models with E5 to enable the multilingual ability of English embedding models.

Works extending *multi-vector dense* retrieval models into multilingual scenarios mainly focus on ColBERT [389], dubbed mColBERT [115, 116] or ColBERT-X [117]. The extension covers monolingual retrieval [115, 122, 116], cross-lingual retrieval [117, 118, 119], and multilingual retrieval [120, 121]. Other than adopting the default model structure, ColBERT-XM [122] adds modular language-specific adapter in XMOD architecture, which shows competitive zero-shot monolingual retrieval performance. BGE-M3 [123] unites the single-vector dense, multi-vector dense and sparse models by distilling the knowledge from the ensemble of the three types of models into each single models, demonstrating strong on both monolingual and cross-lingual retrieval tasks.

5.3 Multilingual Rerankers

Early works multilingual neural rerankers are mostly based on mBERT [390], exploring the translation configuration on the training and inference stages [391, 392]. Later works found that mMiniLM and mT5 serve as better backbones as multilingual rerankers [115, 124].

Recently, a line of works explored using LLM as the zero-shot rerankers in retrieval initiated by RankGPT [125] and LRL [126], dubbed listwise rerankers, followed by works on distilling from the GPTs with enhanced training techniques [128, 129], and on building listwise reranker without relying on the close-sourced GPT-models [130]. One criticism on the listwise rerankers is the sequential inference step caused by the sliding-window aggregation step that merges the ranked documents from different batch. To address the issue, different inference and aggregation strategies have been proposed, including Setwise [127] and TourRank [131]. Limited works explored the listwise rerankers on the multilingual IR tasks, the only one to our best knowledge is Adeyemi et al. [132], which evaluated GPT-based listwise reranker on CIRAL [393], a cross-lingual retrieval benchmark on African languages, finding that GPT-4 yields competitive zero-shot performance on the task and even on par with the zero-shot results with machine-translated documents on some of the languages.

5.4 Challenges and Future Directions on Multilingual Information Retrieval

The aforementioned existing studies demonstrate how LLM-based methods enhance the effectiveness and out-of-domain generalization in information retrieval tasks. Beyond integrating LLMs as components in the established retrieval-reranking pipeline, LLMs also open new possibilities to the paradigm of search process and broader information access: For example, Li et al. [394] and Lee et al. [395] both propose a unified generative framework that integrates retrieval and question answering, where retrieval is considered as an inherent part together with the other generative tasks rather than as a separate component as in RAG.

That said, challenges present in deploying LLM in assessable search systems, which include inherently high latency for indexing and searching, as well as high computational demand during inference and fine-tuning. Current work that distills knowledge from LLM to smaller models strike a balance between effectiveness and efficiency [396].

Model	Prompt-Based Jailbreak						
	JailBroken [135]	GPTFUZZER [398]	AutoDAN [140]	DeepInception [399]	ICA [400]	PAIR [401]	ReNeLLM [402]
GPT-3.5-turbo	100%	35%	45%	66%	0%	19%	87%
GPT-4-0613	58%	0%	2%	35%	1%	20%	38%
LLaMA-2-7B-Chat	6%	31%	51%	8%	0%	27%	31%
LLaMA-2-13B-Chat	4%	41%	72%	0%	0%	13%	69%
Vicuna-7B-v1.5	100%	93%	100%	29%	51%	99%	77%
Vicuna-13B-v1.5	100%	94%	97%	17%	81%	95%	87%
ChatGLM-3	95%	85%	89%	33%	54%	96%	86%
Qwen-7B-Chat	100%	82%	99%	58%	36%	77%	70%
Intern-7B	100%	92%	98%	36%	23%	86%	67%
Mistral-7B	100%	99%	98%	40%	75%	95%	90%

	GCG series	Multilingual Jailbreak		
	GCG [134]	Multilingual [143]	Cipher [148]	CodeChameleon [403]
GPT-3.5-turbo	12%	100%	80%	90%
GPT-4-0613	0%	63%	75%	72%
LLaMA-2-7B-Chat	46%	2%	61%	80%
LLaMA-2-13B-Chat	46%	0%	90%	67%
Vicuna-7B-v1.5	94%	94%	28%	80%
Vicuna-13B-v1.5	94%	100%	76%	73%
ChatGLM-3	34%	100%	78%	92%
Qwen-7B-Chat	48%	99%	58%	84%
Intern-7B	10%	99%	99%	71%
Mistral-7B	82%	100%	97%	95%

Table 4: An overview of **Greedy Coordinate Gradient**, **Prompt-Based** and **Multilingual** attack methods jailbreaking for LLMs on the AdvBench [404]. The evaluation method is consistent with the EasyJailbreak [404] framework, which uses GPT-4-turbo-1106 as the scoring model and the evaluation prompts from GPTFUZZER [398].

Beyond the general challenges of LLM-based retrieval, The open-source state-of-the-art LLM usually have fewer supported languages compared to encoder-only or encoder-decoder models: LLaMA-3 [397] and Command-R+[‡] support around 20 languages, while encoder-only models such as mBERT and XLM-R support 100 languages, and translation-targeting encoder-decoder such as NLLB support 200 languages. Current retrieval methods are applied to LLMs, which mainly regard LLMs as a knowledge store. However, in low-resource languages, LLMs lack generation capabilities and have not been trained with large-scale data, thus they are difficult to serve as a reliable source of knowledge. How can the above methods be applied to languages not yet supported by LLM but available in smaller language models?

6 Security of Multilingual Large Language Models

With the wide deployment of LLMs in various applications, increasing security concerns have emerged. This chapter introduces the security aspects of LLMs in the multilingual scenario, specifically exploring attack methods and the existing research on defense mechanisms. Since there are no clear definitions to distinguish whether an LLM is a multilingual model or not, this survey not only focuses on security issues specific to different languages but also provides a perspective on common security issues. The investigated methods work equally across all languages and can be easily transferred to multilingual scenarios, providing inspiring thoughts on future research.

6.1 Attack Methods

To explore the security of LLMs, a red team attack on LLMs is required. A red-team attack is a cybersecurity exercise where a group of ethical hackers, known as the red team, simulate real-world cyberattacks on an organization’s systems, networks, or infrastructure. The goal of a red-team attack is to identify vulnerabilities, weaknesses, and potential security breaches that malicious actors could exploit [405]. A common practice is the “jailbreak” attack which typically refers to the unauthorized access or modification of the underlying code or functionality of models. Essentially, it involves breaking out of the constraints or limitations imposed by the design or usage policies of LLMs. It includes techniques to bypass security measures or enable functionalities that are not intended or permitted by the developers.

According to the criteria in existing studies [153, 404], the jailbreak methods on LLMs can be divided into three types: Greedy Coordinate Gradient (GCG) jailbreak [133, 134], prompt-based

[‡]<https://docs.cohere.com/v2/docs/command-r-plus>

Characteristic	Attack Method Types		
	GCG series	LLM-Based	Rule-Based
<i>The LLM type for optimizing prompt</i>	Target LLM	Agent LLM	-
<i>The status of Jailbreak prompt</i>	Dynamic	Dynamic	Static
<i>The form of generating new prompts</i>	Auto	Auto	Manual

Table 5: An overview of comparison among **GCG**, **Prompt-based** and **Rule-based** jailbreak methods. Target LLM and Agent LLM refer to the attacked LLM and other LLMs that are different from target LLM, respectively.

jailbreak [135, 136, 137, 138, 139, 144, 140, 141] and multilingual jailbreak [142, 143, 144, 145, 146, 147, 148, 149]. In this section, we focus on these three jailbreak methods, especially the multilingual jailbreak. The first two methods involve generic attacks on LLMs, and the latter emphasizes jailbreaking through multiple languages. All these methods are aimed at bypassing the security measures of LLMs to generate malicious information. Since most of the jailbreaking methods are customized, the effectiveness of each method varies depending on the specific LLMs. To provide a comprehensive comparison, we investigate the performance of different jailbreaking methods across various LLMs based on a unified evaluation framework, as shown in Table 4.

6.1.1 Greedy Coordinate Gradient Jailbreak

The Greedy Coordinate Gradient [134] is an attack method based on greedy algorithms and gradient metric design hints. It first creates a seed prompt, and then iteratively replaces the tokens. The best prompt for attacking the model is determined by calculating the gradient. Sitawarin *et al.* [133] propose GCG++ to increase the attack success rate (ASR) of the original GCG method on LLaMA-2-7B. On the basis of the original GCG, they replace the cross entropy loss with multi-class loss to avoid vanishing gradients in the *Softmax*, which is effective in attacking LLM. Another discovery is that LLMs such as LLaMA-2-7B are format sensitive, having a strong prior for predicting a space token at the beginning of the model response. GCG++ adds a simple format-aware target string (*i.e.*, “[ASSISTENT]:” before the input prompt to force the model to output harmful content. Through the two changes, GCG++ increases the GCG attack success rate on LLaMA-2-7B from 56% to 80%.

6.1.2 Prompt-Based Jailbreak

The prompt-based methods aim to mislead LLM into generating harmful content based on specifically designed templates. Among them, LLM-based [140, 406, 133, 401, 138, 398, 402, 407] and rule-based [135, 399, 136, 137, 144] are the two common used methods for designing attacking prompts. The differences between GCG, LLM-based, and rule-based are presented in Table 5 with various aspects.

Rule-based jailbreak methods are those works that design specific prompts to formulate rules for LLMs [135, 399], or directly collect prompts from various channels such as websites and forums [136, 137, 144]. Rule-based jailbreak methods rely more on human participation because these rules are customized based on empirical experience in specific scenarios. Thus, the produced prompts are effective in a narrow area but lack versatility and are static, which can be easily defended.

LLM-based jailbreak methods leverage the instances of LLMs to optimize existing attack prompts or generate new jailbreak prompts. Different from the GCG series approaches, the principle of LLM-based jailbreak methods acts as using an agent LLM to attack a target LLM. Existing studies [140, 406, 133, 401] usually take the agent LLM as an optimizer, scoring module or evaluator to optimize prompts for attackers. Some other methods [138, 398, 402, 407] use the generation capabilities of LLM to perform multiple operations such as rewriting and shortening feasible attack prompts. They also wrap harmful prompts with scenarios to avoid safe alignment. These operations based on LLMs can enable the original attack prompt to evade the security alignment policy.

6.1.3 Multilingual Jailbreak

Due to the unequal security alignment of LLMs across different languages, with higher security in high-resource languages compared to low-resource languages, the multilingual jailbreak meth-

ods [142, 143, 145, 146, 147] attend to cheat the LLMs via the alignment vulnerabilities between high-resource and low-resource language. Some other methods [148, 149, 403, 135] use special encoding or ciphers to disguise harmful prompts to achieve jailbreak, which can be considered as a type of special language.

The existing studies on the potential security risks of LLMs, primarily focused on the usage of English scenarios. Under the multilingual scenario, Deng *et al.* [143] reveal the presence of multilingual jailbreak challenges within LLMs, who divide potential risks into two scenarios: (1) *unintentional* and (2) *intentional*. The unintentional scenario involves users inadvertently bypassing the safety alignment by querying LLMs with non-English prompts, while the intentional scenario refers to users intentionally combining malicious instructions with multilingual prompts. Compared to high-resource languages, low-resource languages are approximately three times more likely to encounter harmful content in GPT-3.5 and GPT-4, and thus the LLMs are much easier to attack via low-resource languages. This could also be the reason why the model attack approaches are designed with low-resource languages within these two scenarios.

For the *unintentional* scenario, Shen *et al.* [142] indicate that the bottleneck in cross-lingual alignment lies within the training stage of LLMs. Thus, they study the effect of instruction tuning with RLHF and supervised fine-tuning (SFT) on the HH-RLHF dataset [408]. The results show that although training with high-resource languages can improve model alignment, the effect of training with low-resource languages is still negligible. For the *intentional* scenario, various prompts are designed to bypass the security defenses of the LLMs via high-resource languages. In particular, Yong *et al.* [145] successfully circumvent the safeguard of GPT-4 by translating unsafe English prompts into low-resource languages. They propose the LRL-Combined Attacks approach to achieve 79% ASR on the AdvBench dataset [134]. Xu *et al.* [146] study a new type of black box jailbreak attack, Cognitive Overload, which is specifically designed for the cognitive structure and processes of LLMs. With Google Cloud API, they translate original English harmful instructions from AdvBench and MasterKey [138] into 52 other languages and propose multilingual cognitive overload [409, 410] to hinder in-context learning and inference process when the knowledge exceeds the limited capacity of LLMs [411]. By using Google Cloud API to translate English to other 52 languages and nllb-200-distilled-1.3B to translate other non-English responses back to English, they conducted a multilingual version of their attack method. With multilingual Cognitive Overload, their results show that LLMs are more vulnerable to non-English adversarial prompts. The observation indicates that the further a language is from English, the more effective the malicious prompt conveyed is in attacking LLMs. Moreover, Li *et al.* [147] conduct an extensive empirical study on multilingual jailbreak attacks, which develops a novel semantic preservation algorithm to create multilingual jailbreak prompts. With these prompts, they reveal patterns in multilingual jailbreak attacks and implement fine-tuning mitigation methods for defending against cross-lingual jailbreak attacks.

Password jailbreak. From the perspective of writing scripts, special encoding or password can be considered as a language conversion, i.e., an English prompt can be converted into a password representation by encryption. Though the password representation can also be converted to English or other languages via decryption, the encrypted prompts cannot be understood directly by humans but by the LLMs, and thus could lead to secure alignment fails. For example, Huang *et al.* [149] propose the *generation exploitation* attack to manipulate variations of decoding methods (e.g., greedy decoding and sampling-based decoding), which can easily disrupt model alignment because existing alignment procedures are based on default decoding settings. Vulnerabilities are exposed when configurations of decoding change slightly. Yuan *et al.* [148] propose a novel framework CipherChat to examine the generalizability of safety alignment to non-natural languages, where the user can chat with LLMs through cipher prompts. Furthermore, Lv *et al.* [403] introduce a hypothesis for the safety mechanism of LLMs: intent security recognition followed by response generation. Following this hypothesis, they propose CodeChameleon to transform queries into decryptable formats with custom Python functions. This approach enables the modification of the original query and achieves state-of-the-art ASR on 7 LLMs. Besides, Wei *et al.* [135] propose Jailbroken, which obfuscates the queries using base64 to bypass the safety training of LLMs. They observe that LLMs can understand base64 but cannot defend against attacks under base64.

Other jailbreak. Apart from the aforementioned methods, Shayegani *et al.* [412] combine an image targeted towards toxic embeddings with generic prompts to accomplish the jailbreak, which utilizes four embedding space target strategies to poison the vision encoder. Their attacks achieve

Model	Attacker: PAIR [401]		
	No Defense	SmoothLLM [150]	Perplexity Filter [152]
GPT-3.5-turbo	76%	12%	15%
GPT-4-0125-preview	50%	25%	43%
LLaMA-2-7B-chat	4%	1%	4%
Vicuna-13B-v1.5	82%	47%	81%
	Attacker: GCG [134]		
	No Defense	SmoothLLM [150]	Perplexity Filter [152]
GPT-3.5-turbo	34%	1%	1%
GPT-4-0125-preview	1%	3%	0%
LLaMA-2-7B-chat	2%	1%	0%
Vicuna-13B-v1.5	58%	1%	1%
	Attacker: JBC [416]		
	No Defense	SmoothLLM [150]	Perplexity Filter [152]
GPT-3.5-turbo	0%	0%	0%
GPT-4-0125-preview	0%	0%	0%
LLaMA-2-7B-chat	0%	0%	0%
Vicuna-13B-v1.5	79%	64%	79%

Table 6: An overview of defense methods under jailbreaking on listed LLMs. The evaluation method for the Attack Success Rate (ASR) indicator is consistent with JailbreakBench [417]. The responses of LLMs are evaluated using LLaMAGuard-7B.

87% and 63.3% ASR on two vision-language models, LLaVA [325] and LLaMA-Adapter V2 [413], respectively. Rando *et al.* [414] embed a “jailbreak backdoor” into the LLM by poisoning the RLHF training data. Then, users can easily achieve jailbreak by using a trigger word like the “sudo” command in the Linux system. Wolf *et al.* [415] propose a theoretical approach Behavior Expectation Bounds (BEB) that investigates several limitations of alignment in LLMs, which exposes fundamental problems and emphasizes the necessity of designing reliable mechanisms to ensure AI safety.

6.2 Defense Methods

Only a few studies attempt to address the defense methods in the security LLMs, which can be categorized into open-source and close-source LLMs. Based on the available access to the open-source LLMs, the existing studies [143, 147, 150] enhance the security by fine-tuning the foundation models with security instructions. For closed-source LLMs, previous works [154, 153, 150, 152] defend the risks by auditing the input prompts with various security judgment strategies. However, these simple mechanisms cannot achieve satisfactory performance, as shown in Table 6. The results demonstrate that it is difficult to completely eliminate the generation of unsafe content, regardless of the defense mechanism. And “SmoothLLM” [150] performs better than “Perplexity Filter” [152] but still generates over 10% unsafe content in most scenarios. It indicates that current defense methods for LLMs are in the early stages and require further exploration.

6.2.1 Defense Methods for Open-Source LLM

Robey *et al.* [150] propose SmoothLLM, a compatible defense method that acts as a wrapper to smooth the outputs of LLMs by perturbing original attack inputs. Although effective in prohibiting the attacking intent, it also disrupts the semantics of the original input and leads to performance degradation. Deng *et al.* [143] propose a data augment defense framework SELF-DEFENSE to defend the attacks for both unintentional and intentional scenarios. The key idea is to translate some English seed examples into a target language and then merge the language-specific corpora into the original dataset. Li *et al.* [147] implement a fine-tuning mitigation method based on their multilingual jailbreak prompts dataset, reducing the attack success rate by 96.2%. Zhou *et al.* [151] introduce Robust Prompt Optimization (RPO) to LLM security by minimizing the confrontation loss. With less impact on benign cues, the success rate of attacking GPT-4 with GUARD [141] dropped from 96% to 4%.

6.2.2 Defense Methods for Closed-Source LLM

For closed-source LLM, the defense algorithms mainly focus on dealing with the model inputs. Jain *et al.* [152] introduce a filter method, judging the danger of the input based on the perplexity. Wu *et al.* [153] propose a simple and effective defense method SELFDEFEND, which incorporates a shadow stack to check whether harmful prompts exist in the input. Li *et al.* [154] introduce a Rewindable Auto-regressive Inference (RAIN) approach, which has the same evaluation setting as SELFDEFEND but focuses on the output of LLMs. The key component is to leverage another LLM to score the output content and determine whether the output contains harmful content, which achieves good results on LLaMA-base models.

6.3 Limitations and Future Directions on LLM Security

In previous sections, we provide a detailed introduction to the research achievements in attack and defense in terms of LLMs security. Most of the current research on LLM security is tested on those popular models (i.e., GPT-3.5, GPT-4, and LLaMA) with multilingual capabilities. Based on the summary of existing approaches for general attack and defense, we explore the following two aspects as future directions: (1) *Jailbreak by targeting the multilingual ability of LLMs.* (2) *How to improve the robustness of LLMs in multilingualism.*

6.3.1 Jailbreak by Targeting the Multilingual Ability of LLMs

Low-Resource language attack. Although LLMs already have strong multilingual capabilities, they cannot remedy the weakness of low-resource languages in the corpus. The ability of LLMs to identify harmful contents in low-resource languages becomes much worse. Existing studies [145, 143, 142] explore a lot in low-resource languages, while only focusing on GPT-4 with incorporated translation models. Such a pipeline would inevitably introduce noise. Meanwhile, the evaluation standards should be improved to identify the security capacity of LLMs.

The asymmetry between different languages. Language security is highly culturally specific, and each language has its own security vulnerabilities, leading to asymmetry. For example, the word “uso” has insulting connotations only in Basque, thus it needs specific supervised tuning for each language, which is difficult to transfer from other languages. This contradicts the traditional multilingual methods, where knowledge between different languages can be mutually beneficial [264, 265]. Xu *et al.* [418] empirically validate the presence of multilingual human values within LLMs, encompassing many categories of human values across multiple languages and LLM series. However, the problems of asymmetry between different languages have risen, and no existing studies about it.

Customized encryption and language rules. To bypass the security mechanism of LLMs, an innovative way to create a new language “X” by customizing some language or encryption rules [403, 149, 148] from the original input. This is based on the translation paradigm, which can be viewed as a mapping function to transform character set A to character set B. Thus, exploiting the potential loopholes when aligning LLMs in different languages becomes an important problem.

Misleading information in specific languages. The prior method attempts to assign a word with a specific meaning by embedding a backdoor or directly defining it through dialogue [414, 141]. For instance, Rando *et al.* [399] insert the word “SUDO” at the end of the query, causing the LLM to misunderstand and bypass the security defenses. It provides insight for attacking the LLMs through multilingual languages. People can introduce words or phrases with specific meanings into queries provided to LLMs. It can lead to the model misunderstanding the meaning of queries, which results in the generation of harmful information. In particular, the polysemous phenomenon that is prevalent in most languages can be used to mislead LLMs into producing prohibited content.

6.3.2 Robustness of LLMs with Multilingualism

Existing studies intend to attack LLMs to find some leaks, rather than to improve the defense ability and robustness of LLMs. However, an attack or jailbreak cannot ensure the development of LLM security. In this section, we will discuss the potential solutions for improving the security and robustness of LLMs.

Model	Params	Base Model	Training Corpus				
			Name	Non-English proportion	Translated	Size	Languages
BioMistral [156]	7B	Mistral-7B	PMC	1.25%	×	3B	10
MMedLM2 [157]	7B	InterLM2-7B	MMedC	58%	×	25.5B	6
Apollo [158]	0.5/1.8/2/6/7B	Qwen/Gemma/Yi	Apollo	33.72%	×	2.5B	6
Medical mT5 [160]	0.77/3B	mT5	-	66.67%	×	3B	4
L2M3 [159]	70B	Meditron& SeamlessM4T	-	80%	✓	0.9*5B	5

Table 7: An overview of the existing competitive LLMs with multilingualism in the medical domain. **Languages** denotes the number of languages included in the training corpus. **Non-English proportion** denotes the proportion of non-English languages in the training corpus. The training dataset of L2M3 is obtained by translating English into four low-resource languages: Telugu, Hindi, Swahili, and Arabic.

Adversarial training with multilingual samples. Inspired by Mazeika *et al.* [419], the proposed method enhances defense and robustness using adversarial training. Unlike fine-tuning on fixed datasets with harmful prompts, they propose a Robust Refusal Dynamic Defense to fine-tune the LLM on a dynamic pool of samples, which are continuously updated through a strong optimization-based jailbreak method. It is feasible to incorporate multilingual data into the sample pool using multilingual jailbreak methods which are more practical in attacks, making the data in the sample pool more diverse and advantageous for adversarial training. Besides, adversarial training can be introduced in the pre-training stage or fine-tuning stage of LLMs. As a result, the safety and robustness of LLMs with multilingualism can be enhanced at the root by adversarial training.

Multilingual security alignment with data augmentation. Similar to the approach of enhancing LLMs instruction-following capabilities and human values proposed by SFT and RLHF [1], effective data augmentation is the direct way to improve multilingual alignment. Thus, it is beneficial to explore ways to construct multilingual security datasets facing the localization of security information across languages. Depending on the business or scientific requirements, the datasets can contain different harmful question pairs and languages and then fine-tune the generic LLM with customized security datasets to construct a more robust version of LLMs.

Pre-processing prompts or post-processing outputs. Another approach with fewer resources is to add proxy security efforts in small models outside of LLMs. Before constructing prompts for the LLM, we can consider maintaining a harmful vocabulary list or using another LLM as an evaluator to extract dangerous elements and judge the security of prompts, which can help detect unstable factors. The judgment outputs from LLMs with scores indicate whether the risks are identified in the original inputs and need to be rewritten, similar to RAIN [154]. The general goal is to force LLMs to reject harmful answers or replace them with a rule-based template.

7 Multi-Domain LLMs in Multilingual Scenarios

The remarkable capabilities of LLMs have facilitated their application across diverse domains, including finance [27, 420, 421, 422, 423, 424], medicine [425, 426, 427, 428, 429, 430, 431], law [432, 433, 434, 435, 436], education [437, 438], transportation [439] etc. These domain-specific LLMs have demonstrated superb capability and promising perspective within associated domains. However, these LLMs are predominantly focused on English, while fewer cater to medium or low-resource languages, which dramatically hinders the utility of LLMs for a global audience. In this chapter, we present the pioneering multilingual studies conducted in the medical and legal domains[§], and we conclude by offering a comprehensive discussion on the emerging limitations and challenges.

7.1 Medical Domain

Previous works have made substantial strides in integrating LLMs into the medical domain [425, 426, 440]. In particular, Med-PaLM2 [441] notably achieves success by passing the US Medical

[§]To the best of our knowledge, at the time we conduct our survey, there are few pertinent works in other domains such as finance and education in multilingual scenarios.

Model	Benchmark				
	Name	Translated	Task	Metrics	Languages
BioMistral[156]	-	✓	Multi-choice QA	ACC	en,ar,zh,fr,de,pt,ru,es
MMedLM2[157]	MMedBench	✓	Multi-choice QA Rationale eval	ACC ROUGE-1/BLEU-1	en,zh,ja,fr,ru,es
Apollo[158]	XMedBench	×	Multi-choice QA	ACC	en,zh,fr,es,ar,hi
Medical mT5[160]	-	×	Sequence labeling Abstractive QA	F1 score	en, es, it, fr

Table 8: An overview of the existing cross-lingual medical benchmarks. For the Languages column, en, ar, zh, fr, de, pt, ru, es, ja, and hi represent English, Arabic, Chinese, French, German, Portuguese, Russian, Spanish, Japanese, Hindi, and Italian.

Licensing Examination. A common practice to adapt LLMs to the medical domain is to continually train the foundation model with domain corpus as introduced in Section 3.2 [26]. For instance, some models such as BioGPT [26], ClinicalGPT [442], PMC-LLaMA [443] and MedAlpaca [444] have been progressively fine-tuned foundation models on the medical related corpus, achieving dramatic medical performance enhancement over the original foundation model. In particular, ChatDoctors [445] resembles more of a multidisciplinary doctor, built on mixed data instead of solely medical data, capable of conducting patient-doctor dialogues, focusing on comprehensive inquiry services in the real-world scenario. In addition, in the realm of traditional Chinese medicine, HuaTuoGPT2 [446] that is fine-tuned on the Baichuan [44] with four types of data (distilled instructions/conversations from ChatGPT [1] and real-world instructions/conversations from doctors) and capable of mimicking the diagnostic abilities of doctors provides useful medical information. The experimental results demonstrate the capabilities of HuaTuoGPT2 surpassing those of the GPT-4 [2] in the 2023 national medical licensing examination of traditional Chinese medicine. However, the aforementioned models primarily focus on a limited set of high-resource languages and show varying degrees of performance degradation when extended to other languages. Such a phenomenon renders them unreliable, incapable, and insecure for application in linguistically diverse medical environments.

7.1.1 Medical LLMs in Multilingual Scenarios

To alleviate the issue of multilingualism in the medical domain, prior studies attempt to introduce multilingual medical corpus to enhance the multilingual ability of foundation models as shown in Table 7 and Table 8. Specifically, KBioXLM [155] adapts XLM-R [447] to the medical domain, which encompasses diverse medical knowledge. However, KBioXLM explores both the training corpus and evaluation data through translation, adapted to only two languages. To further address the limited availability of data beyond English, L2M3 [159] integrates Meditron-70B with the Meta SeamlessM4T machine translation system and separately fine-tune two components on four extremely low-resource languages. Garcia *et al.* [160] explore the medical LLM on encoder-decoder architecture based on mT5[31]. In the monolingual setting, both in-context learning (ICL) and SFT demonstrate considerable improvements compared to the foundation models [444, 443, 440]. MMedLM2 [157] underscores medical multilingualism by presenting a 25.5B massive cross-lingual training corpus covering a set of 6 languages. By training with this corpus, the multilingual ability of the model improves in all 6 languages, substantially surpassing the prior models and even rivaling GPT-3.5 and Gemini-1.0-pro. Meanwhile, to further assess the multilingual generalization of medical LLMs, BioMistral [156] introduces the first large-scale multilingual medical benchmark of LLMs into 7 languages. Similar to MMedLM2 [157], the Apollo [158] introduces a training dataset “Apollo Corpora”, a benchmark “XMedBench” and a collection of models ranging from 0.5B to 7B. To investigate the effectiveness of LLMs in the multilingual medical domain, they build a benchmark “XMedBench”. The comparison on the XMedBench demonstrates that prior multilingual medical LLMs are limited by the PubMed-Central corpus which is constructed based on the translation technique. To alleviate the issue of training data, they propose a training corpus “Apollo Corpora” which is rich with high-quality medical knowledge in each language. The corpus is meticulously collected from the local language and strictly prohibits any form of translation. As a result, the Apollo-7B is fine-tuned on the “Apollo Corpora” and can achieve better performance compared with prior multilingual medical LLMs with 70B parameters.

Categories	Details
Component	Pile of Law(292 GB), Eurlax Resources2 (179 GB), Native Multi Legal Pile (112 GB), Legal MC43 (106 GB)
Text Type Distribution	case law(51.4%), legal-mc4(16.6%), legislation(12.6%), contracts(9.23%), other(10.2%)
Top 5 Languages	Portuguese(15.93%), German(6.29%), Spanish(6.1%), French(3.32%), Italian(2.92%)
Last 5 Languages	Maltese(0.43%), Lithuanian(0.43%), Latvian(0.42%), Croatian(0.3%), Irish(0.08%)
Non-English proportion	48.27%
Total Words	86.36B

Table 9: The proportion of different languages in MultiLegalPile (689GB multilingual legal corpus).

7.1.2 Discussion and Challenges

Existing studies achieve remarkable progress in medical LLMs for the multilingual scenario, yet numerous challenges are pervasive. First, given the presence of language-specific knowledge that is highly pertinent to the local cultural, historical, political, and regional backgrounds, Wang *et al.* [158] examine whether these language-specific medical knowledge stimulates or deteriorates with each other and investigate whether the model always outperforms its counterpart trained solely on the monolingual language corpus when further trained on the whole multilingual corpus. For instance, the ability of the Spanish model trained in 6 languages surpasses that of a model only trained on a monolingual corpus in Spanish. Despite underlying conflicts between different language-specific medical knowledge and potential biases due to varying data, the performance boost suggests that cross-lingual joint training promotes the performance of medical LLMs, shedding light on the potential of cross-lingual pre-training. Thus, further exploration into the effectiveness of the real-world and pseudo data is yet to be undertaken.

Second, the ongoing scarcity of medical data in various languages persistently hampers further advancement. Although translation can mitigate some of these issues, it may not be effective due to the complex medical terminology and challenges in precise translation. Moreover, each language might carry unique cultural and contextual differences, resulting in abundant language-specific medical knowledge intricately linked to cultural, historical, political, and regional backgrounds. For example, traditional Chinese medicine embodies a rich history deeply intertwined with its cultural heritage, constituting a distinct medical system. Enabling our systems to grasp such language-specific medical knowledge and provide tailored medical assistance for specific groups poses a formidable challenge. Hence, exploring the underlying mechanism of language-specific medical knowledge integration is a promising research direction.

7.2 Legal Domain

7.2.1 Legal LLMs in Multilingual Scenarios

Similar to the medical domain, the applications of LLMs in the legal domain principally center on English. Several precedent attempts such as Chatlaw [436], Lawyer LLaMA [448], SaulLM [449], and LegalBERT [450] expand the general ability of LLMs to the legal domain. The universal performance degradation has been observed when expanding to other languages.

To address the specific problems in the legal domain, the proposed models need to adapt the legal features, which are factual, ambiguous, structured, and timely [451, 452], compared to other domains. Brugger *et al.* [162] take a preliminary step in the multilingual legal Sentence Boundary Detection (SBD) covering 6 languages. Christen *et al.* [163] conduct similar research on the multilingual Negative Scope Resolution (detecting words affected by negation cue) task and Baumgartner *et al.* [164] extend legal judgment prediction to German, French and Italian. Furthermore, for a comprehensive evaluation, Niklaus *et al.* [161] collect 11 natural language understanding legal datasets covering a total of 24 languages and 8 subdivisions, which is the first cross-lingual legal benchmark (LEXTREME) showing there is still improvement room even for the popular models like ChatGPT. After the ChatGPT series models were proposed, Nguyen *et al.* [453] implement a preliminary empirical comparison between ChatGPT and GPT-4 on the “COLIEE” benchmark [454, 455] encompassing Japanese and English, where GPT-4 consistently surpasses its predecessor but still falls behind human performance.

For a more in-depth exploration of LLMs in multilingual legal issues, Niklaus *et al.* [165] construct a multilingual legal-domain corpus with 689GB, MultiLegalPile, whose detail is shown in Table 9. They train two PLMs based on XLM-R [447] and the Longformer [322] with this corpus, achieving

the state-of-the-art performance on the LEXTREME [161] compared to XLM-R in most languages. Moreover, the English version of the model achieves state-of-the-art performance on 5 out of 7 tasks in LexGLUE [456], underscoring the exceptional cross-lingual ability and legal-domain expertise. Trautmann *et al.* [167] focus on employing legal prompt engineering (LPE) to enhance the capabilities of LLMs, thereby mitigating the challenges posed by the scarcity of cross-lingual legal data and the substantial computational resources required. Although improvements over baselines are observed, bridging the performance gap to match the supervised methods remains a significant endeavor.

7.2.2 Discussion and Challenges

Despite current efforts, there is still a lack of robust LLMs capable of effectively and comprehensively performing law-related multilingual tasks, highlighting the need for further exploration in this domain. Beyond the issue of data scarcity, the accumulation of language-specific legal knowledge compounds the complexity, as legal systems and jurisdictions vary significantly across regions. Given that existing LLMs already struggle with representing semantic features in low-resource languages, accurately capturing legal nuances across diverse jurisdictions poses an even greater challenge. Moreover, the temporal dimension adds complexity, as laws undergo constant revision, amendment, or abolition, necessitating that models remain continuously updated.

7.3 Limitations and Future Directions on Multi-Domain

Despite the remarkable advancements in multilingual LLMs, persistent limitations and challenges necessitate further exploration. This survey provides a brief discussion of the current limitations and potential improvement in the following two parts.

Data scarcity and translation issues. A powerful multilingual LLM, especially in specific domains, is predominantly hindered by the scarcity of domain data. Although knowledge transfer provides some relief, the issue of under-representation persists, particularly for low-resource languages, and becomes further compounded when extending to specific domains. Machine translation techniques offer a potential solution to mitigate this issue, however, they lead to new challenges [457]. On one hand, machine translation systems introduce errors, particularly when handling domain-specific terminology across multiple languages. Terms or phrases that native speakers do not use may also be included in the translated corpus. On the other hand, the models suffer from comprehensively understanding and accounting for the local and cultural context of the target language, complicating the task of in-depth and high-level feature learning and capturing.

Language-Specific knowledge integration In specific contexts such as the legal or financial domain, each language harbors distinctive knowledge influenced by diverse historical, cultural, and regional backgrounds. Beyond linguistic semantics, the challenge arises in capturing these nuances among various languages and integrating language-specific domain knowledge into LLMs. For example, disparities in legal definitions between European Council and USA jurisdictions, as well as the contrast between traditional Chinese medicine and Western medicine, indicate these challenges. Current LLMs face challenges in effectively understanding such language-specific knowledge, hindering their capacity to provide customized domain-specific assistance for diverse populations. Further research is necessary to explore how LLMs can integrate and leverage this particular type of knowledge.

These limitations highlight the need for further research efforts in the following directions:

- Development of strategies to construct high-quality, domain-specific multilingual datasets that preserve cultural context.
- Exploration of techniques for LLMs to effectively integrate and leverage language-specific in-domain knowledge.

By addressing these two challenges, researchers can pave the way for the development of truly robust and equitable LLMs that serve a global audience in multilingual scenarios.

Name	Release Time	Languages	Size	Sources	Affiliation
Amazon intent [168]	2022	49	2.02 GB	Amazon	Amazon
Amazon reviews [169]	2020	6	-	Amazon	Amazon
Aya [170]	2024	114	156 GB	Mixed	Cohere
Bactrian-x [171]	2023	51	-	-	MBZUI
Biblelp [172]	2024	861	581 MB	Bible	-
Bloom-lm [18]	2022	364	-	-	SIL International
CC100 [173] [174]	2020	109	185 GB	CC	Facebook
CulturaX [175]	2023	167	27 TB	mC4, OSCAR	University of Oregon
GPT-4 Prompts [176]	2024	5	1.05 GB	GPT-4	-
Guanaco [177]	2023	4	400 MB	-	University of Washington
HPLT [178]	2023	75	22 TB	CC, Internet Archive	HPLT project
IWSLT 2017 [179]	2017	10	4.24 GB	TED Talks	FBK
mC4 [180]	2019	101	9.7 TB	CC	Google
Mewsl-x [181]	2021	50	285 MB	WikiNews and Wikipedia	DeepMind
Minds14 [182]	2021	12	471 MB	Banking Assistant	PolyAI Limited
MLDR [184]	2024	13	-	Wikipeida, Wudao, mC4	BAAI
MMedC [185]	2024	6	105 GB	Multiple	SJTU
MQA [186]	2021	36	122 GB	CC	CLiPS Research
Multi-sentiments [187]	2022	12	141 MB	Multiple Sources	-
Multiconer [188] [189]	2023	12	338 MB	Wikipedia	Amazon
Open Subtitles [191]	2023	58	273 MB	Subtitles	-
OSCAR [192]	2020	166	6.3 TB	CC	University of Orego
Para-pat [193]	2020	15	2.57 GB	Google Cloud	University of Sheffield
Project Gutenberg [194]	2023	11	14.4 GB	eBook	Project Gutenberg
ShareGPT [195]	2023	5	1.08 GB	GPT / Human	Ronso
SREDFM [196]	2023	18	8.29 GB	Wikidata, Wikipedia	Babelscape
TED Talks [197]	2018	55	-	TED Talks	CMU
TED-talks-iwslt [198]	2012	104	25 GB	TED Talks	FBK
Toxi-text [199]	2023	55	1.96 GB	-	-
UD [200]	2023	102	2.19 GB	-	Universal Dependencies
Wikiann [201] [202]	2019	173	143 MB	Wikipedia	RPI
Wikipedia [203]	2024	322	71.8 GB	Wikipedia	Wikimedia Foundation
Wit Base [204]	2021	105	5.15 GB	Wikipedia	Google
xP3 [205]	2022	277	-	-	Coher For AI

Table 10: An overview and statistic detail of the representative multilingual data resource. We only include the large-size datasets with much more supported languages.

8 Multilingual Data Resource

LLMs are data-driven, thus the impressive learning capabilities of LLMs stem from their massive model sizes and extensive training datasets, which have been proven in high-resource languages. However, English stands as the closest approximation to the lingua franca, wielding dominance across various domains. With the largest number of total speakers, its prominence extends far and wide [458], where English reigns as the primary language of the internet [459, 460]. Meanwhile, English is the main language used in the higher economic status countries of the world, such as America, Britain, and other Western countries [461]. Therefore, existing data resources focus on the English-centric, which came at the expense of regional and indigenous languages, exacerbating language endangerment and economic marginalization [462]. Due to the lack of resources, this situation deeply restricts the development of multilingual models, and it is a vicious circle [463]. Moreover, low-resource languages suffer from lower quality, due to mislabeling or inadequate representation of native usage. This situation is especially prevalent with web-crawled data which predominantly consists of pornographic, nonsensical, or non-linguistic content [464].

As shown in Table 10, we collect as much large-scale multilingual data resource as is reliable. We can observe that the scale of existing multilingual resources is much smaller than that of English monolingual resources (only four datasets with the TB level). And the low-/medium-resource languages typically derive data from a narrower range of sources compared to their high-resource counterparts [465]. The available data mainly originates from sources, such as Wikipedia, the Bible, and Common Crawl. In addition, these data suffer from bias and fairness, which we will present in Section 10. For instance, a gender bias exists in Wikipedia, with studies revealing a persistently low percentage of women editing articles [466]. The vicious circle of multilingual data includes the issue of open source issues. Due to the high cost of high-quality multilingual resources, researchers and companies are reluctant to share resources in the open-resource community (i.e., “data island”) [467, 468, 469, 470]. This situation results in multilingual research staying at the data level

and ignoring the competition in the model paradigm. The united governments, companies, and researchers must start a virtuous cycle of multilingual data resources. Access to abundant, meticulously collected datasets in a language empowers researchers and developers to construct models and benchmarks. The abundance of models and benchmarks, in turn, fosters increased publication, facilitates communication, and promotes real-world application scenarios for companies. These outputs have the potential to attract more users, while government-mandated guidelines help generate non-toxic data, which can be repurposed for further research and development.

9 Multilingual Benchmark and Evaluation

With the emergence of novel models and algorithms, researchers inevitably scrutinize the capabilities by evaluating their performance on specific and challenging tasks [473]. Recently, LLMs have garnered significant interest in the academia and industry. The remarkable performance of LLMs has been proven on a variety of tasks, showing strong universality compared with prior PLMs limited to specific tasks. As shown in Table 11, to the best of our knowledge, we list the representative multilingual benchmarks after 2018 in which mBERT [271] was proposed. From the statistical results, we can observe many kinds of existing benchmarks, but there remain some issues with these benchmarks described as follows.

- *Lack of task types.* Most of the multilingual benchmarks focus on understanding tasks and lack generation tasks that mainly consist of machine translation and summarization. However, LLMs are generative paradigms, and generation tasks closer to the real world should be introduced to evaluate the effectiveness of LLMs in multilingual scenarios. In addition, the evaluation dimensions of LLMs need to be richer today, and there is a lack of evaluation tasks for LLMs, such as safety, agents, social simulation, etc.
- *Language culture and domain.* Existing multilingual benchmarks often rely on machine-translated text, which may contain errors or terms not commonly used by native language speakers. The benchmark of native usage with language culture habits is urgently required. Besides, the challenges within different language environments vary significantly, necessitating a thorough exploration of multilingual and multi-domain issues.
- *Unified framework.* The number of benchmarks is sufficient but there is a lack of an authoritative and unified evaluation framework, which can be updated over time, and the evaluation aspect is more comprehensive based on the proposed framework. This phenomenon can be attributed to the dominance of English and individuals’ focus on their native languages. To address this issue, collaborative efforts from the multilingual community are essential.
- *Data leakage.* The main differences between LLMs lie in the training data and model size. The existing systems primarily prioritize real focus on user experience (open test), rather than assessing effectiveness through closed test sets that align with fair training data. Thus, there is a potential for data leakage as models may have inadvertently learned from the test set, especially the closed LLMs. It requires the evaluation methods to adopt a more secure strategy to reduce the risk of data leakage.
- *Evaluation methods.* There are limitations in existing evaluation methods, particularly in generating tasks such as BLEU and ROUGE, thus manual evaluation is more reliable than automatic evaluation. However, due to the diversity of multilingual tasks, performing manual evaluation requires numerous language experts, which leads to increased costs and makes it challenging to achieve multilingual tasks. Therefore, reliable automatic evaluation methods are needed, which would also advance the development of evaluation techniques.

10 Bias and Fairness

10.1 Bias Categories

The bias of LLMs in the multilingual scenario can be divided into two categories: language bias and demographic bias [28]. Intuitively, the former is due to the imbalance of available training corpus for different languages [43, 457], where English possesses the most text corpus [462, 474, 475, 476], resulting in the performance degradation of the LLMs when generalized to other language settings [477, 478]. The demographic bias occurs due to embedded biases and misinformation

Name	Release Time	Languages	Parallel	Type	Affiliation
M-Hellaswag [220]	2023	35	✓	Commonsense NLI	University of Oregon
XNLI [256]	2018	15	✓	NLI	NYU
Multilingual-Fig-QA [235]	2023	7	×	NLI	CMU
NoMIRACL [190] [82]	2023	16	×	RAG	University of Waterloo
MIRAGE-Bench [471]	2024	19	×	RAG	University of Waterloo
Cross-Sum [211]	2021	45	✓	Summarization	BUET
XL-SUM [255]	2021	44	×	Summarization	BUET
Pmindiasum [240]	2023	14	✓	Summarization	IIIT Hyderabad
SEAHORSE [242]	2023	6	×	Summarization	DeepMind
M3LS [222]	2023	20	×	Summarization	IITs
BELEBELE [208]	2023	122	✓	Question Answering	Meta
BioInstructQA [209]	2024	7	✓	Question Answering	Avignon Université
MLQA [231]	2020	7	✓	Question Answering	Facebook
TyDiQA [248]	2020	11	×	Question Answering	Google
XOR-TyDi [386]	2021	11	×	Question Answering	University of Washington
XQuAD [257]	2020	10	✓	Question Answering	University of the Basque Country
MaXM [227]	2023	7	✓	Visual Question Answering	Google
CIRAL [393]	2024	4	×	Information Retrieval	University of Waterloo
MIRACL [183]	2023	18	-	Information Retrieval	University of Waterloo
LAReQA [472]	2020	11	✓	Information Retrieval	Google Research
STSB-multi-mt [245]	2021	10	✓	Text Similarity	-
MasakhaNER [224]	2021	10	✓	Named Entity Recognition	Masakhane
Multi-CoNER [233]	2022	11	×	Named Entity Recognition	Amazon
XCOPA [251]	2020	12	✓	Commonsense Reasoning	Cambridge University
XCSQA [252]	2021	11	✓	Commonsense Reasoning	USC
XStoryCloze [38]	2022	11	✓	Commonsense Reasoning	Meta
XWinograd [261]	2021	6	×	Commonsense Reasoning	Yandex
XCSR [262]	2021	16	✓	Commonsense Reasoning	USC
FLORES-200 [215] [216] [217]	2022	200	✓	Machine Translation	Meta
OPUS-100 [238]	2020	100	✓	Machine Translation	University of Edinburgh
Tatoeba-mt [246]	2020	93	✓	Machine Translation	Tatoeba.org
Humaneval-XL [219]	2024	23	✓	Code Generation	University of Copenhagen
ODEX [237]	2022	14	✓	Code Generation	CMU
MARC [223]	2020	6	×	Text Classification	Amazon
Masakhanews [225]	2023	16	×	News Topic Classification	Masakhane
MULTIEURLEXDOC [234]	2021	23	✓	Legal Topic Classification	University of Copenhagen
Sib200 [243]	2024	205	✓	Topic Classification	UCL
Afrisent [206]	2023	14	×	Sentiment Analysis	U.Porto
ASPEN [207]	2022	31	✓	Story Planning	Cambridge University
Crossmodal-3600 [212]	2022	36	✓	Image Captioning	Google
Exams [213]	2020	15	✓	Examination	Sofia University
Fairlex [214]	2022	5	×	Fairness	University of Copenhagen
GEOMLAMA [218]	2022	5	✓	Knowledge Diversity	University of California
M-MMLU [220]	2023	35	✓	NLU	University of Oregon
M3Exam [221]	2023	9	×	Examination	DAMO Academy
MASSIVE [226]	2022	51	✓	Intent Recognition, Slot Filling	Amazon
Mela [230]	2022	10	×	Linguistic Acceptability	SJTU
MGSM [66]	2022	11	✓	Mathematical Reasoning	Google
MMedBench [232]	2023	6	×	Medical	SJTU
Paws-X [239]	2019	7	✓	Paraphrase Identification	Google
SMILER [244]	2021	14	×	Entity and Relation Extraction	Samsung
TyDip [247]	2022	9	×	Identify Politeness Levels	UT-Austin
X-CLAIM [249]	2023	6	×	Realworld Claims	MBZUAI
X-RiSAWOZ [250]	2023	6	✓	Dialogue Utterances	Stanford University
xDial-Eval [253]	2023	10	✓	Dialogues	NUS
PRESTO [241]	2023	6	×	Conversational Parsing	University of Rochester
Universal Dependencies [200]	2022	146	×	Parser	-
XSEMPLE [258]	2023	22	×	Semantic Parsing	PSU
Bucc-bitext-mining [210]	2022	5	×	Mixed	HuggingFace
MEGA [228]	2023	70	×	Mixed	UW
MEGAverse [229]	2023	83	×	Mixed	Microsoft
NusaX [236]	2023	10	✓	Mixed	Bloomberg
XGLUE [254]	2020	-	×	Mixed	Microsoft
XTREME [259]	2020	40	✓	Mixed	CMU
XTREME-R [260]	2021	50	✓	Mixed	DeepMind

Table 11: An overview of multilingual benchmarks with more than four supported languages after 2018 in which mBERT [271] was proposed. **NLU** and **NLI** denote the natural language understanding and the natural language inference task, respectively.

on the internet, leading to LLMs unavoidably inheriting demographic biases across gender, race, and political backgrounds [479, 480, 481, 482]. This exacerbates existing inequalities, perpetuates stereotypes, and reinforces discrimination.

The core of multilingual LLM research is to improve the language modeling ability in other medium/low-resource languages while maintaining competence in English. Concerning demographic biases, previous attempts to mitigate bias and align LLMs with human values have primarily concentrated on English [483, 484, 485]. Consequently, bias and ethical issues persist in other languages, potentially leading to significant negative impacts for non-English-speaking users.

Name	Languages	Type of Bias	Debias Object	Metrics
RTP-LX [486]	28	Bias, Identity attack, Insult Microaggression, Self-harm Sexual content, Toxicity, Violence	Small LM Large LM	Exact Label Match Interrater Reliability [486]
MGB [487]	zh,en,de,pt,es	Gender Bias	Masked LM	MBE, MGL, LSG, MSG [487]
MIBs [488]	en,es,de,fr	Gender Bias, Occupation Bias	Word Embedding	inBias [488]
MozArt [489]	en,de,es,fr	Gender Bias, Language	Masked LM	Close Test

Table 12: An overview of the multilingual bias evaluation datasets. The 28 languages supported by RTP-LX are Arabic, Hebrew, Indonesian, Danish, Norwegian, Swedish, Dutch, English, German, Russian, Ukrainian, Czech, Polish, Serbian, Bosnian, Croatian, Montenegrin, Spanish, Portuguese, French, Italian, Hindi, Thai, Kiswahili, Chinese, Japanese, Korean, Turkish, Finnish, and Hungarian.

10.2 Multilingual Debias

Language bias of LLMs persists in the multilingual scenario as a consequence of the dominance of English resources and the insufficiency of other languages on the internet. To enhance the model ability on low-resource languages, a common practice is to incorporate large-scale data [475, 462] for training. The extensive training data facilitates language transfer, especially among typologically similar languages. Furthermore, the strategies such as curriculum learning [43] and up-sampling [38, 37, 156] progressively increase the proportion of non-English resource. These techniques expose LLMs to a wider range of languages while maximizing the utilization of existing data.

To mitigate demographic bias in the multilingual scenario, Zhao *et al.* [488] extend word embedding bias to the cross-lingual and Piqueras *et al.* [489] evaluate group bias of three pre-trained LM (mBERT, XLM-R, and mT5) on four languages (En, Es, De, and Fr). Besides, Vashishtha *et al.* [490] extend debiasing strategies such as counterfactual data augmentation and self-debias to non-English languages, revealing a greater potential for debiasing and generalization among linguistically similar languages. However, they only investigate a few Indian languages, without comprehensive mitigation strategies for broader language groups. For a more comprehensive evaluation, De *et al.* [486] introduce RTP-LX, a dataset designed for identifying culture-specific toxic languages with much wider coverage (28 languages and 8 different classes). Experimental results on up-to-date LLMs (Mistral [46], Gemma [491], GPT-4 [148], etc) demonstrate that even the popular models still struggle to judge history or content-dependent toxic content. Moreover, Lin *et al.* [38] and Shliazhko *et al.* [37] analyze safety and bias in multilingual PLMs (XGLM and mGPT), respectively. They observe that multilingual PLMs pronounce gender bias in certain occupations, while few-shot learning has minimal impact on performance improvement. To analyze gender bias robustly, Yu *et al.* [487] propose a novel model-based approach to generate sentence pairs. Based on mBERT [271], Reusens *et al.* [492] investigate cross-lingual transferability of debias techniques on 4 languages and stimulate cross-lingual debiasing effectiveness with additional pre-training.

10.3 Limitations and Discussion

To mitigate the cross-lingual bias is a promising research question and it has profound implications for the welfare, fairness, and esteem of numerous social and racial groups. Due to the scarcity of high-quality data in low-resource languages and the absence of pertinent evaluation benchmarks, effective bias detection and elimination remain largely unexplored, underscoring the necessity and imperative for future research. Besides, machine translation can mitigate the issue of low-resource languages via pseudo data generation [493, 494] but it omits the cultural context or fails to capture the cultural nuances of a specific language [495]. The local and cultural backgrounds are critical to prejudice and hate speech. Thus, leveraging raw corpus in the local original context is important for detecting toxic content by native speakers.

11 Conclusion and Future Directions

In this paper, we summarize the existing representative research efforts on LLMs in the multilingual scenario from multiple perspectives. We first rethink the transitions between previous and current research on pre-trained language models. Based on the main aspect, the survey is divided into several sections from the view of training paradigms, inference strategies, information retrieval, se-

curity, multi-domain, data resources, and benchmark evaluation. Besides, we appeal to the research community for bias and fairness when exploring multilingual models. We also discuss several urgent challenges related to each investigated aspect and provide reflections and potential solutions for future work. Finally, considering the rapid growth of LLM research, we establish a continuously updated repository to provide relevant literature with the latest advancements of LLMs in the multilingual scenario.

In conclusion, LLMs have greatly contributed to the advancement of multilingual applications, progressing toward the goal of user-oriented. However, the existing technologies and algorithms in various multilingual tasks still fall short of expectations, which makes it difficult to meet practical standards. Aiming for language-fair AI, extensive research efforts are required to adapt LLMs for multilingual tasks much more feasible. We summarize the suggestions for both academic and industry as they build, study, and regulate LLMs as follows:

- *Sustainable language adaptation.* The limited data resources of various languages restrict the number of supported languages with the initial model pre-training. An ideal situation is to use the newly available language data to improve the performance and supported languages of LLMs. Although mammalian brains could protect previously acquired knowledge through cortical loops to avoid catastrophic forgetting, the neural network models lack this capability. Therefore, sustainably achieving language adaptation for LLMs is not trivial. The longstanding goal of LLMs with multilingualism is to achieve good performance among multiple languages for all tasks in an incremental learning paradigm.
- *Universal multilingual paradigm.* The existing studies mainly focus on leveraging parameter-tuning techniques and prompt engineering to explore the potential multilingual capabilities of LLMs. Aiming for a universal multilingual paradigm based on LLMs, it is beneficial to investigate the potential mechanisms without additional training to effectively address language-specific issues, such as code-switching, multilingual jailbreaking, cross-domain adaptation, etc.
- *Comprehensive and authoritative evaluation.* The majority popular mainly focus on English and their native languages because of regional and linguistic restrictions, which poses a challenge in bridging the language barrier. To mitigate the language barrier issue, an urgent requirement for the multilingual community is to construct a comprehensive and authoritative benchmark to evaluate the multilingual capabilities of LLMs with various aspects, including language culture, multilingual security, multilingual reasoning, domain knowledge in native languages, etc. This can be achieved by a reasonable combination of multiple benchmarks or guidelines initiated by linguistic experts from corresponding language communities.
- *Bias impact with multilingualism.* Existing LLMs inherit biases from the training corpus because of a lack of feasible data management/processing, which poses generation risks. Besides, the high proportion of Western languages in the training corpus exacerbates the bias issues from a culturally insensitive generation aspect. How to enable LLMs to avoid generating biased/risky content and to possess the ability to generate cultural concepts within different languages are important and meaningful to achieve language-fair technology.

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