QA Analysis in Medical and Legal Domains: A Survey of Data Augmentation in Low-Resource Settings

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Abstract

Large Language Models (LLMs) have revolutionized Natural Language Processing (NLP), but their success remains largely confined to high-resource, general-purpose domains. In contrast, applying LLMs to low-resource domains poses significant challenges due to limited training data, domain drift, and strict terminology constraints. This survey provides an overview of the current landscape in domain-specific, low-resource QA with LLMs. We begin by analyzing the coverage and representativeness of specialized-domain QA datasets against large-scale reference datasets what we refer to as *ParentQA*. Building on this analysis, we survey data-centric strategies to enhance input diversity, including data augmentation techniques. We further discuss evaluation metrics for specialized tasks and consider ethical concerns. By mapping current methodologies and outlining open research questions, this survey aims to guide future efforts in adapting LLMs for robust and responsible use in resource-constrained, domain-specific environments. To facilitate reproducibility, we make our code available at `github.com/kentrachmat/survey-da`.

1 Introduction

Over the years, large language models (LLMs) (OpenAI et al., 2023; Gemini et al., 2024; DeepSeek-AI et al., 2025) have demonstrated remarkable performance across a variety of natural language processing (NLP) tasks. However, these advances remain largely confined to domains for which massive training corpora are available (Kaplan et al., 2020). In contrast, low-resource datasets (Ravichander et al., 2019; Möller et al., 2020) pose significant challenges for LLMs due to data scarcity and underrepresentation. The lack of sufficient quantity and quality of data leads to gaps in lexical coverage (Hangya et al., 2022), cultural knowledge (Li et al., 2024), and syntactic nuances (Lucas et al., 2024). Consequently, LLM performance in low-resource settings is markedly inferior to that observed with well-resourced datasets. This disparity strongly limits AI progress in the affected domains.

This survey article highlights the methods and evaluations employed in low-resource and specialized domains. We argue that the diversity and quality of datasets are more important than the accumulation of large volumes of mediocre data. This perspective is supported by studies showing that the quality of training data has a significant impact on language model performance, especially in low-resource environments (Micallef et al., 2022; Sajith and Kathala, 2024). To mitigate data scarcity, data augmentation has emerged as an effective solution (Seo et al., 2024), allowing the generation of additional examples to enhance model robustness.

Natural language processing encompasses a broad range of tasks, such as text summarization, topic modeling, and text generation (Wikipedia LLMs, 2025). In this study, we focus explicitly on the question answering (QA) task, as it represents a particularly dynamic research area, especially in low-resource contexts. In domain-specific applications notably in the private sector and independent research settings, QA systems and chatbots (Afzal et al., 2024; Megahed et al., 2024) are commonly used to facilitate user interaction with datasets and to evaluate model capabilities. Moreover, with the advent of large language models, QA systems can be adapted to perform other NLP tasks through data restructuring and model fine-tuning. Nonetheless, despite these advances, domain-specific applications continue to face major challenges in low-resource environments.

2 Problem Statement

Overview Low-resource environments for Large Language Models (LLMs) are contexts in which

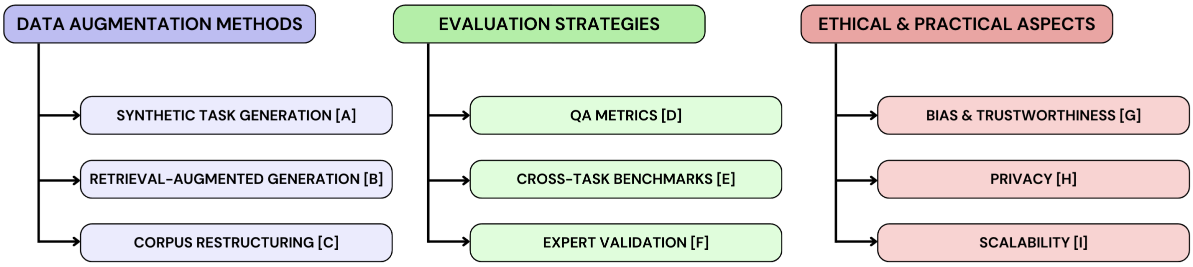

DATA AUGMENTATION METHODS
SYNTHETIC TASK GENERATION [A]
RETRIEVAL-AUGMENTED GENERATION [B]
CORPUS RESTRUCTURING [C]
EVALUATION STRATEGIES
QA METRICS [D]
CROSS-TASK BENCHMARKS [E]
EXPERT VALIDATION [F]
ETHICAL & PRACTICAL ASPECTS
BIAS & TRUSTWORTHINESS [G]
PRIVACY [H]
SCALABILITY [I]

Figure 1: Taxonomy of data-augmentation methods for low-resource QA across three axes and their subcategories (see Appendix B for representative papers)

essential resources such as large and diverse corpora, annotated datasets, domain expertise, or data availability are severely limited or entirely absent. These constraints go well beyond the challenges typically associated with low-resource languages. Even in high-resource languages like English, many specialized domains, such as certain branches of medicine or scientific research, suffer from a chronic lack of data (Seo et al., 2024). Since LLMs are primarily pretrained on large, generic corpora, they often fail to generalize to tasks that require fine-grained and domain-specific knowledge. For example, in the biomedical field, although there is a large volume of general medical text, datasets focused on rare diseases or specific clinical trials remain scarce or even nonexistent, which leads to distributional shifts and reduced model performance (Chen et al., 2024b).

These limitations pose major challenges for question-answering (QA) systems in low-resource domains. QA systems require not only extensive lexical coverage but also precise factual knowledge, domain-specific reasoning abilities, and the capacity to extract or infer information from context. When specialized corpora are scarce, QA models struggle to learn the terminology, background knowledge, and inference patterns necessary to produce accurate and relevant answers. Furthermore, in the absence of expert-designed annotations, it becomes difficult to adapt models to handle specialized question types, which increases the hallucination rate and reduces the reliability of responses. Although there is no universally recognized threshold to define a low-resource environment, we consider a dataset to fall into this category when it is not commonly used for the pretraining of large language models, particularly in the case of datasets absent from standard benchmarks.

Research Questions We also aim to explore several research questions. First, it is essential to identify effective strategies to increase the quantity and quality of domain-specific data using LLMs, particularly in areas where such data is scarce. Second, we seek to understand which approaches can enhance the adaptation of LLMs to domain-specific tasks. Third, it is necessary to establish robust evaluation frameworks and metrics to accurately assess model performance in these contexts. Finally, to consider the ethical, privacy, and fairness implications when deploying LLMs in specialized domains. Accordingly, we formulate the following research questions:

- **Q1**: How can domain-specific data be effectively expanded using LLMs?
- **Q2**: Which approaches improve the adaptation of LLMs to domain-specific tasks?
- **Q3**: How can the performance of LLMs be evaluated in low-resource settings?
- **Q4**: What ethical, privacy, and fairness considerations must be addressed?

3 Taxonomy of Data Augmentation Strategies

To enhance the clarity and structure of our survey, we introduce a taxonomy (Figure 1) derived from the evidence summarized in Table 1. This taxonomy offers a structured overview of augmentation practices, evaluation approaches, and ethical considerations in low-resource QA.

We organize the taxonomy along three axes:

- **Data Augmentation Methods** include (i) *Synthetic Task Generation*, (ii) *Retrieval-Augmented Generation*, and (iii) *Corpus Restructuring*, reflecting how data is created or modified to increase coverage and diversity.

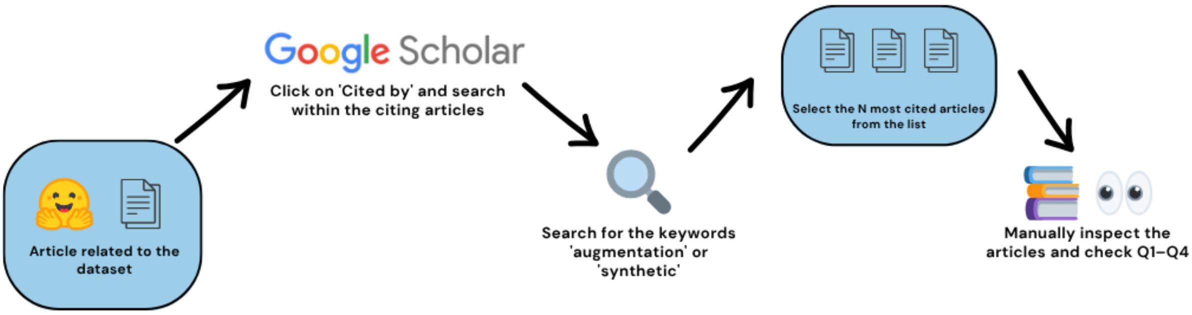

Google Scholar
Click on 'Cited by' and search within the citing articles
Article related to the dataset
Search for the keywords 'augmentation' or 'synthetic'
Select the N most cited articles from the list
Manually inspect the articles and check Q1–Q4

Figure 2: Workflow for identifying relevant papers on dataset augmentation

- **Evaluation Strategies** consist of (i) *QA Metrics*, (ii) *Cross-Task Benchmarks*, and (iii) *Expert Validation*. QA metrics are particularly prevalent due to their simplicity and general applicability across datasets and domains.
- **Ethical and Practical Aspects** address (i) *Bias & Trustworthiness*, (ii) *Privacy*, and (iii) *Scalability*, especially relevant in sensitive domains like biomedical and legal QA.

This taxonomy abstracts recurring patterns across studies and highlights the methodological and ethical clusters that shape the design and evaluation of low-resource QA systems.

4 Related Work

Ding et al. (2024a) propose a domain analysis along two axes data and learning. They define four "data perspectives" (creation, annotation, reformulation, co-annotation) and present various learning paradigms ranging from supervised fine-tuning to alignment-based learning. They also illustrate concrete applications, such as Dr. LLaMA for medical question answering (where ChatGPT or GPT-4 rewrite or generate new question–answer pairs) and the selective masking strategy of DALE. Chai et al. (2025) complement this approach with a clear technical taxonomy, encompassing simple methods, prompt-based techniques, information retrieval based approaches, and hybrid methods. However, neither of these studies offers a systematic comparison of the different paradigms applied to the specific constraints of low-resource biomedical or legal domains, such as privacy requirements or distributional shifts.

Our survey builds on these contributions by focusing specifically on data augmentation for question answering in low-resource biomedical and legal contexts. Using targeted datasets, we evaluate how well different augmentation techniques address the unique constraints of these domains. Rather than proposing a new theoretical framework, our contribution lies in a detailed, data-driven comparison that highlights the practical relevance of each approach in sensitive settings.

5 Literature Review and Analysis

5.1 Article Identification Methodology and Analysis

Article Identification To conduct our analysis, we aim to identify under-represented dataset subsets within their respective domains. We focus specifically on datasets in the biomedical and legal fields, as these two areas have been extensively studied in the large language model (LLM) research community. Although a substantial body of literature exists for these domains, it remains difficult to locate publicly available low-resource datasets, often due to privacy concerns, access restrictions, or the absence of standardized repositories. Consequently, for each domain, we restrict our analysis to three or four dataset types that are accessible and sufficiently documented to permit analysis.

As illustrated in Figure 2, we implemented a structured workflow to identify research on dataset augmentation and synthetic data generation. To explore this issue systematically, we performed a literature review focusing on augmentation techniques and synthetic data generation applied to our selected datasets.

Using Google Scholar, we searched for articles containing either the keyword *augmentation* or the keyword *synthetic*, written in English, then filtered them to retain only those related to natural language processing (NLP). These two keywords were chosen to broadly cover the relevant literature on data

Domain	Papers Citing Datasets	Q1	Q2	Q3	Q4
Medical	(Möller et al., 2020), COVID-QA	–	✓	✓	–
	↪ (Reddy et al., 2020)	✓	✓	✓	–
	↪ (Siriwardhana et al., 2023)	✓	✓	✓	–
	↪ (Samuel et al., 2024)	✓	✓	✓	–
	(Wang et al., 2024), ReDis-QA	✓	✓	✓	–
	↪ (Li et al., 2025)	✓	✓	–	✓
	↪ (Wang et al., 2025a)	✓	✓	✓	✓
	(Arias-Duart et al., 2025), CareQA	✓	✓	✓	–
	↪ (Wang et al., 2025b)	✓	✓	✓	✓
	(Chen et al., 2024a), Medbullets	–	–	✓	✓
	↪ (Kim et al., 2025)	✓	✓	✓	✓
	↪ (Wang et al., 2025b)	✓	✓	✓	✓
	↪ (Wang et al., 2025a)	✓	✓	✓	✓
Legal	(Ravichander et al., 2019), PrivacyQA	–	–	✓	–
	↪ (Vold and Conrad, 2021)	–	✓	✓	–
	↪ (Parvez et al., 2023)	✓	✓	✓	✓
	↪ (Nayak et al., 2024)	✓	✓	✓	–
	(Ahmad et al., 2020), PolicyQA	–	–	✓	–
	(Lin et al., 2022), TruthfulQA	–	–	✓	✓
	↪ (Wang et al., 2023)	–	✓	✓	✓
	↪ (Kim et al., 2023)	✓	✓	✓	✓
	↪ (Ding et al., 2024b)	✓	✓	✓	✓

Table 1: Overview of the intersection between each research question (Q1 to Q4) and the articles describing corpora in the two studied domains. A check mark ✓ indicates that the question is addressed, a dash indicates that it is not, and arrows ↪ denote the reuse of these datasets for various data augmentation methods

augmentation, and Google Scholar's full-text indexing allowed us to identify works where these terms appear beyond the title or abstract. This approach facilitated the identification of potentially relevant contributions. We then selected up to N research articles each dataset, with $N \leq 3$[1], excluding review articles and those that mention augmentation techniques only in their related work sections. Review articles were excluded because, although they provide useful overviews, they generally do not present detailed methodological analyses or empirical results specific to the datasets under study. This filtering based on publication type enabled us to concentrate on the most influential and technically substantial contributions to data augmentation methodologies.

In Table 1, we adopt a structured approach to analyze each of the four research questions in the biomedical and legal domains. This framework enables a systematic examination of augmentation techniques applied to various low-resource datasets. We selected three to four datasets per domain. By mapping augmentation approaches to different dataset types, our study offers insights for researchers aiming to improve the performance of large language models (LLMs) in low-resource environments.

5.2 Embedding Model Selection

To analyze text distributions in embedding space, we selected specialized models for each domain based on the MTEB Leaderboard rankings[2], limiting our choices to models of up to 1 billion parameters to control computational costs. The selected models are available in Table 2.

5.3 Biomedical Domain

5.3.1 Overview of Selected Datasets

The biomedical domain remains one of the most critical for AI applications, given its potential to transform diagnosis, treatment planning, and patient management. Despite these promises, this field faces severe data limitations or inaccessibility outside of hospital settings. Although medical data can take many forms such as images, videos, and other modalities. We restrict this study to textual data to maintain a coherent scope.

Applying our methodology, we selected four low-resource medical QA datasets for in-depth analysis. To assess their representativeness, we compared them against `MedMCQA` (Pal et al., 2022), a large-scale dataset of 160,869 instances covering

[1] Some datasets are recent and still have few specialized methods.

[2] https://huggingface.co/spaces/mteb/leaderboard

various medical subdomains. We refer to this reference corpus as ParentQA. The four specialized datasets are:

- **COVID-QA** (Möller et al., 2020): 2,019 expert-annotated question–answer pairs on COVID-19, using a SQuAD-inspired annotation protocol.
- **ReDis-QA** (Wang et al., 2024): 975 high-quality question–answer pairs covering 205 rare diseases.
- **MedBullets** (Chen et al., 2024a): 616 real clinical cases designed to evaluate reasoning and decision-making in complex clinical scenarios.
- **CareQA** (Arias-Duart et al., 2025): 2,769 instances annotated with both open- and closed-ended questions spanning medicine, nursing, biology, chemistry, psychology, and pharmacology.

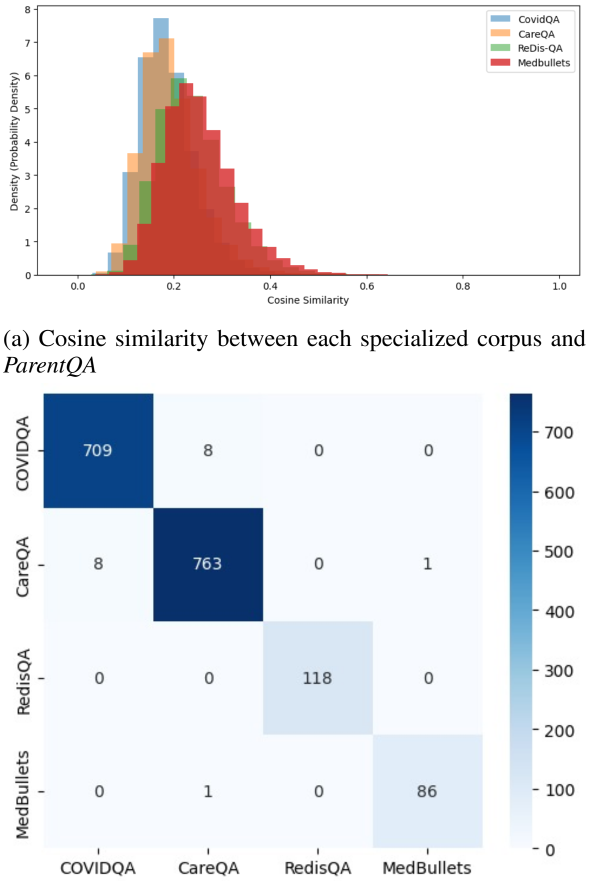
5.3.2 Diversity Analysis

To assess lexical and semantic diversity of the low-resource medical QA corpora relative to the large-scale ParentQA, we conducted two complementary analyses: (i) lexical statistics including out-of-vocabulary (OOV) rates and Shannon entropy (Table 3), and (ii) semantic similarity and OOV overlap analysis (Figure 3).

Lexical Statistics. Table 3 reports for each corpus the unique vocabulary size $|\mathcal{V}|$, the number of vocabulary not found in ParentQA (OOV), and the Shannon entropy

$$H = -\sum_{w \in \mathcal{V}} p(w)\, \log_2 p(w)\,,$$

computed from the empirical unigram distribution $p(w)$. Higher entropy indicates more balanced and extensive vocabulary usage; lower entropy signals concentration on a few frequent terms. All specialized corpora exhibit much smaller $|\mathcal{V}|$ and lower entropy than ParentQA (13.09 bits), reflecting their narrow scope and data scarcity. OOV counts range from 86 in MedBullets to 763 in CareQA, with examples like *creatininuria* and *endosymbionts* highlighting domain-specific terminology.



(a) Cosine similarity between each specialized corpus and *ParentQA*

(b) Vocabulary overlap

Figure 3: Comparison of low-resource medical QA datasets to ParentQA in terms of (a) cosine similarity and (b) out-of-vocabulary (OOV) vocabulary overlap

Semantic Similarity and Implications. Figure 3(a) displays the distribution of cosine similarities between sentence embeddings of each specialized corpus and those of ParentQA (embeddings generated by the model detailed in Table 2).

The four low-resource corpora shift leftwards: COVID-QA peaks near 0.17, CareQA around 0.20, ReDis-QA at 0.22, and MedBullets at 0.27. Their flatter, wider curves reveal greater internal heterogeneity in question phrasing. The more leftward the distribution, the greater the semantic divergence from ParentQA. The large gap relative to ParentQA highlights significant domain-induced divergence, both terminologically and syntactically. This "semantic distance" arises from specialized medical jargon (e.g.,*furin*, *creatininuria*, *arrhythmia*) and question structures unseen in generalist corpora.

Combined with low OOV overlap (Figure 3(b)) and reduced entropy (Table 3), these results confirm that each low-resource corpus is both lexically limited and semantically distant from ParentQA.

These disparities call for domain-sensitive strategies such as targeted vocabulary augmentation, specialized pre-training, or robust adaptation techniques to overcome challenges in low-resource environments.

OOV Overlap. Figure 3(b) shows a heatmap of OOV term overlap between specialized corpora. The overlap is minimal (e.g., only 8 shared OOVs between `COVID-QA` and `CareQA`), indicating that each dataset introduces largely disjoint rare vocabulary. This low overlap underscores the difficulty of transferring lexical knowledge across specialized domains.

5.3.3 Positioning with Respect to the Research Questions

Among the methods examined, Q1 (*how to expand domain-specific data*) falls into two paradigms. On one hand, *few-shot* generation followed by filtering (e.g., *round-trip consistency*), as demonstrated in (Samuel et al., 2024) on CovidQA, enables rapid performance gains without requiring a massive preexisting corpus. On the other hand, large-scale *chain-of-thought* pipelines combine reasoning extraction, synthesis, and document-based revision to generate hundreds of thousands or even billions of medical tokens, but they require extensive access to manuals, knowledge graphs, or clinical databases (Kim et al., 2025; Wang et al., 2025b).

For Q2 (*which approaches for LLM adaptation*), three main directions emerge. Fine-tuning on annotated corpora (e.g., RoBERTa + COVID-QA) provides consistent improvements starting from just a few thousand expert-labeled examples (Möller et al., 2020). *Chain-of-thought* instruction tuning improves accuracy across various medical benchmarks by explicitly incorporating reasoning during training (Kim et al., 2025). Finally, end-to-end or multi-phase RAG architectures combine tailored *retrieval* with reinforcement learning stages for more refined alignment with clinical criteria, but these models are heavily dependent on external knowledge and domain-specific metrics (Siriwardhana et al., 2023; Wang et al., 2025b).

Regarding Q3 (*evaluation and metrics*), generic *close-ended* indicators such as Exact Match, F1, and perplexity remain foundational across all domains (Möller et al., 2020; Samuel et al., 2024). Semantic-based measures (e.g., BERTScore, BLEURT) and automated judges like G-Eval (Chen et al., 2024a; Arias-Duart et al., 2025) provide deeper qualitative insights into generated responses, while human evaluation remains essential for verifying coherence and factual correctness in clinical contexts (Wang et al., 2025a).

Finally, for Q4 *(ethical principles)*, most articles either omit these considerations or address them only superficially, highlighting a critical gap in healthcare applications, where patient safety, data confidentiality, and equitable access are paramount (Wang et al., 2025b,a). Given the potential risks of biased or inaccurate medical advice (Li et al., 2025), it is essential for future research to integrate *bias analysis, privacy-preserving protocols, and regulatory frameworks* into data augmentation strategies for biomedical low-resource settings.

Overall, two families of methods can be distinguished: on one hand, **generic methods** such as few-shot generation, chain-of-thought instruction tuning, and light fine-tuning on small annotated corpora, coupled with standard metrics like Exact Match, F1, and perplexity, offer quick implementation and performance gains of 5–10% with just a few dozen examples (Möller et al., 2020; Samuel et al., 2024; Chen et al., 2024a). On the other hand, **domain-specific methods** require access to specialized resources (manuals, knowledge graphs, expert annotations), careful prompt engineering, architectural modifications, and integration into complex fine-tuning pipelines. These methods are typically employed after applying generic techniques to establish a baseline and then further optimize performance by targeting domain-specific nuances. However, their increased effectiveness comes at the cost of reduced transferability, as they require prior adaptation.

5.4 Legal Domain

5.4.1 Overview of Selected Datasets

As the volume of legal cases increases, artificial intelligence plays a crucial role in reducing workloads, minimizing human errors, and accelerating judicial decisions while ensuring their consistency. By automating repetitive and time-consuming tasks such as document analysis and legal research, AI enables legal professionals to focus more on strategic decision-making and nuanced case evaluations. Furthermore, predictive analysis helps anticipate outcomes, thus promoting transparency and consistency in judicial decisions (Lai et al., 2024).

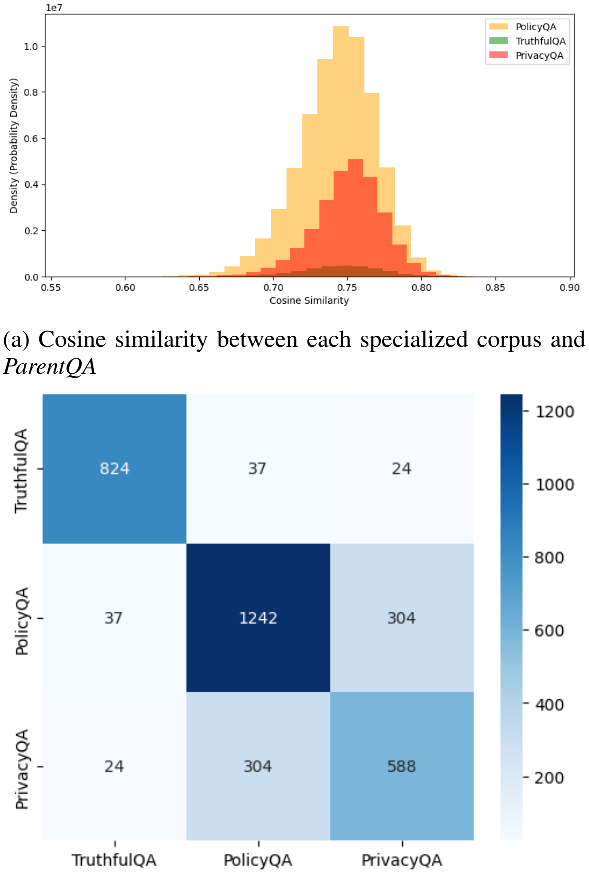
Applying our methodology to this domain, we identified three relevant legal QA datasets for in-depth analysis. We selected a single dataset as the ParentQA corpus: the legal subset of MMLU (Hendrycks et al., 2021), which includes the categories *international law*, *jurisprudence*, *logical fallacies*, *moral disputes*, *moral scenarios*, *professional law*, *public relations*, and *US foreign policy*. These subsets, widely used for pretraining large language models, contain approximately 3,790 examples. The eight specialized datasets selected for this study are as follows:

- **PolicyQA** (Ahmad et al., 2020): a reading comprehension dataset focused on website privacy policies, comprising over 17 000 question-passage-answer triplets aimed at concise responses.
- **PrivacyQA** (Ravichander et al., 2019): a dataset of 7,137 question–answer pairs about mobile app privacy policies, featuring legally grounded annotations to support domain-specific QA in the legal–computational context.
- **TruthfulQA** (Lin et al., 2022): a benchmark consisting of 790 questions, including a subset dedicated to legal questions, designed to evaluate the truthfulness of language model outputs.

5.4.2 Diversity Analysis

To measure both vocabulary range and semantic consistency across our three specialized QA sets versus ParentQA, we ran two complementary analyses: (i) lexical profiling via vocabulary size, out-of-vocabulary (OOV) rates and Shannon entropy (Table 4); and (ii) internal semantic similarity distributions alongside OOV-overlap statistics (Figure 4).

Lexical Statistics. As Table 4 shows, all three specialized corpora possess drastically smaller vocabularies and lower entropy than ParentQA (11.37 bits). **PolicyQA** exhibits the smallest vocabulary (4 093 types) and lowest entropy (8.58 bits). **PrivacyQA** is richer (2 541 types, 9.11 bits), mixing policy-style prompts with occasional technical clarifications, while **TruthfulQA** despite only 2 616 types, yields surprisingly high entropy (10.51 bits). OOV counts against ParentQA mirror this pattern: PolicyQA's 1 242 unseen vocabulary (e.g. *adverts*, *prospectively*) underscore domain-specific framing; TruthfulQA's 824 new terms (e.g. *cage*, *gasper*) reflect idiosyncratic references; PrivacyQA's 588 OOVs (e.g. *adverts*, *recordkeeping*) occupy a middle ground.



(a) Cosine similarity between each specialized corpus and *ParentQA*

(b) Vocabulary overlap

Figure 4: Comparison of low-resource legal QA datasets to ParentQA in terms of (a) cosine similarity and (b) out-of-vocabulary (OOV) vocabulary overlap

Semantic Similarity and Implications. Figure 4(a) displays the distribution of cosine similarities between sentence embeddings of each specialized corpus and those of ParentQA (embeddings generated by the model detailed in Table 2). **PolicyQA** centers at ∼0.75 with a narrow spread and the highest peak density, signifying highly repetitive structure across its many examples. **PrivacyQA** also peaks near 0.75 with a modestly wider shoulder toward 0.65–0.70, indicating occasional outlier phrasings alongside core policy-style questions. By contrast, **TruthfulQA** peaks lower, around 0.72, and displays the broadest distribution (spanning 0.55–0.85), directly reflecting its adversarial design to cover diverse topics and linguistic traps. Compared to the biomedical datasets, the legal corpora exhibit greater similarity to the ParentQA distribution. This may be attributed to the relatively consistent legal vocabulary and framing, where core terms and concepts are reused across different scenarios, even as the case contexts vary.

OOV Overlap. Complementing these semantics, Figure 4(b) shows that OOV-sets are largely distinct: only 37 vocabulary overlap between TruthfulQA and PolicyQA, 24 between TruthfulQA and PrivacyQA, but 304 between PolicyQA and PrivacyQA highlighting their shared legal/policy jargon. Taken together, low entropy and high pairwise similarity in PolicyQA argue for template-like redundancy; TruthfulQA's entropy and spread warn of semantic unpredictability; and PrivacyQA sits in between.

5.4.3 Positioning with Respect to the Research Questions

Among the examined methods, Q1 (how to increase domain-specific data) involves generation and retrieval strategies: generation of semantically equivalent perturbations via paraphrasing with LLMs (Ding et al., 2024b), corpus synthesis through output comparison (Kim et al., 2023), example extraction using multi-retrievers (Parvez et al., 2023), and large-scale instruction generation from meta-templates (Nayak et al., 2024).

Regarding Q2 (approaches for adapting LLMs), the studies combine continual pretraining, fine-tuning, and reinforcement learning: PolicyQA fine-tunes a BERT model pretrained on a corpus of privacy policies to adapt it specifically to the task of extractive QA in this sensitive domain (Ahmad et al., 2020). Rowen activates a generic "retrieve-only-when-needed" mechanism (Ding et al., 2024b); ALMoST combines reward modeling, synthetic demonstrations, and RL (Kim et al., 2023); Citrus integrates CPT, SFT, and reflective RL for clinical tasks (Wang et al., 2025b); and (Vold and Conrad, 2021) demonstrates performance gains of +31% F1 and +41% MRR with RoBERTa fine-tuned on PrivacyQA.

As for Q3 (evaluation and metrics), the studies use standard metrics adapted to each task: EM and F1 for extractive QA (Ahmad et al., 2020), and precision, recall, F1, and MRR for classification and ranking (Ravichander et al., 2019). These metrics are widely recognized for their robustness and ability to reflect performance in low-resource settings.

Finally, regarding Q4 (ethical principles), TruthfulQA warns against misinformation risks and the erosion of user trust caused by misleading answers, advocating for strong safeguards (Lin et al., 2022). ALMoST relies on the HHH benchmark (helpful, harmless, honest) to align models with human values and reduce harmful outputs (Kim et al., 2023). However, most studies do not comprehensively address ethical, privacy, or fairness concerns—yet these dimensions are essential for ensuring user trust, preventing algorithmic bias, and complying with regulations.

Generic approaches rely on paraphrasing, retrieval, and knowledge transfer mechanisms. They enable rapid prototyping and generalization across low-resource domains, but are limited by the consistency and depth of the base model (Kim et al., 2023; Ding et al., 2024a; Nayak et al., 2024). In contrast, domain-specific solutions leverage expert-curated corpora and workflows to achieve peak performance, at the cost of specialized data collection, domain expertise, and computational resources (Vold and Conrad, 2021; Wang et al., 2023). Therefore, it is advisable to start with minimal fine-tuning on a generic transformer, then progressively integrate architectural modules and targeted corpora to meet domain requirements and ensure ethical adoption.

Despite these advancements, a major challenge remains in the availability and structure of legal datasets. Many cases remain undocumented or inaccessible, exacerbating the inherent complexity of domain-specific language, frequent regulatory changes, and the need for high-quality annotated data (Abdallah et al., 2023). Furthermore, several legal subdomains remain largely unexplored in the context of LLMs including international trade agreements[3], space law[4], Antarctic Treaty law[5], and patent law in biotechnology and genetics[6], among others. The datasets available in these areas are still raw and unstructured, requiring significant preprocessing before they can be effectively leveraged for legal research or analysis.

6 Conclusion

In this paper, we presented an in-depth analysis of data augmentation strategies in low-resource settings, focusing on the biomedical and legal do-

[3] https://datatopics.worldbank.org/dta/table.html

[4] https://www.unoosa.org/oosa/en/ourwork/spacelaw/index.html

[5] https://www.ats.aq

[6] https://www.wipo.int/wipolex/en/

mains. We conducted our literature review by first identifying articles that describe relevant datasets, then analyzing papers on Google Scholar that propose data augmentation methods in relation to these datasets. We assessed their treatment of four key research questions: how to increase domain-specific data, which approaches to use for adapting LLMs, how to evaluate their performance, and what ethical implications should be considered. The review was supported by diversity analyses (cosine similarity and lexical overlap) to highlight differences between specialized datasets and their parent corpora, thereby revealing significant challenges related to data scarcity and specificity.

As a continuation of this work, a comparative empirical evaluation of different augmentation strategies applied to each dataset represents an important next step. This initial study also paves the way for identifying augmentation methods suited to low-resource contexts, aligned with the objectives of my thesis. I also plan to broaden this work to multilingual settings and to low-resource verticals such as renewable energy. Dedicated QA benchmarks are still emerging, for example WeQA (Meyur et al., 2024) had to generate its own wind-energy permitting QA pairs directly from Environmental Impact Statements (EIS). Another study from NREL noted that building even a small siting ordinance evaluation set required over 1,500 hours of expert annotation (Buster et al., 2024). Underscoring the data scarcity in this domain and reinforcing its value as a testbed for evaluating the robustness and generalizability of augmentation strategies.

7 Limitations

Although this study offers insights into data augmentation and synthetic data generation for low-resource datasets, several limitations must be acknowledged.

Domain specificity This analysis is limited to the biomedical and legal fields. While these domains present diverse and complex challenges, expanding the scope to sectors such as renewable energy or other specialized areas could uncover further insights and strengthen the broader applicability of augmentation techniques.

Keyword-based search constraints The literature search relied exclusively on the keywords *augmentation* and *synthetic*. This targeted approach may have excluded relevant works that use alternative terminology or methodologies, thus limiting the scope of our findings.

Parent dataset selection The parent dataset used in our analysis consists of a single large-scale collection, selected under the assumption that its diversity offers a robust reference point. However, incorporating additional and more diverse parent datasets would likely enhance the breadth and generalizability of our analysis.

Language bias We chose to use English-language datasets due to their accessibility and relative availability, which facilitated the identification of a broader literature base. However, this choice may introduce biases: LLMs trained primarily on English data tend to present Anglo-American perspectives as universal truths, thereby overlooking non-English viewpoints (Ramesh et al., 2023). This phenomenon can lead to systematic sampling bias and hinder faithful representation of the true diversity of subjects and opinions.

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A Additional Analyses

Table 2 lists the embedding models we selected for the biomedical and legal domains, along with their embedding dimensions and GPU memory requirements.

Domain	Model	Dim.	GPU Mem. (GB)
Biomedical	`jasper_en_vision_language_v1`	8960	3.8
Legal	`inf-retriever-v1-1.5b`	1536	2.9

Table 2: Characteristics of the selected embedding models

Table 3 and Table 4 report lexical statistics for the medical and legal evaluation corpora, respectively, including vocabulary size, out-of-vocabulary (OOV) counts relative to ParentQA, Shannon entropy, and example OOV.

Corpus	Vocab. Size	OOV Count	Entropy (bits)	Sample OOV
ParentQA	275 944	—	13.09	—
COVIDQA	6 062	709	11.13	*furin, endosymbionts, . . .*
CareQA	9 943	763	11.87	*creatininuria, cathodic, . . .*
ReDisQA	3 041	118	10.42	*arrhythmia, ophthalmos, . . .*
MedBullets	4 280	86	9.97	*escherchia, nonrebreather, . . .*

Table 3: Lexical statistics of the evaluation corpora, including vocabulary size, OOV counts relative to ParentQA, Shannon entropy, and example OOV

Corpus	Vocab. Size	OOV Count	Entropy (bits)	Sample OOV
ParentQA	13 656	—	11.37	—
PolicyQA	4 093	1 242	8.58	*adverts, prospectively, registrations, . . .*
TruthfulQA	2 616	824	10.51	*gasper, cage, moderation, . . .*
PrivacyQA	2 541	588	9.11	*adverts, recordkeeping, acquirer, . . .*

Table 4: Lexical statistics of the evaluation corpora: vocabulary size, out-of-vocabulary (OOV) counts and rate relative to ParentQA, and example OOV terms

B Representative Papers for Taxonomy Categories

[A] Synthetic Task Generation	(Reddy et al., 2020), (Samuel et al., 2024), (Wang et al., 2025a), (Wang et al., 2025b), (Kim et al., 2025), (Nayak et al., 2024), (Kim et al., 2023)
[B] Retrieval-Augmented Generation	(Reddy et al., 2020), (Siriwardhana et al., 2023), (Wang et al., 2024), (Li et al., 2025), (Parvez et al., 2023), (Wang et al., 2023), (Ding et al., 2024b)
[C] Corpus Restructuring	(Möller et al., 2020), (Reddy et al., 2020), (Wang et al., 2024), (Li et al., 2025), (Wang et al., 2025a), (Ahmad et al., 2020), (Ravichander et al., 2019), (Nayak et al., 2024)
[D] QA Metrics	(Möller et al., 2020), (Reddy et al., 2020), (Siriwardhana et al., 2023), (Samuel et al., 2024), (Wang et al., 2024), (Li et al., 2025), (Wang et al., 2025a), (Arias-Duart et al., 2025), (Chen et al., 2024a), (Ahmad et al., 2020), (Ravichander et al., 2019), (Vold and Conrad, 2021), (Parvez et al., 2023), (Nayak et al., 2024), (Lin et al., 2022), (Wang et al., 2023), (Kim et al., 2023), (Ding et al., 2024b)
[E] Cross-Task Benchmarks	(Reddy et al., 2020), (Siriwardhana et al., 2023), (Samuel et al., 2024), (Wang et al., 2024), (Arias-Duart et al., 2025), (Wang et al., 2025b), (Chen et al., 2024a), (Kim et al., 2025), (Nayak et al., 2024), (Wang et al., 2023), (Kim et al., 2023)
[F] Expert Validation	(Möller et al., 2020), (Wang et al., 2025b), (Ravichander et al., 2019), (Kim et al., 2023)
[G] Bias & Trustworthiness	(Li et al., 2025), (Wang et al., 2025a), (Chen et al., 2024a), (Lin et al., 2022), (Wang et al., 2023), (Ding et al., 2024b)
[H] Privacy	(Wang et al., 2025b), (Ahmad et al., 2020), (Ravichander et al., 2019), (Parvez et al., 2023), (Kim et al., 2023)
[I] Scalability	(Reddy et al., 2020), (Siriwardhana et al., 2023), (Samuel et al., 2024), (Wang et al., 2024), (Wang et al., 2025a), (Kim et al., 2025), (Ahmad et al., 2020), (Ravichander et al., 2019), (Vold and Conrad, 2021), (Parvez et al., 2023), (Nayak et al., 2024), (Wang et al., 2023), (Kim et al., 2023), (Ding et al., 2024b)

Table 5: Mapping between taxonomy labels (Figure 1) and representative papers