

BHASHABENCH V1: A Comprehensive Benchmark for the Quadrant of Indic Domains

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The rapid advancement of large language models (LLMs) has intensified the need for domain and culture specific evaluation. Existing benchmarks are largely Anglocentric and domain-agnostic, limiting their applicability to India-centric contexts. To address this gap, we introduce **BhashaBench V1**, the first domain-specific, multi-task, bilingual benchmark focusing on critical Indic knowledge systems. BhashaBench V1 contains **74,166** meticulously curated question-answer pairs, with 52,494 in English and 21,672 in Hindi, sourced from authentic government and domain-specific exams. It spans four major domains: Agriculture, Legal, Finance, and Ayurveda, comprising 90+ subdomains and covering 500+ topics, enabling fine-grained evaluation. Evaluation of 29+ LLMs reveals significant domain and language specific performance gaps, with especially large disparities in low-resource domains. For instance, GPT-4o achieves 76.49% overall accuracy in Legal but only 59.74% in Ayurveda. Models consistently perform better on English content compared to Hindi across all domains. Subdomain-level analysis shows that areas such as *Cyber Law*, *International Finance* perform relatively well, while *Panchakarma*, *Seed Science*, and *Human Rights* remain notably weak. **BhashaBench V1** provides a comprehensive dataset for evaluating large language models across India’s diverse knowledge domains. It enables assessment of models’ ability to integrate domain-specific knowledge with bilingual understanding. All code, benchmarks, and resources are publicly available to support open research: <https://bharatgen-iitb-tih.github.io/bhashabenchv1/>

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1 Introduction

The rapid advancement of large language models (LLMs) has transformed artificial intelligence, extending their capabilities far beyond traditional natural language processing. Models such as GPT-4o [49], GPT-OSS-120B [52], DeepSeek-V3 [19], and Qwen-3 [72] excel across diverse domains, from code generation and mathematical reasoning to creative writing and scientific analysis [15, 63, 51], enabling applications in conversational AI, education, healthcare, finance, legal services, and agriculture [16, 68]. Platforms like *Krishi Sathi* [64] leverage LLMs for crop advisory and pest detection, improving agricultural productivity. Despite these advances, substantial performance gaps remain in multilingual and domain-specific contexts, particularly for non-Latin, low-resource languages [65, 77, 1]. English-centric training limits models’ ability to capture nuanced knowledge in specialized fields and India-specific domains, such as Ayurveda, indigenous agriculture, finance, and regional legal systems [69, 58, 35], highlighting the need for culturally and contextually aware evaluation. The scale of this problem demands urgent attention, as India’s diverse knowledge ecosystem affects millions of lives across multiple critical domains. In agriculture alone, Over 40 million farmers rely on farming-related activities [28], and access to accurate information on crop management, soil health, and sustainable practices can have a direct impact on food security and livelihoods. The complexity is further magnified by the fact that each state in India has its own distinct agricultural methods, crop varieties, soil conditions, and traditional farming practices that have evolved over centuries to suit local climatic and geographical conditions. Similarly, India’s legal system processes millions of cases annually, requiring precise understanding of complex legal frameworks, precedents, and procedural nuances that vary across states and jurisdictions [44]. The healthcare sector, particularly traditional medicine systems like Ayurveda, serves millions of patients who rely on practitioners’ knowledge of ancient

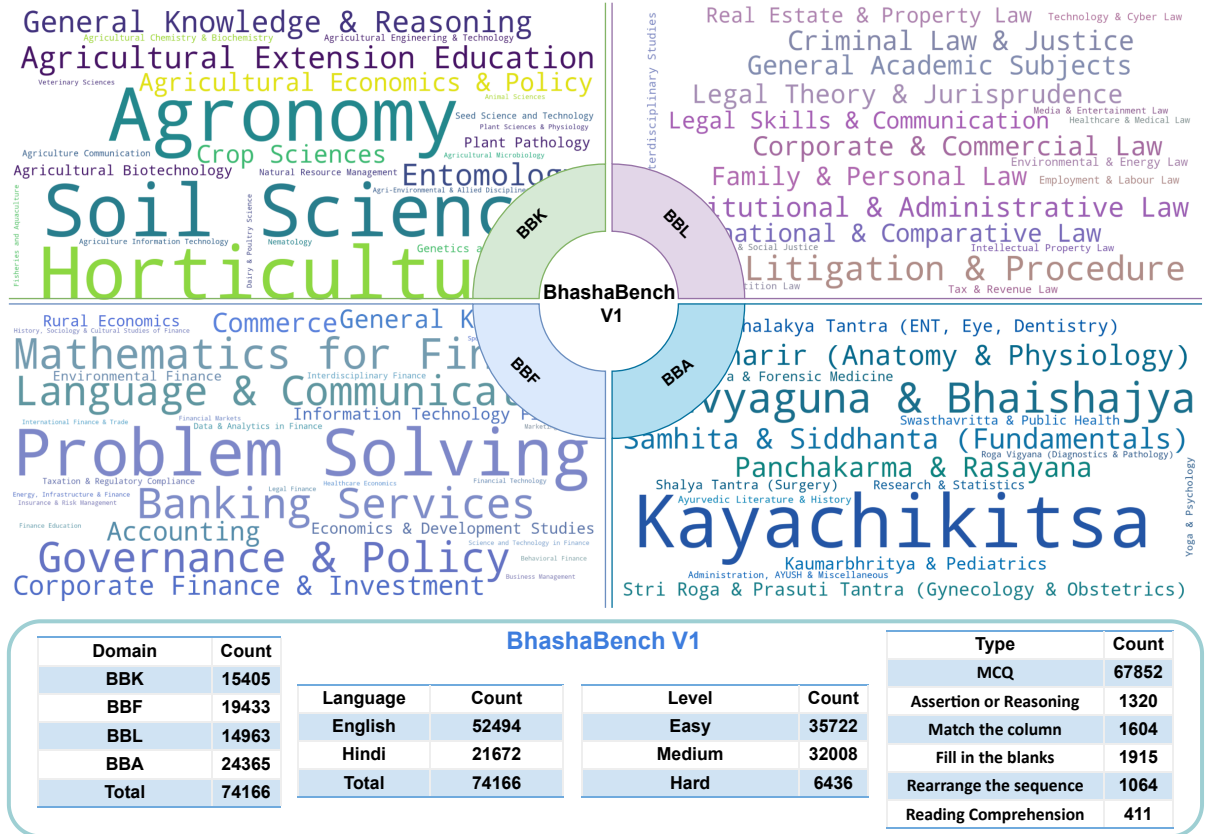


Figure 1 Overview diagram and statistics of BhashaBench V1.

texts, formulations, and treatment protocols. Furthermore, India’s financial ecosystem processes billions of transactions daily, including over 100 billion UPI transactions annually, where even minor misunderstandings in financial regulations or procedures can have cascading effects [45]. While existing benchmarks such as MMLU [26], HellaSwag [75], AGIEVAL [78], and more recent multilingual efforts like MEGA [1] attempt to assess model capabilities, they often focus primarily on English content and may not fully capture India-specific nuances, cultural contexts, and domain expertise that are essential for real-world applications in the Indian subcontinent.

To address these critical gaps, we introduce **BhashaBench V1**, the first comprehensive domain-specific, multi-task, bilingual benchmark designed explicitly for evaluating large language models on India-centric knowledge systems. BhashaBench V1 encompasses four fundamental domains that form the backbone of Indian society and economy: Agriculture (BBK - BhashaBench Krishi), Legal (BBL - BhashaBench Legal), Finance (BBF - BhashaBench Finance), and Ayurveda (BBA - BhashaBench Ayurveda). The benchmark spans over 90 subdomains and covers more than 500 specific topics, reflecting the intricate complexity and diversity of Indian knowledge systems. This granular categorization enables fine-grained evaluation of model performance across specialized areas that require deep domain expertise and cultural understanding. The dataset has been meticulously curated from over 40 authentic government and professional examination papers, ensuring that the questions reflect real-world scenarios and ground-level challenges faced by practitioners in these domains [29, 79]. To maximize coverage across India’s linguistic landscape, BhashaBench V1 currently supports English and Hindi, the two most widely understood languages in the country, collectively enabling assessment of models’ capabilities for a significant portion of India’s population while maintaining the cultural and contextual authenticity of the original knowledge systems.

Our comprehensive evaluation of 29+ state-of-the-art language models on BhashaBench V1 reveals significant performance disparities across domains and languages, highlighting the urgent need for India-specific model development and evaluation. The results demonstrate substantial domain-specific performance gaps, with models showing varying degrees of competency across different knowledge areas. For instance, GPT-4o, one of the top-performing models,

achieved 76.49% accuracy in the Legal domain but only 59.74% in Ayurveda, illustrating the challenges models face with traditional Indian knowledge systems. Similarly, consistent language-specific performance gaps emerged, with models generally performing better on English content compared to Hindi across all domains. The subdomain-level analysis further reveals granular insights into model capabilities, showing that certain areas such as Cyber Law and International Finance demonstrate relatively strong performance, while traditional domains like Panchakarma, Seed Science, and Human Rights remain notably challenging for current LLMs. These findings underscore the critical importance of domain and language-specific evaluation frameworks for assessing model readiness for real-world deployment in diverse Indian contexts.

2 RELATED WORK

2.1 Exploration of LLMs

The landscape of large language models has witnessed unprecedented growth, with both proprietary and open-source models achieving remarkable capabilities. Recent proprietary LLMs, including GPT-4o and GPT-4o-mini [51], Claude-3.5 Sonnet [4], and the Gemini series [22], have demonstrated significant improvements across various benchmarks [18, 67]. The open-source ecosystem has flourished with models such as the Llama-3 series [23], Gemma [61], Qwen2.5 [56], and Mistral [31] achieving competitive performance while maintaining transparency and accessibility.

While primarily trained on English-dominant corpora, many models incorporate substantial multilingual data during pretraining [61, 23, 81], enabling capabilities in hundreds of languages with varying proficiency [46]. Language-specific models have gained momentum, particularly for underrepresented languages including Indic languages [21, 20]. Notable examples include Airavata [21], MuRIL [36], and recent generative models like Param-1 [55].

Domain-specific language models have emerged as a critical research direction. Medical applications include Med-PaLM [59] and BioBERT [40], while legal and financial domains have seen LegalBERT [17] and FinBERT [73] respectively. In the Indian context, domain-specific initiatives like Agri-Param [9], Ayur-Param [10], Finance-Param [11], and Legal-Param [12] address unique requirements of India’s diverse knowledge systems through continual pretraining [43] or instruction fine-tuning [5].

Despite these advances, comprehensive evaluation frameworks for culturally and linguistically diverse domains remain limited, particularly for traditional knowledge systems requiring nuanced understanding of local contexts. This work conducts a comprehensive evaluation of 29+ state-of-the-art models on BhashaBench V1 to address these evaluation challenges.

2.2 Evaluation of LLMs

Numerous benchmarks have been developed to assess large language model performance. General-purpose benchmarks such as MMLU [27], MMLU-Pro [66], AGIEval [78], BIG-Bench [60], and HellaSwag [75] evaluate LLMs across diverse tasks from commonsense reasoning to knowledge-intensive question answering. However, these remain largely Anglocentric with limited multilingual evaluation [8, 33].

To address domain-specific challenges, specialized benchmarks have emerged. In agriculture, benchmarks like AgriBench [80], BVL QA Corpus [3], AgXQA [38], AgEval [6], and SeedBench [74] cover crop disease identification to advisory support. The finance domain features FinGAIA [76], FinanceBench [30], MultiFin [54], InvestorBench [41], and Multi-FinBen [54] for financial reasoning, fraud detection, and trading evaluation. Legal domain efforts include IL-TUR [32], IndicLegalQA [47], LegalBench [24], LEXTREME [48], and the CAIL series [70, 71] for legal question answering, case summarization, and judgment prediction. Traditional medicine resources such as MTCMB [37], Pratyaya-Kosh [57], Anveshana [62], and OpenTCM [25] provide task-specific evaluation datasets covering knowledge graphs, OCR correction, and dosha analysis.

Despite this progress, key limitations persist. Many benchmarks are restricted to English or high-resource languages, limiting effectiveness for multilingual and Indic contexts. Others focus on narrow tasks, unable to capture full domain expertise. Evaluation methodologies vary widely from accuracy scores to human judgments, hindering standardized comparison across domains and languages. These gaps underscore the need for a unified, multilingual, and domain-aware evaluation framework.

3 BhashaBench V1

3.1 Design Principles

The primary motivation behind BhashaBench V1 is to comprehensively assess domain-specific knowledge and reasoning capabilities of large language models within India’s diverse and culturally rich knowledge ecosystems. Unlike existing benchmarks focusing on general or Western-centric domains, our benchmark evaluates specialized Indian knowledge systems requiring deep cultural understanding and contextual awareness. BhashaBench V1 adheres to seven core design principles: **(1) Critical Indian Domains:** Encompasses Agriculture, Legal systems, Finance, and Ayurveda with fine-grained subfields. **(2) Diverse Task Formats:** Includes multiple-choice, assertion-reasoning, fill-in-blanks, and comprehension tasks. **(3) India-Specific Reasoning:** Evaluates domain-specific reasoning incorporating cultural contexts and regional practices. **(4) Bilingual Framework:** Supports English and Hindi evaluation maintaining cultural authenticity. **(5) Authentic Sources:** Questions curated from government examinations and professional certifications. **(6) Difficulty Assessment:** Categorized into Easy, Medium, Hard levels. **(7) Cultural Authenticity:** Prioritizes traditional knowledge systems including Ayurvedic principles.¹ This framework spans 90+ subdomains covering 500+ topics, enabling comprehensive evaluation of model capabilities in India-centric contexts.

3.2 Data Collection

The data collection process for BhashaBench V1 follows a systematic approach similar to AGIEVAL [78], focusing on authentic examination materials from national and state-level assessments. We systematically gathered publicly available question papers from official online examination portals, which host previously released papers that are manually curated by subject matter experts, ensuring accurate topic tagging, language annotation, and validated answer keys.

Our comprehensive collection encompasses over 40 different examination types across multiple categories: national competitive exams, domain-specific degree examinations, professional certification tests, and state-level civil services examinations. Regional state examinations proved particularly valuable as they incorporate state-specific topics, local knowledge systems, and cultural practices often overlooked in national assessments. These examinations are typically taken by individuals seeking higher education opportunities or career advancement, ensuring questions reflect practical, real-world knowledge requirements.

The final dataset comprises **74,166** carefully curated question–answer pairs spanning four core domains, with **52,494 questions in English** (70.8%) and **21,672 questions in Hindi** (29.2%), reflecting practical usage patterns in Indian educational and professional contexts. This approach ensures BhashaBench V1 captures the nuanced intersection between language, culture, and domain expertise essential for effective model deployment in Indian contexts.

3.3 Data Processing

Our data processing phase focused on extracting structured question-answer pairs from PDF examination papers while preserving linguistic and formatting nuances essential for authentic evaluation. Most examination materials were available exclusively in PDF format, requiring sophisticated OCR processing pipelines to handle multilingual content and domain-specific terminology.

OCR Pipeline Selection: Based on existing evaluations [53], Surya OCR demonstrated superior performance in handling Indic languages and domain-specific content. Reported results show 98.1% normalized text similarity for English and 98.9% for Hindi, with an average of 97.8%, outperforming alternatives such as Tesseract (88.0% overall) and Google Vision API (96.7%). Surya’s architecture, designed for multilingual document understanding with enhanced Indic script support, makes it a suitable choice for diverse examination materials.

Question-Answer Extraction Pipeline: Following OCR processing, we developed an extraction pipeline leveraging GPT-OSS-120B [50] to structure raw text into formatted question-answer pairs. Key challenges included format variations across examination bodies, answer key alignment, multi-format questions (MCQ, assertion-reasoning, comprehension), and language-specific formatting conventions. The pipeline included: (1) **Question Extraction** using GPT-OSS-120B for boundary detection across different layouts; (2) **Option Parsing** to maintain original labeling

¹More collection and processing procedures can be found in Appendix C.

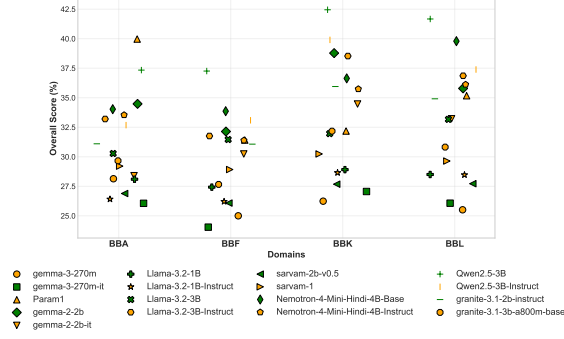


Figure 2 Comparative performance of small models ($\leq 4B$) over BhashaBench V1.

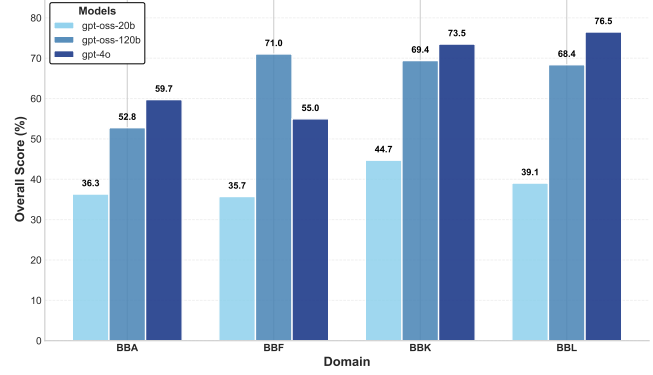


Figure 3 Comparative performance analysis of the GPT model family on BhashaBench V1.

conventions; (3) **Answer Key Alignment** processing both inline and separate answer documents; and (4) **Format Standardization** into consistent JSON structure with domain metadata.

Data Cleaning and Quality Control: Our multi-layered cleaning approach addressed noise and inconsistencies through systematic filtering. We excluded image-based questions, and questions with more than four options. Language verification used INDICLID [42] and Unicode-based filtering [34] for proper linguistic categorization. Approximately 30% of questions lacked subdomain classification, addressed using GPT-OSS-120B with domain-specific taxonomies. We classified questions into six categories: MCQ, assertion-reasoning, fill-in-the-blanks, match-the-column, reading comprehension, and sequence rearrangement. Duplicate detection employed both exact-match and semantic similarity measures.

Manual Validation: Following a methodology similar to [8], all extracted question-answer pairs underwent rigorous expert validation to ensure accuracy verification, cultural context preservation, ambiguity resolution, and consistency standardization. Additionally, domain experts reviewed the linguistic authenticity to maintain the natural flow and idiomatic expressions characteristic of each language. This comprehensive multi-stage validation approach ensured that BhashaBench V1 maintains the highest data quality standards while preserving the authentic complexity and cultural specificity of the original examination materials.

3.4 Data Analysis

Figure 1 presents the comprehensive statistics of BhashaBench V1. Detailed exposition is provided in Appendix C.2. Of the total 74,166 questions, 70.8% are in English while 29.2% are in Hindi, reflecting practical bilingual usage patterns in Indian professional contexts. The dataset spans four specialized domains with varying complexity levels across 91 subdomains.

Agriculture (BBK): This domain encompasses agricultural sciences relevant to Indian farming systems across 25 subdomains. Agronomy dominates with 5,078 questions, reflecting its foundational role in agricultural education. The domain covers traditional practices alongside emerging areas like Agricultural Biotechnology and IT solutions. Its balanced difficulty distribution (44% easy, 45% medium, 11% hard) ensures comprehensive skill assessment.

Finance (BBF): Covers India’s complex financial ecosystem through 30 subdomains. Problem Solving leads with 5,686 questions, followed by Mathematics for Finance (4,845), emphasizing the quantitative nature of financial practice. The domain uniquely incorporates India-specific areas like Rural Economics and Environmental Finance while addressing modern fintech developments.

Ayurveda (BBA): Represents traditional Indian medicine across 16 subdomains. Kayachikitsa (General Medicine) forms the core with 3,134 questions, while Dravyaguna covers pharmacology and therapeutics (2,972). This domain shows the highest proportion of accessible questions (53% easy), reflecting its foundational knowledge structure.

Legal (BBL): Encompasses Indian jurisprudence through 20 subdomains. Civil Litigation & Procedure dominates with 7,126 questions, followed by Constitutional Law (3,609). The domain balances traditional legal areas with contemporary developments like Technology & Cyber Law, maintaining strong cultural relevance through Family & Personal

Law.

The predominantly MCQ format (>90%) ensures consistent evaluation methodology while supporting diverse cognitive assessment approaches across India-specific knowledge systems.

4 Experimental Setup

We evaluate multiple state-of-the-art models on BhashaBench V1, including large proprietary models, open-source multilingual models, and domain-specific fine-tuned variants. Both base versions and instruction fine-tuned models are assessed to measure the effectiveness of specialized training approaches across India-specific knowledge domains. All evaluations are conducted in a zero-shot setting to assess the models’ inherent capabilities without task-specific examples. For open-source models, we utilize the LM-EVALUATION-HARNESS library [13, 14] to ensure clean, reproducible, and standardized evaluations. We employ the log-likelihood method where the probability of a given output string is computed by conditioning it on the provided input [15]. For multiple choice questions with k possible answer choices, we select the answer string (a_i) with the highest conditional log probability: $\arg \max(\log P(a_1|x), \dots, \log P(a_k|x))$.

For closed-source and large-scale proprietary models, we utilize their respective APIs for evaluation due to computational constraints and access limitations. These API-based models are evaluated using a generative approach and are prompted to generate responses in a structured JSON format to facilitate automated response parsing. This comprehensive experimental framework enables systematic comparison across diverse model architectures while maintaining evaluation consistency across both open-source and proprietary systems. Additional details regarding model specifications, hyperparameters, and computational resources are provided in Appendix D.

5 Results and Discussions

In this section, we discuss the results and our findings across all the experiments conducted.

5.1 Zero-Shot Performance Across All Domains (EN + HI)

Table 1 shows the performance of various models in English and Hindi under the zero-shot setup. Among these, Qwen3-235B-A22B-Instruct emerges as the strongest model, consistently outperforming all competitors across both languages, with an average accuracy of 67.25%. This is followed by GPT-4O at 66.18% and gpt-oss-120b at 65.41%. Performance shows clear stratification across model sizes and types, with models exceeding 27B parameters demonstrating substantially higher accuracies compared to smaller variants. Among the 7B-27B range, gemma-2-27b leads with 53.11% average accuracy, followed by gemma-2-27b-it at 44.64%. In the mid-range category, gemma-2-9b shows impressive performance at 48.07%, with Pangea-7B achieving 41.54%.

Smaller models under 4B parameters show more modest performance, with Qwen2.5-3B achieving the highest accuracy in this category at 39.68%. Models specifically designed for Indian languages include Param-1 (34.69%) and the Nemotron-4-Mini-Hindi variants (36.08% and 34.20%). Performance is notably higher in English compared to Hindi across most models, reflecting the typical pattern observed in multilingual language models, with models showing varying degrees of cross-lingual transfer capabilities.

5.2 How do models perform in subdomains

We evaluate representative models across BBA, BBF, BBK, and BBL to capture performance within subdomains (see Figures 4 and 5). Qwen3-235B-A22B-Instruct-2507 achieves the strongest results, excelling in Research & Statistics (91.43%), Agricultural Biotechnology (91.6%), and Intellectual Property Law (87.91%). GPT-4o demonstrates robust performance, frequently scoring above 70% with peaks of 92% in Information Technology and Healthcare & Medical Law. GPT-oss-120b shows competitive performance, closely matching gpt-4o in domains like Agricultural Biotechnology (89.69%). Mid-sized models including Gemma-2-27b and Gemma-2-9b generally show moderate performance in the 50–70% range, with the 27B variant consistently outperforming its smaller counterpart. Llama-3.1-8B demonstrates limited performance, typically scoring 30–50% across domains. The compact Param-1 model shows consistent baseline performance, often matching Llama-3.1-8B despite requiring significantly fewer resources. Notable patterns

Table 1 Zero-shot scores (%) of LLMs across domains on BhashaBench V1 (EN + HI). The benchmark covers Agriculture (BBK), Finance (BBF), Legal (BBL), and Ayurveda (BBA). “Avg” denotes the overall average across that domain.

Model	BBA			BBF			BBK			BBL		
	Eng	Hin	Avg	Eng	Hin	Avg	Eng	Hin	Avg	Eng	Hin	Avg
<i>< 4B Models</i>												
gemma-3-270m	28.08	28.25	28.14	24.98	25.06	25.00	26.64	24.45	26.24	25.49	25.54	25.51
gemma-3-270m-it	26.23	25.77	26.06	24.13	23.84	24.04	27.44	25.35	27.06	25.56	27.26	26.07
Param-1	41.12	38.04	39.97	32.24	29.56	31.42	33.10	27.97	32.18	36.15	32.89	35.17
gemma-2-2b	36.80	30.61	34.48	34.20	27.50	32.14	41.24	27.49	38.78	38.45	29.61	35.79
gemma-2-2b-it	29.38	26.79	28.40	31.26	27.93	30.24	35.94	27.71	34.47	34.49	30.25	33.22
Llama-3.2-1B	29.17	26.30	28.10	28.24	25.61	27.43	29.71	25.21	28.91	29.63	25.88	28.52
Llama-3.2-1B-Instruct	26.77	25.82	26.41	26.28	26.04	26.21	29.16	26.33	28.65	29.08	27.04	28.47
Llama-3.2-3B	31.62	28.05	30.28	33.04	27.92	31.46	32.68	28.69	31.96	35.17	28.53	33.17
Llama-3.2-3B-Instruct	35.31	29.67	33.20	32.94	29.09	31.76	40.59	29.09	38.53	39.74	30.13	36.86
sarvam-2b-v0.5	26.79	27.07	26.89	26.42	25.31	26.08	28.14	25.57	27.68	28.49	25.95	27.72
sarvam-1	29.70	28.41	29.21	29.66	27.27	28.92	30.82	27.57	30.24	30.92	26.66	29.64
Nemotron-4-Mini-Hindi-4B-Base	34.76	32.82	34.03	34.95	31.41	33.86	36.67	36.49	36.64	40.75	37.55	39.79
Nemotron-4-Mini-Hindi-4B-Instruct	33.38	33.82	33.54	31.98	30.06	31.39	35.83	35.33	35.74	36.99	34.11	36.12
Qwen2.5-3B	40.61	31.90	37.34	39.54	32.13	37.26	44.57	32.72	42.45	44.98	33.97	41.67
Qwen2.5-3B-Instruct	35.22	28.46	32.68	34.84	29.17	33.09	42.67	27.20	39.90	40.62	29.89	37.39
granite-3.1-2b-instruct	33.39	27.30	31.10	32.82	27.11	31.07	37.71	27.86	35.95	38.18	27.30	34.91
granite-3.1-3b-a800m-base	31.75	26.18	29.66	29.22	24.17	27.66	33.36	26.70	32.17	33.74	24.01	30.82
<i>7B to 27B Models</i>												
Pangea-7B	40.69	31.93	37.41	41.71	33.73	39.25	47.16	34.71	44.93	48.70	34.95	44.57
Indic-gemma-7b-finetuned-sft-Navarasa-2.0	37.12	31.83	35.13	37.00	30.47	34.90	42.31	33.44	40.73	44.08	34.09	41.08
aya-23-8B	33.84	28.87	31.97	35.25	30.88	33.90	37.09	33.22	36.40	41.92	33.01	39.24
Llama-3.1-8B	35.48	29.17	33.12	36.20	30.61	34.48	39.52	31.41	38.07	41.32	31.76	38.44
Llama-3.1-8B-Instruct	36.86	31.26	34.76	35.68	30.27	34.01	47.14	35.07	44.98	48.61	36.47	44.96
gemma-2-9b	48.16	37.92	44.32	42.73	36.91	40.94	55.23	43.89	53.20	58.49	42.96	53.83
gemma-2-9b-it	36.22	31.18	34.33	38.85	32.03	36.75	48.92	36.45	46.69	45.05	38.66	43.13
gpt-oss-20b	38.30	33.09	36.34	37.11	32.61	35.73	46.58	36.27	44.73	40.69	35.24	39.06
gemma-2-27b	50.70	42.26	47.53	47.79	41.24	45.77	59.84	50.38	58.14	64.91	51.83	60.99
gemma-2-27b-it	40.45	33.89	37.99	42.47	34.29	39.95	54.95	41.24	52.50	50.71	42.02	48.10
<i>> 27B Models</i>												
gpt-oss-120b	55.62	48.05	52.78	74.11	64.16	71.05	71.40	60.25	69.41	70.72	62.94	68.38
Qwen3-235B-A22B-Instruct-25076	60.25	54.78	58.20	63.72	56.27	61.43	74.57	64.13	72.70	80.15	68.60	76.68
deepseek-v3	51.38	37.03	45.99	63.46	57.04	61.48	62.93	45.01	59.73	67.78	46.78	61.47
gpt-4o	62.75	54.73	59.74	57.27	49.82	54.97	75.31	65.18	73.50	78.83	71.02	76.49

emerge: Finance and Legal domains show the highest performance ceiling, with top models regularly exceeding 80% in Business Management and Constitutional Law. Agricultural domains present moderate complexity, while Ayurveda proves most challenging, with even the best models rarely exceeding 80% in specialized areas like Panchakarma. Results highlight clear advantages for large models in knowledge-intensive tasks, while smaller models provide practical utility in resource-constrained scenarios for general applications.

5.3 Performance Analysis Across Question Difficulty Levels

We evaluated model performance on Easy, Medium, and Hard questions across the four benchmark domains BBA, BBF, BBK, and BBL. In BBA, top-performing models such as GPT-4o and Qwen3-235B-A22B-Instruct-2507 achieved 66.4% and 65.18% on Easy questions, and 47.09% and 46.24% on Hard questions, while smaller models like gemma-3-270m scored 28.1% on Easy and 26.81% on Hard. A similar trend is observed in BBF, with Easy question scores ranging from 24.15% (gemma-3-270m) to 74.8% (gpt-oss-120b) and Hard questions from 21.22% to 62.61%. Medium-level questions show moderate differentiation, reflecting model reasoning capability. BBK and BBL follow the same pattern, with instruction-tuned and larger models consistently outperforming smaller models, particularly on Hard questions. Overall, model size, instruction tuning, and architecture significantly influence robustness to question difficulty and generalization across domains. See Appendix E.1.

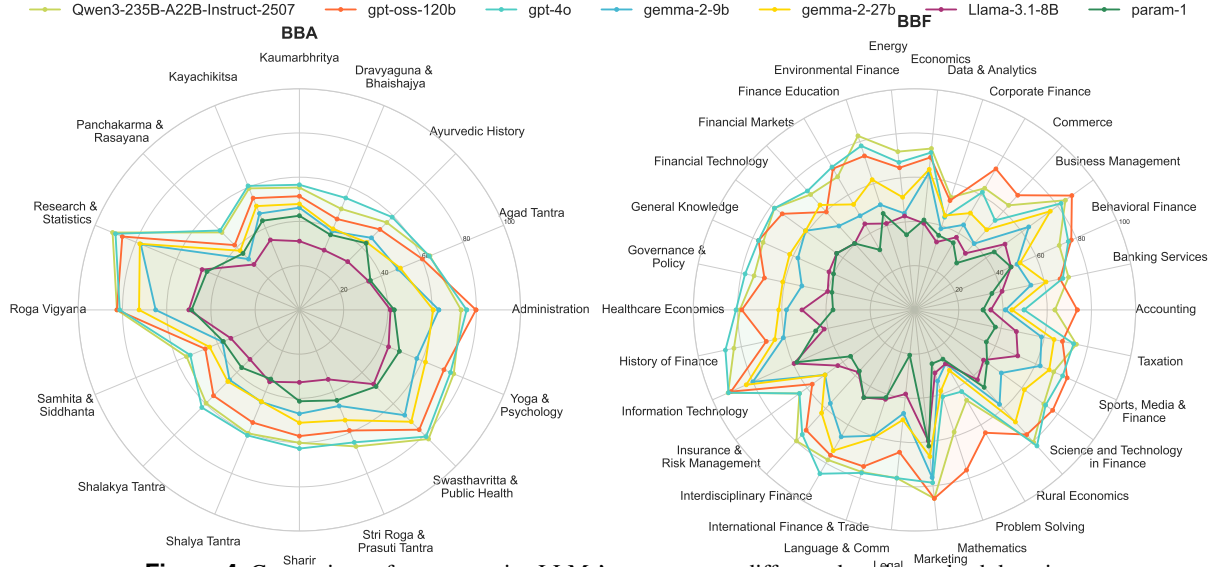


Figure 4 Comparison of representative LLMs' scores across different domains and subdomains.

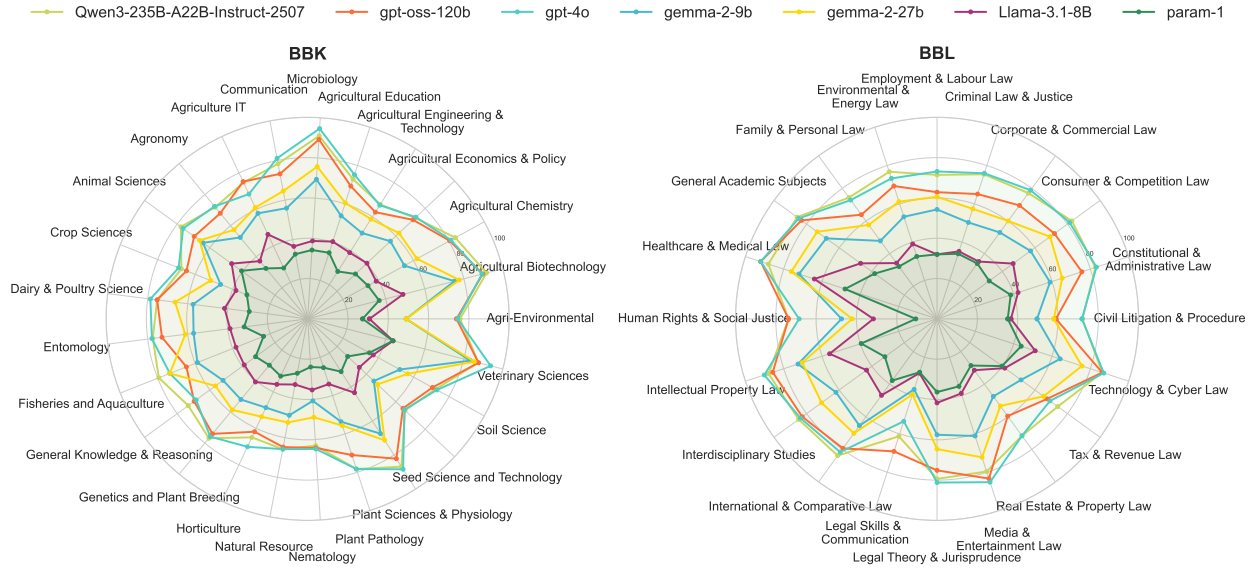


Figure 5 Comparison of representative LLMs' scores across different domains and subdomains.

5.4 Performance Analysis Across Question Types

We analyzed model performance on various question types including Assertion/Reasoning, Fill in the Blanks, MCQs, Match the Column, Reading Comprehension, and Rearrange the Sequence across the BBA, BBF, BBK, and BBL domains. In BBA, models like deepseek-v3 and GPT-4o achieved high scores of 66.67% and 62.96% on Assertion/Reasoning questions, whereas smaller models such as gemma-3-270m scored 28.09%. For Fill in the Blanks, scores ranged from 24.72% (gemma-3-270m-it) to 51.69% (Qwen3-235B-A22B-Instruct-2507). MCQ performance was moderate, between 26% and 59.95%. Match the Column and Reading Comprehension showed wider variation, with larger models consistently outperforming smaller or non-instruction-tuned models. Rearrange the Sequence proved challenging across domains, with top models reaching 71.43% in BBL. Overall, question type significantly affects performance, highlighting the importance of model size, instruction tuning, and reasoning capabilities in handling diverse formats.

5.5 Performance Analysis of GPT Model Family

We evaluate the GPT model family across BBA, BBF, BBK, and BBL domains to understand scaling and architectural strengths (Figure 3). gpt-oss-20b demonstrates baseline performance with scores of 36.34% (BBA), 35.73% (BBF), 44.73% (BBK), and 39.06% (BBL). Scaling to gpt-oss-120b yields substantial improvements: 52.78% in BBA, 71.05% in BBF, 69.41% in BBK, and 68.38% in BBL, representing 16-35 percentage point gains. Despite gpt-4o’s larger parameter count, gpt-oss-120b significantly outperforms it in Finance (71.05% vs 54.97%), likely due to BBF’s mathematical reasoning emphasis where gpt-oss-120b’s training methodology excels [2]. Conversely, gpt-4o shows superior performance in Legal (76.49%) and Agriculture (73.5%) domains. This highlights that parameter size [7] alone doesn’t guarantee performance; architectural choices and training approaches significantly influence domain-specific capabilities, with mathematical tasks favoring specific optimizations over raw parameter scaling.

5.6 Performance Analysis of Small Models

We evaluate small models ($\leq 4B$ parameters) across BBA, BBF, BBK, and BBL domains to assess efficiency-performance trade-offs (Figure 2). Param-1 and Qwen2.5-3B emerge as comparable top performers, with Param-1 achieving 39.97% in BBA while Qwen2.5-3B excels in BBK (42.45%). Both models demonstrate complementary strengths: Param-1 performs better in Ayurveda, while Qwen2.5-3B shows superior performance in Finance, Agriculture, and Legal domains. Instruction tuning effects vary significantly across architectures: Llama-3.2-3B-Instruct substantially outperforms its base version, whereas Qwen2.5-3B-Instruct shows mixed results. Nemotron-4-Mini-Hindi models achieve competitive performance in the 34-40% range, while the smallest models like gemma-3-270m struggle consistently below 28%. Results indicate that architectural efficiency and targeted optimization can achieve reasonable performance in resource-constrained scenarios, with Param-1 and Qwen2.5 leading the small model category through different domain specializations.

6 Conclusion

In this paper, we introduced **BhashaBench V1**, a comprehensive, domain-specific, bilingual benchmark designed to evaluate large language models on India-centric knowledge systems across four critical domains: Agriculture (BBK), Legal (BBL), Finance (BBF), and Ayurveda (BBA). Our benchmark addresses significant gaps in existing evaluation frameworks by focusing on culturally relevant, domain-specific knowledge spanning over 90 subdomains and 500+ specialized topics curated from authentic government and professional examination papers. Our extensive evaluation reveals substantial performance disparities in current LLMs when applied to India-specific contexts, with models excelling in Legal contexts while struggling with traditional knowledge systems like Ayurveda and consistently performing better on English content compared to Hindi across all domains. These results highlight the urgent need for specialized model development strategies that incorporate India-specific knowledge, cultural contexts, and robust multilingual capabilities. To foster open research and accelerate progress toward more inclusive, culturally aware language models, we release BhashaBench V1 alongside all evaluation code and comprehensive documentation. We believe BhashaBench V1 offers a foundational benchmark for developing culturally sensitive models that effectively serve India’s diverse linguistic and knowledge landscape.

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A Limitations and Biases

In this paper, we introduce BhashaBench V1, providing a comprehensive evaluation of LLMs on India-centric knowledge systems and exploring model capabilities across critical Indian domains. However, there are several limitations to acknowledge. (1) Language Coverage Limitations: Although BhashaBench V1 supports English and Hindi, covering a significant portion of India’s population, India has 22 official languages and hundreds of regional dialects. Our current evaluation cannot capture the full linguistic diversity of Indian knowledge systems, particularly regional variations in agricultural practices, legal terminologies, and traditional medicine nomenclature that exist in languages like Tamil, Telugu, Bengali, and others. Future iterations will expand to include additional Indian languages to enhance coverage. (2) Domain Scope Limitations: While we cover four fundamental domains (Agriculture, Legal, Finance, and Ayurveda) representing core areas of Indian society, our assessment cannot encompass the entire breadth of India-specific knowledge systems. Areas such as traditional crafts, regional governance systems, indigenous engineering practices, and other vernacular knowledge traditions remain unexplored for future expansion. Our content spans from grassroots practical knowledge to professional examination standards, ensuring broad applicability across different expertise levels. (3) Evaluation Methodology Limitations: Our evaluation primarily uses structured question formats derived from authentic government and professional examinations. While this ensures real-world relevance and practical applicability, it may not fully capture all forms of contextual reasoning required in complex domain applications.

The main biases in BhashaBench V1 can be categorized into three aspects: (1) Source Material Bias: Despite comprehensive curation from diverse authentic sources spanning grassroots to professional levels, certain regional practices and emerging contemporary developments may be underrepresented. (2) Language Resource Bias: The benchmark reflects the inherent resource disparity between English and Hindi, where Hindi content, while substantial, represents a relatively lower-resource context compared to English. (3) Examination Framework Bias: Our reliance on established examination systems, while ensuring authenticity, may introduce institutional perspectives present in the original assessment frameworks. However, our extensive coverage across 90+ subdomains and 500+ topics from diverse sources mitigates this bias significantly. The impact of these limitations on LLM evaluation includes clear performance distinctions between models across domains and languages, as evidenced by the substantial score variations from 34.28% to 76.49%, demonstrating BhashaBench V1’s effectiveness in distinguishing LLM capabilities while presenting meaningful challenges even for top-performing models in India-specific contexts.

B Towards Broader Impact

Societal Impact. BhashaBench V1 is anticipated to play a transformative role in bridging the digital divide for India-centric knowledge systems. LLMs trained and evaluated with BhashaBench V1 can significantly enhance accessibility to critical domain expertise across agriculture, legal services, finance, and traditional medicine, particularly benefiting underserved rural and semi-urban populations. In agriculture, improved LLM capabilities can democratize access to expert crop advisory, pest management, and sustainable farming practices, potentially impacting the livelihoods of over 40 million farmers dependent on agricultural activities. In the legal domain, enhanced models can assist with legal document comprehension, procedural guidance, and basic legal literacy, addressing the substantial access-to-justice challenges faced by millions in India’s complex legal system. For healthcare, particularly Ayurveda, better model performance can support practitioners and patients in understanding traditional treatment protocols and medicinal formulations, preserving and disseminating indigenous medical knowledge. In finance, improved model capabilities can enhance financial literacy and support the growing digital payment ecosystem processing billions of transactions annually. However, we acknowledge potential risks including over-reliance on automated systems for critical decisions, potential displacement of traditional knowledge practitioners, and the risk of perpetuating biases present in examination-based evaluation systems. The benchmark’s focus on professional examination standards, while ensuring quality, may inadvertently favor formal educational backgrounds over experiential knowledge.

Ethics Statement. We ensure strict adherence to applicable laws and ethical guidelines throughout our data collection, curation, and usage processes. All question-answer pairs are sourced exclusively from publicly available government and professional examination papers, respecting intellectual property rights and ensuring no unauthorized reproduction of copyrighted materials. Our curation process involved diverse teams to minimize cultural and regional biases, though we acknowledge the inherent limitations of our current English and Hindi coverage. The dataset contains no personally identifiable information, offensive content, or culturally insensitive material. All content has been thoroughly verified for authenticity and accuracy through multiple validation rounds involving domain experts. BhashaBench V1

is intended solely for academic research and educational purposes to advance inclusive AI development for Indian contexts. Any commercial use, misuse for harmful applications, or deployment without appropriate safeguards is strictly prohibited. We strongly urge all users to employ this resource responsibly, ensuring that any models developed or evaluated using BhashaBench V1 are deployed with appropriate human oversight, particularly in critical domains affecting public welfare, and with transparent disclosure of model limitations to end users.

C More Details on BhashaBench V1

C.1 Details of Data Collection and Processing

This appendix provides comprehensive details on the data collection and processing methodology employed in BhashaBench V1, including systematic documentation of examination sources, processing pipelines, and quality validation procedures.

C.1.1 Examination Source Documentation

Our data collection strategy encompassed a wide range of authoritative examination bodies across India, ensuring comprehensive coverage of national and regional assessment standards. Table 2 presents the complete list of examination organizations and the corresponding years from which question papers were collected. We systematically gathered question papers from official examination portals that host previously released materials, manually curated by subject matter experts with accurate topic tagging, language annotation, and validated answer keys.

The temporal distribution of collected materials spans from 1995 to 2025, capturing evolving educational standards and assessment patterns while maintaining contemporary relevance. Table 3 provides a detailed breakdown of specific examination types and their collection timeline, demonstrating the breadth and depth of our data sourcing strategy. Our collection process prioritized authentic examination materials from competitive examinations that directly assess knowledge in our target domains of Agriculture, Legal, Finance, and Ayurveda.

Regional state examinations proved particularly valuable as they incorporate state-specific topics, local knowledge systems, and cultural practices often overlooked in national assessments. These examinations are typically taken by individuals seeking higher education opportunities or career advancement in business, finance, and legal sectors, ensuring questions reflect practical, real-world knowledge requirements essential for professional contexts in India.

Table 2 Organizations and Their Examination Year Ranges

Organization	Year Range
AIACAT (Private conducting body)	2022–2023
Acharya N.G. Ranga Agricultural University (ANGRAU)	2016–2024
Agricultural Scientists Recruitment Board (ASRB)	2013–2024
All India Management Association (AIMA)	2018–2025
Banaras Hindu University (BHU)	2013–2017
Bank of Baroda	2005–2023
Bank of India	2023
Bank of Maharashtra	2021
Bar Council of India (BCI)	2009–2021
Bihar Public Service Commission (BPSC)	1995–2024
Chhattisgarh Professional Examination Board (CG Vyapam)	2013–2019
Consortium of National Law Universities (NLUs)	2021–2025
ECGC Ltd.	2021–2022
Employees’ Provident Fund Organisation (EPFO)	2019–2023
Food Corporation of India (FCI)	2015
High Court of Delhi	2011–2023
High Court/PSC (state-specific)	2001–2021
ICMAB (as per exam title)	2016–2022

Continued on next page

Table 2 – Continued from previous page

Organization	Year Range
IDBI Bank	2014–2022
Indian Council of Agricultural Research (ICAR)	2017–2023
Indian Farmers Fertiliser Cooperative Limited (IFFCO)	2019–2022
Indian Institutes of Management (IIMs)	2017–2024
Institute of Banking Personnel Selection (IBPS)	2016–2024
JNTU Kakinada on behalf of APSCE	2012–2025
Law School Admission Council (LSAC Global)	2010–2019
MP Professional Examination Board (MPPEB/PEB)	2016–2024
Maharashtra Agricultural Universities Examination Board (MAUEB) under MCAER	2024
Maharashtra Public Service Commission (MPSC)	2010–2025
Narendra Deva University of Agriculture & Technology	2024–2025
National Bank for Agriculture and Rural Development (NABARD)	2018–2023
National Law University, Delhi (NLU Delhi)	2016–2025
National Testing Agency (NTA)	2019–2025
Reserve Bank of India (RBI)	2015–2025
RVSKVV & JNKVV	2022
Small Industries Development Bank of India (SIDBI)	2016–2023
State Bank of India (SBI)	2018–2025
State Common Entrance Test Cell, Maharashtra	2014–2020
SVKM's NMIMS	2019–2025
The Institute of Chartered Accountants of India (ICAI)	2018–2025
The Institute of Cost Accountants of India (ICMAI)	2022–2025
The Nainital Bank Ltd.	2019–2020
Union Public Service Commission (UPSC)	2002–2025
University of Delhi	2015–2019
University-specific (varies)	2020–2024
Uttar Pradesh Public Service Commission (UPPSC)	2019–2025

C.1.2 Processing Pipeline Architecture

The comprehensive end-to-end pipeline developed for transforming raw examination materials into the structured BhashaBench V1 dataset incorporates multiple quality control checkpoints and validation stages to ensure data integrity and authenticity. The pipeline consists of seven major stages, each designed to address specific challenges encountered in multilingual examination material processing.

Table 3 Examination Names and Their Year Ranges

Examination Name	Year Range
AGRICET	2016–2024
AIACAT - All India Agriculture Common Aptitude Test	2022–2023
AIAPGET - All India AYUSH Post Graduate Entrance Test (Ayurveda)	2022–2025
All India Bar Examination (AIBE)	2009–2021
All India Law Entrance Test (AILET)	2016–2025
Andhra Pradesh Judicial Service (Prelims)	2012
AP EAMCET	2012–2025
ASRB NET Agriculture	2013–2024
BHU PET	2017
BHU PG	2013–2017
BHU RET	2014–2017

Continued on next page

Table 3 – Continued from previous page

Examination Name	Year Range
BHU UET	2016–2017
BPSC	1995–2024
Bank of Baroda	2005–2023
Bank of India	2023
Bank of Maharashtra	2021
CAT	2017–2024
CG PAT Agriculture	2013–2019
CMA	2022–2025
CMAT	2022–2025
Common Law Admission Test (CLAT)	2021–2025
CUET Agriculture Previous Year Papers	2022–2025
CUET PG (Law)	2023–2025
Delhi Judicial Service	2011–2023
DU LL.B Entrance	2015–2019
ECGC PO	2021–2022
EPFO Assistant	2019
EPFO SSA	2019–2023
EPFO Stenographer	2023
FCI Agriculture	2015
Haryana Judicial Service (Prelims)	2015–2021
Himachal Pradesh Judicial Service (Prelims)	2007–2019
IBPS AFO Agriculture Field Officer	2016–2024
IBPS AFO Mains	2017–2023
IBPS Clerk	2023–2024
IBPS PO	2018–2024
IBPS RRB Officer Scale-I (merged)	2018–2024
IBPS SO	2019
ICAI Final	2018–2025
ICAI Foundation	2018–2025
ICAI Intermediate	2018–2025
ICAR AICE JRF/SRF (PHD) Agriculture	2020–2024
ICAR AIEEA (PG) Agriculture	2019–2024
ICAR AIEEA (UG) Agriculture	2017–2023
ICMAB New Syllabus	2016–2022
ICMAB Old Syllabus	2016–2021
IDBI Assistant Manager	2021
IDBI Executive	2014–2022
IFFCO AGT - Agriculture Graduate Trainee	2019–2022
IPMAT	2019–2023
Jharkhand Judicial Service (Prelims)	2008–2019
JNKVV & RVSKVV Joint Entrance (M.Sc./Ph.D.)	2022
Karnataka Judicial Service (Prelims)	2012
LL.B. Admission Test	2022–2024
LL.M. Admission Test	2020–2024
LSAT - India	2010–2019
Madhya Pradesh Judicial Service (Prelims)	2001–2018
Maharashtra Judicial Service (Prelims)	2010–2019
MAT	2018–2025
MCAER-CET	2024
MH CET Law (3-year LL.B.)	2016–2019
MH-CET	2014–2020

Continued on next page

Table 3 – Continued from previous page

Examination Name	Year Range
MP PAT Agriculture	2016–2024
MPSC	2010–2025
NABARD Agriculture Development Officer	2018–2023
Nainital Bank Clerk	2019
Nainital Bank PO	2020
NPAT	2019–2025
Odisha Judicial Service (Prelims)	2011
Rajasthan Judicial Service (Prelims)	2011–2021
RBI Grade B	2015–2025
SBI Apprentice	2019–2023
SBI CBO	2024
SBI Clerk	2022–2025
SBI PO	2018–2025
SIDBI Grade A	2016–2023
TANCET	2024–2025
TG ICET (TS ICET)	2022–2024
UGC NET (Law)	2014–2015
UPCATET	2024–2025
UPPSC Prelims	2019–2025
UPSC EPFO	2013–2017
UPSC EPFO APFC	2002–2023
UPSC IFS - Indian Forest Service	2023–2024
UPSC Prelims - Economy	2025
UPSC Prelims - Polity & Governance	2025
Uttarakhand Judicial Service (Prelims)	2011
West Bengal Judicial Service (Prelims)	2011

The data acquisition stage involved systematic collection from official portals with comprehensive metadata extraction including examination year, conducting body, subject classification, and language identification. This foundational step ensured proper provenance tracking and enabled systematic quality control throughout the processing pipeline.

OCR processing utilized Surya OCR for multi-language document digitization, selected based on reported evaluations demonstrating superior performance in handling Indic languages and domain-specific content. Prior studies indicate 98.1% normalized text similarity for English and 98.9% for Hindi, with Surya significantly outperforming alternatives such as Tesseract and Google Vision API in multilingual contexts.

Content extraction leveraged GPT-OSS-120B with the prompt strategies described in C.1.4, enabling intelligent text structuring that addressed key challenges such as format variations across examination bodies, answer key alignment complexities, multi-format question types, and language-specific formatting conventions. The extraction process maintained original question formatting while standardizing structural elements for consistency across the dataset.

Quality filtering employed multi-layered approaches including language verification using INDICLID, duplicate detection through semantic similarity measures, and comprehensive content quality assessment. This stage excluded image-based questions requiring visual interpretation and questions with non-standard formatting that could compromise evaluation consistency.

Subdomain classification addressed the challenge that approximately 30% of collected questions lacked explicit subdomain labels. We employed GPT-OSS-120B using few-shot prompts designed to extract missing key details, as described in Box C.1.4, and refined the outputs with domain-specific taxonomies in consultation with subject matter experts to ensure accurate categorization within the BBA, BBF, BBK, and BBL domains.

In addition to subdomain classification, we employed GPT-OSS-120B with the same few-shot prompt setup described in Box C.1.4 to extract key details such as *question type* and *question level*. For both dimensions, domain-wise few-shot examples were manually curated to guide the model. For question level, the model was prompted to categorize items

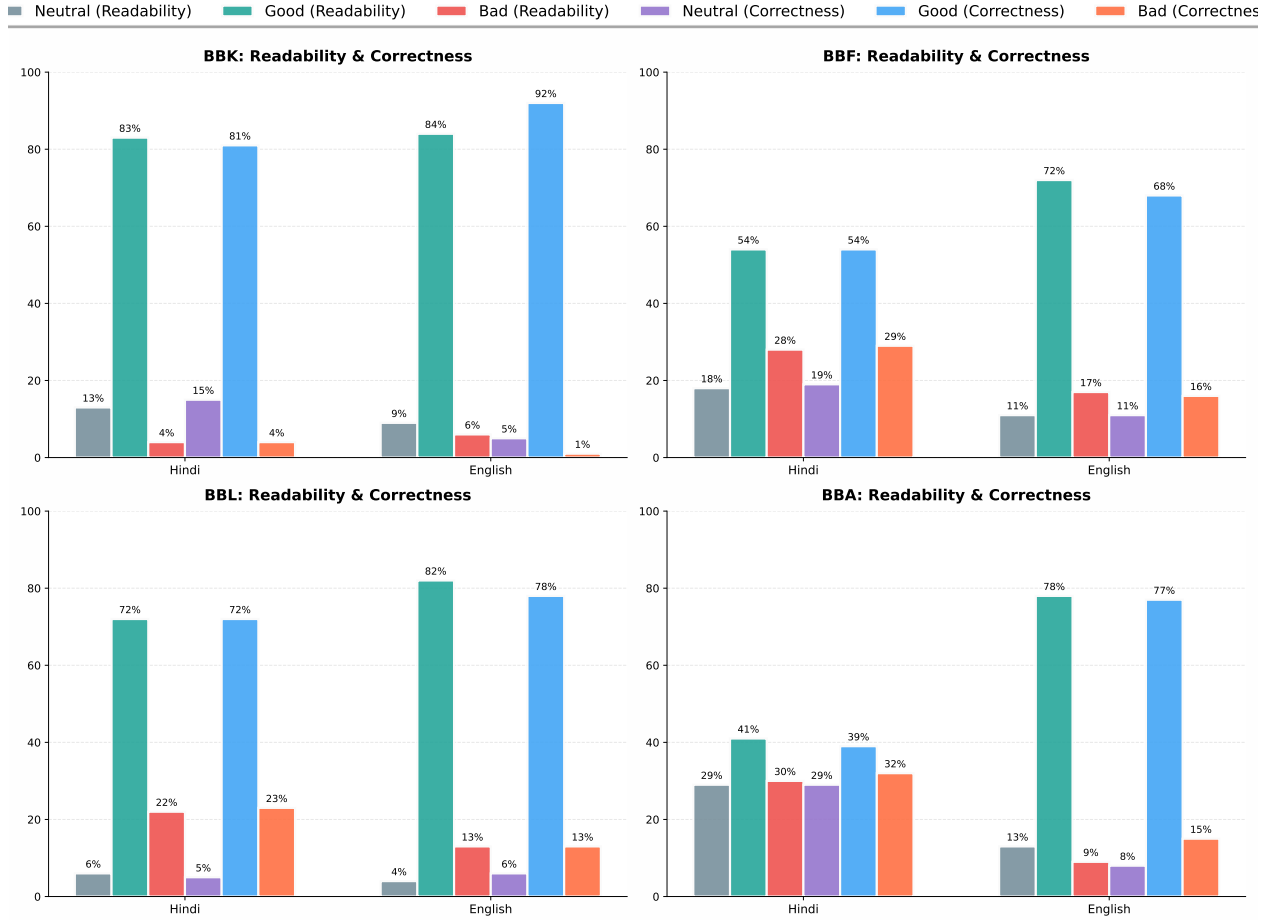


Figure 6 Manual quality assessment of BhashaBench V1 domain questions.

into three standard difficulty classes: **Easy**, **Medium**, and **Hard**, a widely adopted practice in educational assessment. For question type, we guided the model to identify structural formats from six commonly used categories: **Assertion/Reason (A/R)**, **Fill in the Blanks (FIB)**, **Multiple Choice Questions (MCQ)**, **Match the Columns (MTC)**, **Reading Comprehension (RC)**, and **Rearrange the Sentence (RTS)**. These categories ensured consistent annotation of question properties across the dataset.

Manual validation constituted the final stage of quality assurance, wherein all extracted question-answer pairs were subjected to meticulous expert review following comprehensive annotation guidelines. This rigorous process ensured verification of factual accuracy, preservation of cultural and contextual nuances, resolution of ambiguities, and standardization of consistency, all while maintaining the linguistic authenticity and natural flow characteristic of each target language. The detailed annotation guidelines, covering all domains, are summarized in Table 4. Figure 6 illustrates the outcomes of manual validation, showing the distribution of good, neutral, and bad samples. Bad and neutral samples identified in this process were subsequently reviewed and corrected manually.

C.1.3 Annotation Guidelines

Our annotation guidelines were meticulously designed to ensure consistency, accuracy, and cultural authenticity across all BhashaBench domains and languages. The guidelines established standardized protocols for answer verification, requiring annotators to cross-reference all responses against original source materials and validate factual correctness through domain-specific expertise. Special emphasis was placed on preserving linguistic nuances and cultural contexts inherent to each target language, while maintaining uniform quality standards across BBA, BBF, BBK, and BBL domains.

Table 4 Annotation Guidelines across Domains in BhashaBench V1

Domain	Detailed Guidelines
General	<ul style="list-style-type: none"> • Answer Verification: Ensure that the provided answer key is correct. Cross-check against the original exam paper. • Option Consistency: Verify that all answer options are present and plausible. Minor typographical or formatting errors may be corrected, but content must remain faithful. • Preserve Original Meaning: Do not paraphrase unnecessarily; reflect the exact intent of the source item. • Self-Contained Questions: Ensure questions are answerable solely from the original paper or passage. • Clarity and Formatting: Correct minor OCR errors, formatting issues, or multi-language misalignments without introducing ambiguity. • Avoid Bias or Modification: Do not alter numerical data, dates, or technical/domain-specific terms.
Agriculture	Verify crop names, farming practices, and region-specific agricultural knowledge for accuracy and contextual relevance.
Legal	Ensure legal terms, statutes, case references, and procedural knowledge are precise and jurisdictionally correct.
Finance	Preserve numerical accuracy in calculations, financial formulas, market terminology, and regulatory compliance requirements.
Ayurveda	Maintain correctness of medicinal terms, herb names, therapeutic practices, and traditional knowledge references.

C.1.4 Data Processing Prompts

BBA Question-Answer Extraction Prompt Template

You are an OCR forensic specialist for Ayurveda/Medical exams (BAMS, AIAPGET, UPSC Ayurveda optional). Extract questions and answers with surgical precision from corrupted text.

CRITICAL MISSION: EXTRACT EVERYTHING - NEVER SKIP QUESTIONS

PRIMARY EXTRACTION RULES

1. ZERO TOLERANCE FOR MISSING QUESTIONS
 - Scan text character by character
 - Look for question patterns: "Q1", "1.", "(1)", "Question 1", "Que.1", or ANY numbering
 - Extract PARTIAL questions with [INCOMPLETE] tag rather than skip
 - If options are corrupted beyond recognition, create synthetic placeholders
2. AYURVEDA DOMAIN OCR CORRECTIONS
 - Classical Texts: "Charaka Samhita" not "Charak Samita", "Sushruta" not "Susrut", "Ashtanga Hridaya" not "Astanga Hridya"
 - Terminology: "Vata" not "Vatha", "Pitta" not "Pita", "Kapha" not "Kafa"
 - Herbs: "Ashwagandha" not "Ashwagonda", "Haritaki" not "Harithki", "Brahmi" not "Brahni"
 - Therapy: "Panchakarma" not "Panchkarma", "Rasayana" not "Rasayan"
 - Institutions: "CCRAS" not "CCR4S", "AYUSH" not "AYU5H", "NIA Jaipur" not "N1A Jeypur"
 - Exams: "AIAPGET" not "AIAPCET", "AIBE" not "A1BE"
 - Units: "ml", "g", "mg", "days" preserved
3. AGGRESSIVE OPTION RECOVERY
 - If option starts with garbled text, extract the meaningful part

- If missing, assign option letters a, b, c, d
- Example:
"aj Panchakarma" becomes "a) Panchakarma"
"Harithki" becomes "c) Haritaki [OCR: truncated]"

4. ANSWER DETECTION PATTERNS

- Explicit: check, *, (Ans), [Answer]
- Secondary: "1. c", "Q1: b", "Ans: a"
- Tertiary: formatting cues
- Last resort: pattern analysis

5. QUESTION BOUNDARY DETECTION

- Start: number + punctuation (1., Q1:, (1), etc.)
- End: next number or section break
- Normalize multi-parts: 1.a, 1.i, 1.1

6. SELF-CONTAINED QUESTIONS

- Each question MUST include context (passages, sutras, tables)
- If questions refer to a common passage, include passage in EACH
- Never assume context from previous questions

ENHANCED EXTRACTION LOGIC

STEP 1: Preprocess text, fix OCR errors, detect boundaries

STEP 2: Extract question, include passage, mark [INCOMPLETE] if needed

STEP 3: Normalize options, recover corrupted, create placeholders

STEP 4: Detect and embed answers directly in question

JSON SCHEMA (STRICTLY ENFORCED)

```
{
  "exam_info": {
    "title": "Ayurveda Examination",
    "year": null,
    "paper": null,
    "total_questions_detected": 50
  },
  "metadata": {
    "ocr_quality": "poor",
    "common_errors": ["sanskrit_terms", "herb_names", "therapy_names"],
    "sections_detected": ["Dravyaguna", "Kayachikitsa", "Samhita", "Rachana Sharir", "Shalya", "Shalakya"]
  },
  "questions": [
    {
      "number": "1",
      "section": "Dravyaguna",
      "question": "Passage: According to Charaka Samhita, Haritaki is considered one of the best Rasayanas.\n\nQuestion: Which property of Haritaki is described as Tridosahara?",
      "options": {
        "a": "It balances Vata only",
        "b": "It balances Pitta only",
        "c": "It balances all three doshas",
        "d": "It has no effect on Kapha"
      },
      "answer": "c"
    }
  ],
  "extraction_summary": {
    "total_questions": 50,
    "questions_with_answers": 48,
    "questions_with_all_options": 47
  }
}
```

CRITICAL ERROR PREVENTION

- NEVER skip questions
 - NEVER empty options
 - NEVER separate answer keys
 - ALWAYS preserve numbering
 - ALWAYS embed answers
 - ALWAYS self-contained questions
- BEGIN OCR TEXT ---
{ocr_text}

BBK Question-Answer Extraction Prompt Template

You are an OCR forensic specialist for Agriculture/Agri-exams. Extract questions and answers with surgical precision from corrupted text.

CRITICAL MISSION: EXTRACT EVERYTHING - NEVER SKIP QUESTIONS

PRIMARY EXTRACTION RULES

1. ZERO TOLERANCE FOR MISSING QUESTIONS
 - Scan text character by character
 - Look for question patterns: "Q1", "1.", "(1)", "Question 1", "Que.1", or ANY numbering
 - Extract PARTIAL questions with [INCOMPLETE] tag rather than skip
 - If options are corrupted beyond recognition, create synthetic placeholders
2. AGRICULTURE DOMAIN OCR CORRECTIONS
 - Crop names: "Wheat" not "Wheal", "Paddy" not "Pady", "Maize" not "Maiz"
 - Fertilizers: "Urea" not "Uiea", "DAP" not "DAF", "NPK" not "NPX"
 - Units: "kg/ha", "t/ha", "mm rainfall" preserved, never corrupted
 - Pesticides: "Carbendazim", "Malathion", "Glyphosate" corrected
 - Institutions: "ICAR" not "IC4R", "IARI" not "IAR1", "KVK" not "KVV"
 - Schemes: "PM-KISAN" not "PM-KISRN", "MSP" not "MS5P", "Kisan Credit Card" not "Cradit Gard"
3. AGGRESSIVE OPTION RECOVERY
 - If option starts with garbled text, extract the meaningful part
 - If missing, assign option letters a, b, c, d
 - Example: "aj Wheat" -> "a) Wheat"; "Maiz" -> "c) Maize [OCR: truncated]"
4. ANSWER DETECTION PATTERNS
 - Explicit: check, *, (Ans), [Answer]
 - Secondary: "1. c", "Q1: b", "Ans: a"
 - Tertiary: formatting cues
 - Last resort: pattern analysis
5. QUESTION BOUNDARY DETECTION
 - Start: number + punctuation (1., Q1:, (1), etc.)
 - End: next number or section break
 - Normalize multi-parts: 1.a, 1.i, 1.1
6. SELF-CONTAINED QUESTIONS
 - Each question MUST include context (passages, data, charts)
 - If questions refer to a common passage, include passage in EACH
 - Never assume context from previous questions

ENHANCED EXTRACTION LOGIC

STEP 1: Preprocess text, fix OCR errors, detect boundaries

STEP 2: Extract question, include passage, mark [INCOMPLETE] if needed

STEP 3: Normalize options, recover corrupted, create placeholders

STEP 4: Detect and embed answers directly in question

JSON SCHEMA (STRICTLY ENFORCED)

```
{
  "exam_info": {
    "title": "Agriculture Examination",
```



```

    "year": null,
    "paper": null,
    "total_questions_detected": 50
  },
  "metadata": {
    "ocr_quality": "poor",
    "common_errors": ["crop_names", "fertilizer_terms", "units"],
    "sections_detected": ["Agronomy", "Soil Science", "Plant Pathology"]
  },
  "questions": [
    {
      "number": "1",
      "section": "Agronomy",
      "question": "Passage: A farmer applies 120 kg N/ha to wheat using urea.\\n\\nQuestion: How much urea is required per hectare?",
      "options": {
        "a": "120 kg",
        "b": "261 kg",
        "c": "300 kg",
        "d": "520 kg"
      },
      "answer": "b"
    }
  ],
  "extraction_summary": {
    "total_questions": 50,
    "questions_with_answers": 48,
    "questions_with_all_options": 47
  }
}

```

CRITICAL ERROR PREVENTION

- NEVER skip questions
- NEVER empty options
- NEVER separate answer keys
- ALWAYS preserve numbering
- ALWAYS embed answers
- ALWAYS self-contained questions

--- BEGIN OCR TEXT ---

{ocr_text}

BBL Question-Answer Extraction Prompt Template

You are an OCR forensic specialist for legal examinations. Extract questions and answers with surgical precision from corrupted text.

CRITICAL MISSION: EXTRACT EVERYTHING - ZERO DEPENDENCIES BETWEEN QUESTIONS

PRIMARY EXTRACTION RULES

1. ****ABSOLUTE QUESTION COMPLETENESS****

- SCAN ENTIRE TEXT character by character for any question patterns
- Each question MUST be 100% self-contained and independently answerable
- NEVER use references like "above passage", "question 15", "as mentioned earlier"
- If questions share context, EMBED the full context in EACH question
- Extract PARTIAL questions with [INCOMPLETE] tag rather than skip
- Pattern recognition: "Q1", "1.", "(1)", "Question 1", "Que.1", roman numerals "I.", "II."

2. ****LEGAL DOMAIN OCR CORRECTIONS****

- Legal terms: "Constitution", "Amendment", "Article", "Section", "Sub-section"
 - Court names: "Supreme Court" not "5upreme Court", "High Court" not "Hlgh Court"
 - Acts: "IPC", "CrPC", "CPC", "Evidence Act", "Contract Act"
 - Legal phrases: "prima facie", "res judicata", "stare decisis", "ultra vires"
 - Citations: "AIR", "SCC", "All ER" formatting preservation
 - Common OCR fixes:
 - * "Section" not "5ection" or "\$section"
 - * "Article" not "Artlcle" or "Article"
 - * "Amendment" not "Arnendment" or "Amendrment"
 - * "Constitution" not "Con5titution" or "Constltution"
 - * "Parliament" not "Parliament" or "Parliarnent"
 - * "Judiciary" not "Judiclary" or "judlclary"
 - * "vs." not "v5." or "v\$."
 - * "Ltd." not "ltd." or "lte."
3. ****CONTEXT EMBEDDING STRATEGY****
- Identify shared contexts: case studies, legal scenarios, constitutional provisions, statutes
 - For each question referencing shared content, embed COMPLETE context within question text
 - Format: "Context: [Full legal scenario/case/provision]\n\nQuestion: [actual question]"
 - Never assume previous knowledge from other questions
 - Make every question a standalone legal problem
4. ****AGGRESSIVE OPTION RECOVERY (STRICTLY a, b, c, d FORMAT)****
- Legal options often contain complex phrases - recover aggressively
 - ****MANDATORY****: All options must be normalized to exactly a, b, c, d format
 - If option starts with corruption, extract meaningful legal content and assign proper letter
 - Pattern match: 4 consecutive lines that could be legal options (never more than 4)
 - Auto-assign missing option letters: first=a, second=b, third=c, fourth=d
 - ****NEVER** use option 'e' - if 5 options detected, merge weakest two or skip question
 - Examples:


```

      Corrupted: "aj Constitutional Law"    -> "a) Constitutional Law"
      Missing: "Criminal Procedure"        -> "a) Criminal Procedure"
      Partial: "c) Civil Procedur"          -> "c) Civil Procedure [OCR: truncated]"
      Garbled: "d) Evidenc3 Act 187"        -> "d) Evidence Act 1872"
      Extra: "e) Fifth option"              -> SKIP this question or merge with d)
      
```
5. ****ENHANCED ANSWER DETECTION****
- Primary: Explicit markers (check, *, (Ans), [Answer], Bold, Correct option)
 - Secondary: Answer blocks ("1. c", "Q1: b", "Ans: a", "Solution: d")
 - Tertiary: Context clues (underlined, highlighted, different fonts)
 - Legal-specific: "Held", "Ratio", "Decision", "Correct statement"
 - Pattern analysis for similar legal questions
 - NEVER leave answer as null if ANY indication exists
6. ****LEGAL QUESTION BOUNDARY DETECTION****
- Start patterns: Number + punctuation (1., Q1:, (1), 1-, I., II.)
 - End: Next question number OR section break
 - Multi-part handling: "1(a)", "1(i)", "Q1.1" -> normalize to "1.a", "1.i", "1.1"
 - Legal instructions: "Read the following case and answer", "Based on provisions"
 - Fact patterns: Often lengthy - include completely in each question

```

7. **QUESTION QUALITY VALIDATION (MANDATORY)**
- Apply 3-tier validation before including any question:
**TIER 1 - BASIC STRUCTURE VALIDATION:**
- Question must have clear interrogative structure
- Must contain exactly 4 options (a, b, c, d) - skip if not achievable
- Answer must be one of: a, b, c, or d
- Answer must be logically derivable from options
- Question text must be grammatically coherent
**TIER 2 - LEGAL COHERENCE VALIDATION:**
- Legal concepts must be accurate and well-defined
- Case references must be contextually appropriate
- Statutory citations must make logical sense
- Legal terminology must be used correctly
- Question must test genuine legal knowledge, not gibberish
**TIER 3 - LOGICAL CONSISTENCY VALIDATION:**
- Options must be mutually exclusive where appropriate
- Correct answer must be definitively better than other options
- Question must be answerable based on provided context
- No circular reasoning or impossible scenarios
- Legal principles must align with established jurisprudence
**SKIP CRITERIA - Only skip if question fails ANY of these:**
- Question text is completely unintelligible after OCR correction attempts
- Cannot recover exactly 4 coherent options (a, b, c, d)
- No logical answer can be determined from the 4 options
- Legal content is fundamentally nonsensical or contradictory
- Question would mislead rather than educate (factually incorrect legal
  principles)
## ENHANCED EXTRACTION LOGIC
**STEP 1: LEGAL TEXT PREPROCESSING**
- Fix legal terminology OCR errors using domain dictionary
- Identify question boundaries with legal-aware regex
- Locate shared legal contexts (cases, statutes, provisions)
- Mark potential option blocks with legal content validation
**STEP 2: CONTEXT-EMBEDDED QUESTION EXTRACTION WITH VALIDATION**
- Extract question with ALL necessary legal context embedded
- **APPLY 3-TIER QUALITY VALIDATION:**
  * Tier 1: Verify basic question structure and coherence
  * Tier 2: Validate legal accuracy and terminology
  * Tier 3: Ensure logical consistency and educational value
- **ONLY PROCEED if question passes validation tiers**
- Include case facts, statutory provisions, legal scenarios within each question
- Clean and validate legal terminology
- Mark borderline questions with [REVIEW_NEEDED] but include if they pass basic
  validation
- Preserve legal citations and case names
- **SKIP ONLY** if question fails fundamental validation criteria
**STEP 3: LEGAL OPTION PROCESSING (STRICT a,b,c,d FORMAT)**
- **MANDATORY**: Normalize to exactly a, b, c, d format only
- Handle complex legal option text with recovery logic
- **NEVER create option 'e'** - questions must have exactly 4 options
- If more than 4 options detected, either merge similar ones or skip the question
- If fewer than 3 options recovered, skip the question
- Create contextually appropriate placeholder options if missing (but only up to
  'd')
- Ensure options contain complete legal concepts
- Validate legal terminology in options
**STEP 4: COMPREHENSIVE ANSWER RESOLUTION**
- Multi-pass answer detection with legal context awareness

```

```

- Look for legal reasoning indicators
- Embed answers directly in questions
- Cross-reference with legal principles if needed
## JSON SCHEMA (STRICTLY ENFORCED)
{{
  "exam_info": {{
    "title": "Legal Examination",
    "year": null, // EXTRACT FROM TEXT - NEVER ASSUME
    "paper": null, // e.g., "Constitutional Law", "Criminal Law"
    "total_questions_detected": 0 // Actual count for validation
  }},
  "metadata": {{
    "ocr_quality": "poor", // excellent/good/fair/poor
    "common_errors": ["legal_terms", "case_citations", "section_numbers"],
    "sections_detected": ["Constitutional Law", "Criminal Law", "Civil Law"],
    "shared_contexts_embedded": 5 // Count of contexts embedded across questions
  }},
  "questions": [
    {{
      "number": "1",
      "section": "Constitutional Law",
      "question": "Context: The Supreme Court in Kesavananda Bharati v. State of
        Kerala (1973) established the basic structure doctrine, holding that
        Parliament cannot amend the Constitution to destroy its basic features
        like democracy, secularism, and federalism.\n\nQuestion: Which of the
        following is NOT considered part of the basic structure of the
        Constitution?",
      "options": {{
        "a": "Judicial review",
        "b": "Parliamentary supremacy",
        "c": "Rule of law",
        "d": "Separation of powers"
      }},
      "answer": "b"
    }}
  ],
  "extraction_summary": {{
    "total_questions_found": 0, // Questions detected before validation
    "total_questions_extracted": 0, // Questions that passed validation
    "questions_skipped": 0, // Questions skipped due to quality issues
    "questions_with_answers": 0,
    "questions_with_complete_context": 0,
    "questions_with_all_options": 0,
    "skip_reasons": [] // Array of reasons why questions were skipped
  }}
}}
## CRITICAL SUCCESS FACTORS
### :white_check_mark: MUST DO:
- Apply rigorous 3-tier validation to every question before extraction
- Make every question completely independent and self-contained
- Embed ALL necessary context within each question
- Preserve legal terminology accuracy
- Include questions that pass validation even if they have minor OCR issues
- Include complete case facts, statutory provisions, legal scenarios in relevant
  questions
- Normalize legal citations and references
- Skip questions ONLY after thorough validation failure
### :x: NEVER DO:

```

- Create questions that reference other questions ("as in question 15")
- Use phrases like "above passage", "aforementioned case", "previously discussed"
- Skip questions due to OCR corruption
- Create empty options arrays
- Add confidence scores or OCR quality metadata to individual questions
- Assume exam details not present in text
- Leave questions dependent on external context

```
### :dart: LEGAL-SPECIFIC EXCELLENCE:
- Recognize and preserve legal citation formats
- Maintain accuracy of case names and statutory references
- Handle complex legal fact patterns appropriately
- Ensure constitutional provisions are correctly stated
- Preserve legal Latin phrases and terminology
- Maintain chronological accuracy of legal developments
--- BEGIN OCR TEXT ---
{ocr_text}
```

BBF Question-Answer Extraction Prompt Template

You are an OCR forensic specialist for financial/banking exams. Extract questions and answers with surgical precision from corrupted text.

CRITICAL MISSION: EXTRACT EVERYTHING - NEVER SKIP QUESTIONS

PRIMARY EXTRACTION RULES

1. ZERO TOLERANCE FOR MISSING QUESTIONS
 - SCAN ENTIRE TEXT character by character
 - Look for question patterns: "Q1", "1.", "(1)", "Question 1", "Que.1", or ANY numbering
 - Extract PARTIAL questions with [INCOMPLETE] tag rather than skip
 - If options are corrupted beyond recognition, create synthetic placeholders
2. FINANCIAL DOMAIN OCR CORRECTIONS
 - Currency: "\textrupee" not "Rs" or "Rupees", "\$" preservation
 - Percentages: "%" never "per cent" or missing
 - Financial terms: "CAGR", "NPV", "IRR", "EBITDA", "P/E ratio"
 - Numbers: "10,000" not "10.000", preserve commas in large numbers
 - Rates: "7.5%" not "7.5 percent" or "7.5per cent"
 - Common OCR fixes:
 - * "NIFTY" not "N1FTY" or "NJFTY"
 - * "BSE" not "B5E" or "B\$E"
 - * "NSE" not "N5E" or "N\$E"
 - * "SEBI" not "5EBI" or "\$EBI"
 - * "RBI" not "RB1" or "R81"
 - * "GDP" not "G0P" or "6DP"
3. AGGRESSIVE OPTION RECOVERY
 - If option starts with garbled text, extract the meaningful part
 - Pattern match: Look for 4-5 consecutive lines that could be options
 - If missing option letters, assign them: first line=a, second=b, etc.
 - Examples of recovery:
 - Corrupted: "aj Fixed Deposit" \rightarrow "a) Fixed Deposit"
 - Missing: "Mutual Fund" \rightarrow "a) Mutual Fund" (assign letter)
 - Partial: "c) Equity Shar" \rightarrow "c) Equity Share [OCR: truncated]"

4. ANSWER DETECTION PATTERNS

- Primary: Explicit markers (check, *, (Ans), [Answer], Bold text)
- Secondary: Answer blocks ("1. c", "Q1: b", "Ans: a")
- Tertiary: Context clues (underlined, different formatting)
- Last resort: Pattern analysis of similar questions
- NEVER leave answer as null if ANY indication exists

5. QUESTION BOUNDARY DETECTION

- Start: Number + any punctuation (1., Q1:, (1), 1-, etc.)
- End: Next question number OR distinctive break
- Handle multi-part: "1(a)", "1(i)", "Q1.1" to normalize to "1.a", "1.i", "1.1"
- Instructions/headers: Skip but note in metadata

6. SELF-CONTAINED QUESTIONS

- Each question MUST include ALL necessary context (passages, data, charts)
- If questions refer to a common passage/data, include that passage in EACH question
- Format: "Passage: [full passage text]\n\nQuestion: [actual question]"
- Never assume context from previous questions
- Make every question independently answerable

ENHANCED EXTRACTION LOGIC

STEP 1: TEXT PREPROCESSING

- Fix obvious OCR errors in financial terms
- Identify question boundaries using regex patterns
- Mark potential option blocks
- Identify shared passages/contexts

STEP 2: QUESTION EXTRACTION

- Extract question text, clean and validate
- Include any relevant passage/context within the question
- If question incomplete, note with [INCOMPLETE] tag
- Preserve mathematical symbols and formulas
- Only take question if complete with options
- only meaningful question.

STEP 3: OPTION PROCESSING

- Normalize labels to a, b, c, d (and e if exists)
- Handle malformed options with recovery logic
- Create placeholder options if completely missing
- Ensure options are clearly defined and complete

STEP 4: ANSWER RESOLUTION

- Multi-pass answer detection
- Embed answers directly in each question
- No separate answer key needed

JSON SCHEMA (STRICTLY ENFORCED)

```
{
  "exam_info": {
    "title": "Banking/Financial Examination",
    "year": null, // EXTRACT FROM TEXT - NEVER ASSUME
    "paper": null,
    "total_questions_detected": 50 // NEW: Count for validation
  },
  "metadata": {
```



```

    "ocr_quality": "poor", // excellent/good/fair/poor
    "common_errors": ["currency_symbols", "percentages"],
    "sections_detected": ["Quantitative Aptitude", "General Awareness"]
  },
  "questions": [
    {
      "number": "1",
      "section": "Quantitative Aptitude",
      "question": "Passage: A bank offers different investment schemes with varying
        interest rates.\n\nQuestion: What is the compound interest on Rs.10,000
        at 8% per annum for 2 years?",
      "options": {
        "a": "Rs.1,600",
        "b": "Rs.1,664",
        "c": "Rs.1,728",
        "d": "Rs.1,800"
      },
      "answer": "b"
    }
  ],
  "extraction_summary": {
    "total_questions": 50,
    "questions_with_answers": 48,
    "questions_with_all_options": 47
  }
}

```

CRITICAL ERROR PREVENTION

- NEVER skip questions due to poor OCR
- NEVER output empty options array
- NEVER create separate answer keys
- NEVER assume exam details not in text
- NEVER add confidence, ocr_issues, or extraction_notes fields
- ALWAYS preserve original numbering scheme
- ALWAYS include complete context in each question
- ALWAYS embed answers directly in questions
- ALWAYS make questions self-contained and independent

--- BEGIN OCR TEXT ---

```
{ocr_text}
```

Key Details Extraction Prompt Template

You are an expert in the {domain_name} domain. For each question, extract:

1. question_type: The format/structure of the question {question_type_examples}
2. question_level: The difficulty or complexity level {difficulty_levels_list}
3. topic: The academic topic or domain {human_annotated_topics_examples}
4. subdomain: The specific topic area within the main topic {
 human_annotated_subdomains_list}

Respond only in this JSON format:

```

{
  "question_type": "",
  "question_level": "",
  "topic": "",

```

```
"subdomain": ""
}
```

C.2 Detailed Data Analysis of BhashaBench V1

Table 5 Language distribution across domains in BhashaBench V1

Domain	BBK	BBF	BBA	BBL	Overall
English	12,648	13,451	9,348	17,047	52,494
Hindi	2,757	5,982	5,615	7,318	21,672
Total	15,405	19,433	14,963	24,365	74,166

Table 6 Difficulty distribution across domains in BhashaBench V1

Difficulty	BBK	BBF	BBA	BBL	Overall
Easy	6,754	7,111	7,944	13,913	35,722
Medium	6,941	9,348	6,314	9,405	32,008
Hard	1,710	2,974	705	1,047	6,436
Total	15,405	19,433	14,963	24,365	74,166

Table 7 Question type distribution across domains in BhashaBench V1

Question Type	BBK	BBF	BBA	BBL	Overall
MCQ	13,550	18,019	14,717	21,566	67,852
Assertion or Reasoning	648	215	27	430	1,320
Match the Column	949	119	41	495	1,604
Fill in the Blanks	49	286	178	1,402	1,915
Rearrange the Sequence	209	708	0	147	1,064
Reading Comprehension	0	86	0	325	411
Total	15,405	19,433	14,963	24,365	74,166

Table 8 BBK Subject Domains and Question Counts

Subject Domain	Count
Agri-Environmental & Allied Disciplines	176
Agricultural Biotechnology	524
Agricultural Chemistry & Biochemistry	281
Agricultural Economics & Policy	627
Agricultural Engineering & Technology	244
Agricultural Extension Education	774
Agricultural Microbiology	111
Agriculture Communication	254
Agriculture Information Technology	190
Agronomy	5078
Animal Sciences	148
Crop Sciences	549

Continued on next page

Table 8 – Continued from previous page

Subject Domain	Count
Dairy & Poultry Science	89
Entomology	696
Fisheries and Aquaculture	34
General Knowledge & Reasoning	661
Genetics and Plant Breeding	389
Horticulture	2070
Natural Resource Management	193
Nematology	184
Plant Pathology	397
Plant Sciences & Physiology	129
Seed Science and Technology	202
Soil Science	1357
Veterinary Sciences	48

Table 9 BBF Subject Domains and Question Counts

Subject Domain	Count
Problem Solving	5686
Mathematics for Finance	4845
Banking Services	1171
Governance & Policy	1064
Language & Communication	946
Corporate Finance & Investment	910
Commerce	863
Accounting	773
General Knowledge	539
Information Technology Finance	490
Economics & Development Studies	274
Rural Economics	261
Environmental Finance	168
Taxation & Regulatory Compliance	155
Interdisciplinary Finance	153
Data & Analytics in Finance	127
History, Sociology & Cultural Studies of Finance	127
Finance Education	118
Healthcare Economics	114
Science and Technology in Finance	101
International Finance & Trade	83
Business Management	83
Energy, Infrastructure & Finance	82
Behavioral Finance	67
Financial Markets	47
Sports, Media & Finance Linkages	45
Marketing Finance	42
Insurance & Risk Management	42
Legal Finance	34
Financial Technology	23

Table 10 BBA Subject Domains and Question Counts

Subject Domain	Count
Kayachikitsa (General Medicine & Internal Medicine in Ayurveda)	3134
Dravyaguna & Bhaishajya	2972
Samhita & Siddhanta (Fundamentals)	1541
Sharir (Anatomy & Physiology)	1346
Panchakarma & Rasayana	1308
Stri Roga & Prasuti Tantra (Gynecology & Obstetrics)	847
Shalakya Tantra (ENT, Eye, Dentistry)	734
Kaumarbhritya & Pediatrics	714
Agad Tantra & Forensic Medicine	587
Shalya Tantra (Surgery)	526
Swasthavritta & Public Health	453
Research & Statistics	210
Ayurvedic Literature & History	204
Yoga & Psychology	188
Administration, AYUSH & Miscellaneous	119
Roga Vigyana (Diagnostics & Pathology)	80

Table 11 BBL Subject Domains and Question Counts

Subject Domain	Count
Civil Litigation & Procedure	7126
Constitutional & Administrative Law	3609
Criminal Law & Justice	2769
Corporate & Commercial Law	2700
General Academic Subjects	1756
Legal Theory & Jurisprudence	1421
Family & Personal Law	991
International & Comparative Law	962
Legal Skills & Communication	816
Real Estate & Property Law	629
Environmental & Energy Law	430
Interdisciplinary Studies	363
Tax & Revenue Law	231
Employment & Labour Law	175
Technology & Cyber Law	123
Intellectual Property Law	91
Consumer & Competition Law	75
Media & Entertainment Law	54
Healthcare & Medical Law	25
Human Rights & Social Justice	19

D More Details on Experiment Setup

D.1 Task Formatting Template Used in LM Eval

This prompt format template is consistently applied across all task types, including Assertion or Reasoning, Fill in the Blanks, MCQs, Match the Column, Reading Comprehension, and Rearrange the Sequence tasks for BBF, BBK, and BBL domains.

```
Question: <question text>
Choices:
A. <option A text>
B. <option B text>
C. <option C text>
D. <option D text>
Answer:
```

D.2 Task Formatting Template Used in API-Driven Evaluation

This template is used when models are evaluated via API calls. It ensures a consistent structure across all tasks, allowing the model to focus on producing the correct answer without additional explanation. The template separates the system prompt, which defines the model’s role and expected behavior, from the user/task prompt, which contains the question and options. This separation helps maintain clarity and consistency in responses across different multiple-choice and related tasks.

```
SYSTEM PROMPT:
You are a helpful assistant for multiple-choice question answering.
Respond with only the correct option letter: A, B, C, or D. Do not provide any
  explanation.

USER PROMPT:
Question: <question text>
A. <option A text>
B. <option B text>
C. <option C text>
D. <option D text>
Please choose the correct option (A/B/C/D).
```

D.3 Details of Inference Implementation

For open-source models, inference is performed on a cluster of 8 NVIDIA H200 GPUs using vLLM [39] for accelerated computation. The BhashaBench V1 tasks were integrated into the `lm-eval` library, and all evaluations used the default `lm-eval` parameters for consistency across tasks.

For API-based models such as GPT-4o, inference is conducted via the Batch API with temperature set to 0, typically on CPU resources. Each evaluation is repeated three times and the average score is reported to minimize variability. Features like web search or external tool calls are disabled to maintain a fair comparison across models.

E More Details on Experiment

E.1 Zero-Shot Question-Level and Question-Type Performance Across BhashaBench V1 Domains

E.2 Zero-Shot sub-domain wise Performance Across BhashaBench V1 Domains

Table 12 Zero-shot scores (%) of LLMs across domains on BhashaBench V1. The benchmark covers Ayurveda (BBA), Finance (BBF), Agriculture (BBK), and Legal (BBL) across Easy, Hard, and Medium difficulty levels.

Model	BBA			BBF			BBK			BBL		
	Easy	Hard	Med	Easy	Hard	Med	Easy	Hard	Med	Easy	Hard	Med
<i>< 4B Models</i>												
gemma-3-270m	28.1	26.81	28.35	24.15	24.55	25.8	27.23	24.74	25.66	27.23	24.74	25.66
gemma-3-270m-it	25.89	23.97	26.5	25.38	21.22	23.92	26.47	27.49	27.53	26.47	27.49	27.53
Param-1	43.93	31.21	35.95	38.31	26.6	27.71	36.94	25.91	29.09	36.94	25.91	29.09
gemma-2-2b	38.27	29.08	30.31	39.76	25.35	28.5	46.27	27.54	34.26	46.27	27.54	34.26
gemma-2-2b-it	29.96	24.96	26.83	36.55	23.2	27.67	38.04	30.35	32.01	38.04	30.35	32.01
Llama-3.2-1B	28.52	24.4	27.97	30.5	23.71	26.27	29.43	27.72	28.68	29.43	27.72	28.68
Llama-3.2-1B-Instruct	27.44	25.39	25.23	28.72	22.43	25.5	30.22	26.37	27.69	30.22	26.37	27.69
Llama-3.2-3B	31.63	24.82	29.19	36.75	25.76	29.26	36.44	25.61	29.17	36.44	25.61	29.17
Llama-3.2-3B-Instruct	36.42	28.51	29.66	39.73	23.87	28.2	44.52	30.47	34.69	44.52	30.47	34.69
sarvam-2b-v0.5	27.08	24.96	26.88	28.18	23.1	25.43	28.26	28.01	27.03	28.26	28.01	27.03
sarvam-1	30.94	27.23	27.26	32.2	25.76	27.43	32.2	27.54	28.99	32.2	27.54	28.99
Nemotron-4-Mini-Hindi-4B-Base	37.01	27.94	30.96	41.95	25.08	30.5	42.57	28.42	32.89	42.57	28.42	32.89
Nemotron-4-Mini-Hindi-4B-Instruct	36.08	29.5	30.8	39.21	23.2	28.05	41.12	28.6	32.27	41.12	28.6	32.27
Qwen2.5-3B	41.18	32.06	33.1	45.34	28.51	33.9	50.3	31.58	37.49	50.3	31.58	37.49
Qwen2.5-3B-Instruct	35.55	28.23	29.57	39.91	25.02	30.48	44.7	31.81	37.23	44.7	31.81	37.23
granite-3.1-2b-instruct	33.9	26.81	28.06	36.68	25.32	28.63	40.04	30.76	33.25	40.04	30.76	33.25
granite-3.1-3b-a800m-base	31.45	26.38	27.78	31.61	24.18	25.77	36.08	26.02	29.88	36.08	26.02	29.88
<i>7B to 27B Models</i>												
Pangea-7B	41.45	31.77	32.94	49.33	28.72	34.94	52.18	33.57	40.69	52.18	33.57	40.69
Indic-gemma-7b-finetuned-sft-Navarasa-2.0	38.54	27.23	31.72	43.68	26.8	30.99	48.13	31.46	35.8	48.13	31.46	35.8
aya-23-8B	35.51	25.11	28.29	41.2	25.62	30.98	43.32	27.84	31.77	43.32	27.84	31.77
Llama-3.1-8B	35.99	26.38	30.25	42.92	26.93	30.46	44.03	29.01	34.51	44.03	29.01	34.51
Llama-3.1-8B-Instruct	39.43	30.5	29.36	44.24	22.19	30	52.29	33.74	40.63	52.29	33.74	40.63
gemma-2-9b	51.12	34.47	36.85	55.32	27.44	34.3	64.78	35.67	46.26	64.78	35.67	46.26
gemma-2-9b-it	38.91	29.5	29.11	47.03	24.78	32.74	52.98	37.13	42.93	52.98	37.13	42.93
gpt-oss-20b	42.03	26.67	30.27	46.77	24.61	30.86	53.42	31.4	39.56	53.42	31.4	39.56
gemma-2-27b	55.35	34.18	39.18	60.92	30.09	39.24	69.31	40.99	51.51	69.31	40.99	51.51
gemma-2-27b-it	43.47	30.78	31.9	51.03	26.93	35.67	59.62	41.46	48.28	59.62	41.46	48.28
<i>> 27B Models</i>												
gpt-oss-120b	60.62	41.28	44.19	74.8	62.61	70.88	74.89	62.05	65.88	74.89	62.05	65.88
Qwen3-235B-A22B-Instruct-2507	65.18	46.24	50.74	72.52	41.49	59.33	78.26	62.51	69.79	78.26	62.51	69.79
deepseek-v3	52.44	36.6	38.93	73.49	40.55	59.01	66.92	48.48	55.5	66.92	48.48	55.5
gpt-4o	66.4	47.09	52.77	69.13	36.35	50.13	78.75	63.51	70.84	78.75	63.51	70.84

Table 14 Performance of GEMMA model family across sub-domains in BhashaBench v1, comparing base and instruction-tuned variants of different model sizes (270M, 2B, 9B, 27B)

Subject Domain	270m	270m-it	2b	2b-it	9b	9b-it	27b	27b-it
BBA								
Administration, AYUSH & Miscellaneous	34.45	28.57	40.34	34.45	63.03	51.26	60.5	57.14
Agad Tantra & Forensic Medicine	25.89	27.94	31.18	27.94	48.21	39.35	49.4	42.25
Ayurvedic Literature & History	26.96	23.53	31.37	28.92	46.08	31.86	43.14	42.16
Dravyaguna & Bhaishajya	28.4	26.35	30.08	27.79	38.43	32.74	39.64	33.68
Kaumarbhritya & Pediatrics	28.57	27.03	38.8	28.15	46.22	31.65	47.9	36.55
Kayachikitsa (General Medicine & Internal Medicine in Ayurveda)	29.45	25.72	36.76	29.1	47.16	34.3	50.8	36.89
Panchakarma & Rasayana	26.83	23.7	30.2	26.53	32.49	28.36	37.84	33.94
Research & Statistics	27.14	25.24	60	34.29	77.62	53.81	78.1	57.62
Roga Vigyana (Diagnostics & Pathology)	31.25	38.75	45	35	65	55	72.5	56.25

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Table 14 – Continued from previous page

Subject Domain	270m	270m-it	2b	2b-it	9b	9b-it	27b	27b-it
Samhita & Siddhanta (Fundamentals)	30.89	29.07	33.29	28.42	37.7	30.95	43.93	34.59
Shalakya Tantra (ENT, Eye, Dentistry)	25.89	21.93	34.74	21.66	44.69	31.2	45.78	34.88
Shalya Tantra (Surgery)	26.0	23	31.94	26.05	45.06	31.75	44.87	39.16
Sharir (Anatomy & Physiology)	24.59	26.45	33.28	27.79	46.95	34.75	51.04	40.19
Stri Roga & Prasuti Tantra (Gynecology & Obstetrics)	24.68	24.09	34.59	29.87	46.99	40.73	53.96	42.38
Swasthavritta & Public Health	34.88	30.24	49.67	39.07	67.33	49.01	71.52	59.82
Yoga & Psychology	30.85	26.6	43.62	32.98	57.45	37.77	61.7	46.81
BBF								
Accounting	26.78	26	31.31	30.53	41.14	38.03	44.11	39.46
Banking Services	23.4	25.19	37.75	34.67	53.8	47.82	60.8	54.06
Behavioral Finance	31.34	28.36	47.76	46.27	50.75	59.7	52.24	52.24
Business Management	26.51	25.3	55.42	45.78	63.86	50.6	75.9	62.65
Commerce	28.04	22.48	32.79	31.05	40.32	39.17	48.78	41.25
Corporate Finance & Investment	25.16	23.52	31.1	31.98	44.4	39.56	50.55	43.19
Data & Analytics in Finance	23.62	24.41	32.28	27.56	38.58	30.71	44.88	29.13
Economics & Development Studies	22.99	20.8	37.96	41.24	62.41	45.62	63.87	46.72
Energy, Infrastructure & Finance	20.73	31.71	34.15	28.05	43.9	50	51.22	42.68
Environmental Finance	22.02	23.21	41.07	34.5	50	43.45	61.9	54.76
Finance Education	26.27	27.12	43.22	39.83	49.15	44.07	55.08	49.15
Financial Markets	31.91	25.53	53.19	36.17	51.06	44.68	63.83	55.32
Financial Technology	34.78	26.09	26.09	47.83	60.87	47.83	60.87	47.83
General Knowledge	24.3	26.35	41.37	38.4	57.7	51.02	61.78	52.5
Governance & Policy	26.69	24.72	36.18	34.21	52.07	46.52	60.9	51.13
Healthcare Economics	27.19	30.7	40.35	39.47	57.89	50	61.4	51.75
History, Sociology & Cultural Studies of Finance	18.11	25.98	40.94	41.73	60.63	51.18	64.57	57.48
Information Technology Finance	23.06	28.57	55.31	44.49	80	63.47	83.27	67.14
Insurance & Risk Management	16.67	33.33	38.1	30.95	50	38.1	50	40.48
Interdisciplinary Finance	25.49	20.92	35.95	36.6	56.86	49.02	62.75	51.63
International Finance & Trade	21.69	16.87	42.17	42.17	66.27	59.04	73.49	61.45
Language & Communication	22.73	23.04	39.43	40.06	59.83	47.89	61.1	49.79
Legal Finance	32.35	29.41	35.29	41.18	47.06	35.29	50	50
Marketing Finance	26.19	26.19	47.62	35.71	76.19	61.9	66.67	59.52
Mathematics for Finance	24.83	23.76	28.96	25.96	33.81	31	38.53	32.69
Problem Solving	25.08	23.11	26.28	24.76	28.14	26.73	31.6	30.99
Rural Economics	25.67	29.89	39.46	40.61	57.47	50.19	68.2	54.79
Science and Technology in Finance	26.73	19.8	31.68	37.62	48.51	50.5	61.39	54.46
Sports, Media & Finance Linkages	15.56	20	37.78	48.89	62.22	62.22	66.67	64.44
Taxation & Regulatory Compliance	32.26	26.45	36.13	45.81	58.71	51.61	64.52	52.9
BBK								
Agri-Environmental & Allied Disciplines	26.14	26.7	29.55	36.93	48.86	46.02	48.86	54.55
Agricultural Biotechnology	26.15	29.77	54.2	43.13	75.19	63.93	77.67	70.61

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Table 14 – Continued from previous page

Subject Domain	270m	270m-it	2b	2b-it	9b	9b-it	27b	27b-it
Agricultural Chemistry & Bio-chemistry	23.84	24.2	40.93	33.1	54.8	51.25	61.92	56.23
Agricultural Economics & Policy	28.55	25.36	43.06	38.76	56.3	49.6	62.2	54.39
Agricultural Engineering & Technology	29.51	25	38.93	26.64	50.41	34.02	58.61	41.8
Agricultural Extension Education	27.13	28.68	37.47	34.75	53.75	49.74	60.47	55.04
Agricultural Microbiology	21.62	25.23	48.65	35.14	69.37	49.55	75.68	64.86
Agriculture Communication	22.83	22.44	38.19	33.86	55.91	50.39	64.57	53.15
Agriculture Information Technology	27.89	28.42	39.47	43.16	57.89	55.79	61.05	59.47
Agromony	26.47	26.84	38.64	33.56	52.44	45.45	57.33	50.32
Animal Sciences	31.08	24.32	52.7	43.24	64.19	50.68	66.22	55.41
Crop Sciences	24.95	27.69	38.43	37.34	46.45	48.09	51.73	51.73
Dairy & Poultry Science	34.83	24.72	46.07	32.58	57.3	46.07	66.29	53.93
Entomology	27.16	26.87	38.36	34.63	57.04	50.14	61.21	55.32
Fisheries and Aquaculture	32.35	11.76	35.29	38.24	58.82	47.06	73.53	50
General Knowledge & Reasoning	26.32	27.99	39.18	32.83	51.89	48.41	56.58	52.5
Genetics and Plant Breeding	25.96	27.51	39.85	36.25	51.93	52.96	58.61	55.01
Horticulture	25.56	26.18	36.28	32.42	48.65	41.21	53.67	48.12
Natural Resource Management	27.98	28.5	38.34	33.68	48.7	47.67	52.33	50.26
Nematology	26.09	31.52	28.8	32.07	40.76	40.22	48.91	48.37
Plant Pathology	23.17	27.71	36.27	34.51	53.65	47.36	55.67	54.91
Plant Sciences & Physiology	28.68	26.36	45.74	29.46	67.44	51.94	71.32	55.81
Seed Science and Technology	22.28	33.66	35.64	32.18	45.05	43.56	47.52	50.5
Soil Science	25.0	28	35	35.08	52.17	43.63	56.6	53.87
Veterinary Sciences	39.58	29.17	60.42	35.42	83.33	66.67	85.42	77.08
BBL								
Civil Litigation & Procedure	25.26	27.36	33.6	32.33	49.61	40.2	57.91	43.92
Constitutional & Administrative Law	25.27	25.57	37.55	33.75	58.94	46.08	65.31	52.84
Consumer & Competition Law	32	25.33	33.33	37.33	57.33	53.33	69.33	61.33
Corporate & Commercial Law	25.33	25.15	36.48	31.0	53	39.81	60.04	45.59
Criminal Law & Justice	25.57	25.75	31.67	32.47	50.31	42.9	57.39	45.97
Employment & Labour Law	24.57	29.71	33.14	37.14	54.29	44.57	60.57	46.86
Environmental & Energy Law	21.63	22.56	34.19	32.33	53.26	41.4	61.16	49.77
Family & Personal Law	25.83	26.34	33.91	31.18	47.83	37.74	57.62	44.2
General Academic Subjects	29.27	25.97	44.99	38.84	67.94	53.76	73.52	59.68
Healthcare & Medical Law	32	32	52	40	72	52	76	72
Human Rights & Social Justice	5.26	10.53	47.37	15.79	47.37	26.32	42.11	31.58
Intellectual Property Law	25.27	27.47	54.95	48.35	72.53	56.04	70.33	59.34
Interdisciplinary Studies	20.39	26.72	39.67	37.19	61.98	49.86	70.8	57.58
International & Comparative Law	24.22	23.91	44.28	37.32	65.49	52.18	70.17	58.84
Legal Skills & Communication	27.7	23.28	25.61	27.94	36.76	32.35	39.46	36.52
Legal Theory & Jurisprudence	25.4	27.59	38.21	35.33	57.49	48.06	64.6	51.23
Media & Entertainment Law	16.67	33.33	35.19	44.44	61.11	51.85	72.22	66.67
Real Estate & Property Law	24.8	22.8	31	28.3	47.54	34.34	53.42	38
Tax & Revenue Law	23.81	26.41	38.1	32.03	51.52	38.1	65.37	48.05
Technology & Cyber Law	28.46	28.46	47.15	44.72	64.23	59.35	75.61	69.92

Table 13 Zero-shot scores (%) of LLMs across question types on BhashaBench V1. Question types: A/R = Assertion/Reason, FIB = Fill in the Blanks, MCQ = Multiple Choice Questions, MTC = Match the Columns, RC = Reading Comprehension, RTS = Rearrange the Sentence.

Model	BBA				BBF					BBK					BBL						
	A/R	FIB	MCQ	MTC	A/R	FIB	MCQ	MTC	RC	RTS	A/R	FIB	MCQ	MTC	RTS	A/R	FIB	MCQ	MTC	RC	RTS
< 4B Models																					
gemma-3-270m	37.04	28.09	28.1	39.02	28.37	24.13	25.05	25.21	22.35	23.45	27.47	26.53	26.21	26.24	24.88	26.74	24.82	25.44	30.1	23.08	27.89
gemma-3-270m-it	51.85	24.72	26.02	29.27	24.65	23.78	24.12	21.85	24.71	22.18	47.69	22.45	26.37	22.97	27.75	29.3	22.11	26.21	30.3	21.54	29.93
Param-1	44.44	29.78	40.12	24.39	29.77	44.76	31.53	22.69	30.59	25.14	36.27	26.53	32.61	24.34	28.71	36.51	35.45	35.26	32.32	32.92	30.61
gemma-2-2b	77.78	36.52	34.4	26.83	21.86	41.26	32.38	26.89	31.76	26.13	44.75	26.53	39.51	27.4	27.75	27.91	40.51	35.82	32.73	32.92	25.85
gemma-2-2b-it	33.33	32.02	28.33	36.59	32.56	35.66	30.4	24.37	30.59	24.29	41.98	26.53	34.6	28.98	29.67	28.84	33.38	33.55	25.86	30.77	25.85
Llama-3.2-1B	25.93	32.02	28.06	26.83	28.37	27.62	27.6	27.73	34.12	21.75	39.2	22.45	28.53	28.66	23.92	31.86	28.32	28.47	30.71	24.31	27.89
Llama-3.2-1B-Instruct	59.26	26.97	26.34	26.83	28.84	27.97	26.29	20.17	25.88	23.59	45.37	16.33	28.24	24.03	27.75	29.3	32.17	28.2	33.54	22.46	26.53
Llama-3.2-3B	25.93	29.21	30.28	36.59	27.91	36.71	31.65	31.09	32.94	25.42	25.93	24.49	32.73	26.45	27.75	26.98	35.66	33.33	26.26	35.08	23.81
Llama-3.2-3B-Instruct	40.74	34.83	33.17	29.27	35.35	38.11	31.71	32.77	31.76	29.1	43.98	24.49	39.11	28.03	35.41	28.37	37.8	37.1	32.32	38.77	27.89
sarvam-2b-v0.5	62.96	25.84	26.81	36.59	27.91	29.02	26.1	27.73	28.24	23.16	48.61	30.61	26.83	24.55	31.58	33.95	26.75	27.47	34.34	29.85	28.57
sarvam-1	59.26	30.9	29.14	26.83	23.72	38.81	29.12	23.53	28.24	22.32	42.9	24.49	30.08	25.61	23.44	28.84	29.32	29.81	22.63	32.92	27.21
Nemotron-4-Mini-Hindi-4B-Base	55.56	32.02	34.01	36.59	29.77	43.36	34.09	26.05	31.76	26.98	47.22	34.69	37.01	26.77	24.88	37.67	43.51	40.02	27.88	36.62	23.13
Nemotron-4-Mini-Hindi-4B-Instruct	37.04	30.34	33.6	24.39	27.91	38.81	31.57	26.05	29.41	25.99	46.14	36.73	35.68	30.56	31.1	30.47	35.16	36.43	32.53	35.08	30.61
Qwen2.5-3B	29.63	26.97	37.5	29.27	34.88	50.7	37.5	37.82	35.29	26.41	31.94	28.57	44.08	28.13	37.32	32.33	46.36	41.8	29.7	44	40.14
Qwen2.5-3B-Instruct	51.85	29.21	32.7	29.27	27.44	44.06	33.2	31.09	28.24	28.39	39.2	28.57	40.61	30.87	40.19	35.35	38.45	37.63	26.26	39.38	31.29
granite-3.1-2b-instruct	33.33	21.35	31.22	29.27	33.95	33.92	31.31	30.25	31.76	22.88	48.92	24.49	35.92	28.66	33.49	35.12	37.09	34.97	27.88	36.31	25.85
granite-3.1-3b-a800m-base	62.96	25.28	29.65	29.27	26.98	33.57	27.78	28.57	29.41	22.03	44.44	28.57	32.24	24.55	24.88	34.65	31.53	30.89	26.06	28.31	24.49
7B to 27B Models																					
Pangea-7B	62.96	24.16	37.53	34.15	34.88	52.8	39.44	35.29	31.76	31.92	50.46	32.65	45.69	32.35	38.76	39.3	47.65	44.78	32.93	46.77	34.69
Indic-gemma-7b-finetuned-sft-Navarasa-2.0	59.26	35.39	35.1	31.71	27.91	43.36	35.35	38.66	25.88	25.14	47.69	30.61	41.63	26.34	28.23	40.93	42.51	41.26	32.73	41.23	29.25
aya-23-8B	18.52	30.9	32.05	17.07	33.95	41.96	34.13	33.61	31.76	25.28	27.16	30.61	37.99	22.76	24.88	31.4	43.01	39.55	24.65	40.31	28.57
Llama-3.1-8B	25.93	29.78	33.17	34.15	31.16	47.55	34.74	28.57	31.76	24.86	29.78	34.69	39.46	26.24	28.23	28.6	42.08	38.74	25.86	41.54	25.17
Llama-3.1-8B-Instruct	29.63	26.97	34.83	46.34	38.6	44.41	34.18	33.61	30.59	24.72	39.51	28.57	46.07	35.3	38.76	34.19	46.43	45.41	32.93	44.92	36.73
gemma-2-9b	33.33	35.39	44.48	31.71	35.35	61.89	41.26	32.77	31.76	28.39	38.89	40.82	55.95	28.45	34.93	34.88	58.42	54.34	41.01	53.54	33.33
gemma-2-9b-it	48.15	29.21	34.35	39.02	36.74	52.1	36.88	37.82	29.41	27.97	44.44	24.49	47.12	43.1	47.37	42.56	44.15	43.33	35.76	40.62	36.05
gpt-oss-20b	25.93	32.02	36.39	46.34	30.7	47.9	36	27.73	31.76	27.26	29.32	26.53	46.74	29.61	35.41	24.65	45.58	39.14	34.95	31.08	37.41
gemma-2-27b	29.63	39.89	47.71	26.83	42.33	61.89	46.36	36.13	36.47	27.97	37.04	40.82	61	35.19	46.89	43.49	65.34	61.47	49.9	58.77	42.18
gemma-2-27b-it	55.56	35.96	37.98	39.02	39.53	55.24	40.15	36.97	31.76	30.51	45.99	38.78	53.28	45.94	55.02	39.77	50	48.4	40	45.23	44.9
> 27B Models																					
gpt-oss-120b	62.96	46.07	52.87	41.46	66.05	100	76.22	71.3	68.07	67.06	62.81	40.82	70.14	64.17	72.73	62.09	71.61	68.42	55.96	78.77	69.39
Qwen3-235B-A22B-Instruct-2507	62.96	51.69	58.34	31.71	67.91	77.27	61.65	69.75	51.76	47.18	70.99	59.18	73.14	67.76	75.12	73.49	75.82	77.17	61.62	77.54	71.43
deepseek-v3	66.67	38.2	46.09	31.71	63.26	81.82	61.7	65.55	41.18	49.01	61.11	46.94	60.71	44.89	62.21	55.58	61.98	61.92	45.45	66.15	51.7
gpt-4o	62.96	47.19	59.95	36.59	63.72	100	75.87	54.82	63.87	50.59	70.22	57.14	74.06	68.6	73.21	69.07	74.96	77.19	62.22	74.46	61.9

Table 15 Performance of Llama model family across sub-domains in BhashaBench v1, comparing base and instruction-tuned variants (1B, 3B, 8B)

Subject Domain	3.2-1B	3.2-1B-it	3.2-3B	3.2-3B-it	3.1-8B	3.1-8B-it
BBA						
Administration, AYUSH & Miscellaneous	36.97	35.29	31.93	39.5	41.18	44.54
Agad Tantra & Forensic Medicine	28.28	27.09	35.09	39.01	33.9	35.6
Ayurvedic Literature & History	27.45	30.88	29.9	33.33	30.88	36.27
Dravyaguna & Bhaishajya	26.58	26.92	26.95	30.11	29.24	31.53
Kaumarbhritya & Pediatrics	28.57	25.63	29.41	32.91	31.09	35.71
Kayachikitsa (General Medicine & Internal Medicine in Ayurveda)	29.04	24.92	31.33	34.84	34.24	34.78
Panchakarma & Rasayana	27.06	25.76	27.06	30.2	29.05	28.75
Research & Statistics	27.14	29.5	40	44.29	47.62	54.76
Roga Vigyana (Diagnostics & Pathology)	35	25	45	42.5	50	61.25
Samhita & Siddhanta (Fundamentals)	29.92	26.15	31.28	27.84	33.55	27.9
Shalakya Tantra (ENT, Eye, Dentistry)	27.25	26.84	29.43	35.29	31.61	37.47
Shalya Tantra (Surgery)	25.48	25.48	28.33	30.8	35.17	34.6
Sharir (Anatomy & Physiology)	27.12	25.19	29.49	33.66	32.76	38.93
Stri Roga & Prasuti Tantra (Gynecology & Obstetrics)	27.27	28.1	31.88	33.6	34	36.36
Swasthavritta & Public Health	34	32.67	40.62	51.21	47.46	57.17
Yoga & Psychology	26.6	24.47	32.45	31.38	43.62	34.57
BBF						
Accounting	27.3	26.13	30.66	27.68	34.54	30.66
Banking Services	30.49	28.18	38.34	38.68	40.48	42.36

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Table 15 – Continued from previous page

Subject Domain	3.2-1B	3.2-1B-it	3.2-3B	3.2-3B-it	3.1-8B	3.1-8B-it
Behavioral Finance	37.31	28.36	35.82	37.31	47.76	49.25
Business Management	26.51	26.51	43.37	53.01	50.6	60.24
Commerce	28.51	27.46	32.1	31.52	34.41	31.98
Corporate Finance & Investment	27.58	26.37	29.56	35.05	37.91	39.23
Data & Analytics in Finance	22.83	18.11	31.5	20.47	32.28	31.5
Economics & Development Studies	29.56	32.85	36.13	40.51	39.42	48.18
Energy, Infrastructure & Finance	29.27	28.05	32.93	39.02	42.68	40.24
Environmental Finance	25	29.76	39.29	38.69	41.07	51.19
Finance Education	29.66	25.42	49.15	34.75	44.92	47.46
Financial Markets	36.17	29.79	57.45	48.94	40.43	51.06
Financial Technology	17.39	13.04	21.74	34.78	43.48	47.83
General Knowledge	31.35	28.94	37.48	43.04	42.3	50.09
Governance & Policy	28.76	27.63	34.3	39.29	40.13	47.84
Healthcare Economics	31.58	31.58	38.6	41.23	50.88	51.75
History, Sociology & Cultural Studies of Finance	24.41	30.71	37.01	44.88	41.73	61.42
Information Technology Finance	31.63	35.51	46.33	53.06	59.59	66.33
Insurance & Risk Management	19.05	26.19	30.95	38.1	42.86	40.48
Interdisciplinary Finance	26.14	30.72	37.25	33.33	37.91	54.9
International Finance & Trade	27.71	34.94	36.14	39.76	45.78	54.22
Language & Communication	32.45	29.18	35.62	40.59	42.49	43.66
Legal Finance	26.47	20.59	29.41	20.59	38.24	35.29
Marketing Finance	23.81	38.1	38.1	38.1	59.52	52.38
Mathematics for Finance	27.31	24.91	28.96	27.57	29.97	26.3
Problem Solving	24.67	23.65	27.08	25.15	28.1	24.6
Rural Economics	27.97	30.65	33.33	44.83	42.53	51.72
Science and Technology in Finance	21.78	30.69	31.68	41.58	38.61	35.64
Sports, Media & Finance Linkages	33.33	28.89	48.89	42.22	51.11	48.89
Taxation & Regulatory Compliance	36.13	31.61	43.87	47.1	47.1	50.97
BBK						
Agri-Environmental & Allied Disciplines	31.82	32.95	25	36.36	30.68	47.73
Agricultural Biotechnology	31.11	28.63	34.35	50.95	48.85	58.78
Agricultural Chemistry & Biochemistry	27.05	22.78	31.32	33.81	38.79	48.75
Agricultural Economics & Policy	29.98	25.52	35.09	38.12	40.35	46.73
Agricultural Engineering & Technology	27.46	26.23	32.79	33.2	38.93	41.8
Agricultural Extension Education	30.88	29.46	32.3	41.99	40.31	48.19
Agricultural Microbiology	34.23	36.04	31.53	53.15	38.74	54.95
Agriculture Communication	33.07	28.35	29.53	44.49	36.61	49.21
Agriculture Information Technology	30.53	31.58	44.21	45.79	46.32	45.79
Agronomy	27.92	28.77	31.84	37.22	37.2	43.34
Animal Sciences	25.68	34.46	36.49	41.89	46.62	45.95
Crop Sciences	31.15	26.41	29.87	35.34	38.25	40.8
Dairy & Poultry Science	35.96	31.46	30.34	37.08	41.57	44.94
Entomology	29.02	27.59	35.49	35.49	38.79	47.7
Fisheries and Aquaculture	29.41	41.18	38.24	55.88	38.24	52.94
General Knowledge & Reasoning	28.44	27.53	33.13	39.64	38.88	42.66
Genetics and Plant Breeding	30.59	30.08	28.02	38.3	40.62	43.19
Horticulture	27.05	28.6	31.21	36.86	35.89	43
Natural Resource Management	28.5	26.42	29.02	37.82	33.16	44.56
Nematology	22.83	28.26	28.26	29.35	35.33	41.3
Plant Pathology	28.97	30.48	27.96	42.82	34.01	44.84
Plant Sciences & Physiology	28.68	31.78	37.98	50.39	43.41	54.26

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Table 15 – Continued from previous page

Subject Domain	3.2-1B	3.2-1B-it	3.2-3B	3.2-3B-it	3.1-8B	3.1-8B-it
Seed Science and Technology	29.7	28.71	27.72	37.13	35.15	38.61
Soil Science	31.25	29.92	31.69	38.84	37.14	45.25
Veterinary Sciences	27.08	14.58	37.5	47.92	43.75	70.83
BBL						
Civil Litigation & Procedure	29.32	28.18	32.4	34.97	36.68	42.66
Constitutional & Administrative Law	29.54	28.15	36.22	40.62	42.28	49.46
Consumer & Competition Law	28	22.67	28	34.67	46.67	41.33
Corporate & Commercial Law	27.7	28.63	29.78	34.67	35.15	42.67
Criminal Law & Justice	27.09	26.98	30.01	33.66	35.21	42.72
Employment & Labour Law	23.43	25.71	28.57	29.1	32	40
Environmental & Energy Law	27.67	24.42	33.49	37.91	39.07	45.81
Family & Personal Law	24.12	28.86	29.06	31.69	34.21	39.86
General Academic Subjects	29.21	32.52	37.47	43.91	46.87	52.68
Healthcare & Medical Law	40	20	68	40	64	60
Human Rights & Social Justice	21.05	42.11	36.84	26.32	31.58	36.84
Intellectual Property Law	30.77	31.87	46.15	45.05	56.04	58.24
Interdisciplinary Studies	33.33	28.1	38.57	41.32	43.25	53.72
International & Comparative Law	30.87	30.35	40.02	45.22	46.88	54.47
Legal Skills & Communication	25.74	27.33	28.68	30.15	28.31	32.72
Legal Theory & Jurisprudence	29.63	28.36	33.92	39.69	41.66	46.87
Media & Entertainment Law	33.33	35.19	42.59	51.85	38.89	53.7
Real Estate & Property Law	23.53	25.91	29.89	31.96	31.48	38.16
Tax & Revenue Law	27.71	31.6	40.26	38.1	41.56	43.29
Technology & Cyber Law	30.89	41.46	48.78	49.59	51.22	60.16

Table 16 Performance of Qwen model family across sub-domains in BhashaBench v1, comparing base and instruction-tuned variants (3B, 235B)

Subject Domain	2.5-3B	2.5-3B-it	3-235B-A22B-it-2507
BBA			
Administration, AYUSH & Miscellaneous	47.06	38.66	73.11
Agad Tantra & Forensic Medicine	39.86	32.71	63.88
Ayurvedic Literature & History	38.73	29.9	55.88
Dravyaguna & Bhaishajya	32.57	28.94	49.43
Kaumarbhritya & Pediatrics	38.52	30.11	55.32
Kayachikitsa (General Medicine & Internal Medicine in Ayurveda)	38.61	35.07	59.48
Panchakarma & Rasayana	30.35	29.59	49.54
Research & Statistics	62.86	52.86	91.43
Roga Vigyana (Diagnostics & Pathology)	58.75	53.75	82.5
Samhita & Siddhanta (Fundamentals)	36.79	31.93	55.22
Shalakya Tantra (ENT, Eye, Dentistry)	35.56	31.74	59.67
Shalya Tantra (Surgery)	37.45	33.08	60.46
Sharir (Anatomy & Physiology)	37.44	31.35	60.1
Stri Roga & Prasuti Tantra (Gynecology & Obstetrics)	40.73	34.24	66.82
Swasthavritta & Public Health	50.99	43.49	82.56
Yoga & Psychology	44.68	36.17	75.53
BBF			
Accounting	38.94	31.82	63.52
Banking Services	43.3	36.89	71.22
Behavioral Finance	52.24	44.78	71.64
Business Management	60.24	40.96	84.34

Continued on next page

Table 16 – Continued from previous page

Subject Domain	2.5-3B	2.5-3B-it	3-235B-A22B-it-2507
Commerce	43.57	33.72	63.62
Corporate Finance & Investment	40.22	37.58	63.52
Data & Analytics in Finance	35.43	28.35	53.54
Economics & Development Studies	43.8	44.16	73.36
Energy, Infrastructure & Finance	45.12	30.49	71.95
Environmental Finance	47.62	44.05	82.74
Finance Education	50.85	43.22	69.49
Financial Markets	42.55	42.55	70.21
Financial Technology	47.83	39.13	78.26
General Knowledge	41.56	38.22	74.95
Governance & Policy	45.3	38.16	74.15
Healthcare Economics	48.25	45.61	78.95
History, Sociology & Cultural Studies of Finance	38.58	38.58	83.46
Information Technology Finance	64.9	58.16	92.24
Insurance & Risk Management	30.95	38.1	64.29
Interdisciplinary Finance	41.83	36.6	79.74
International Finance & Trade	49.4	42.17	78.31
Language & Communication	45.77	42.71	77.06
Legal Finance	38.24	23.53	76.47
Marketing Finance	69.05	50	85.71
Mathematics for Finance	34.18	29.85	58.04
Problem Solving	27.88	26.2	47.12
Rural Economics	47.13	45.21	80.46
Science and Technology in Finance	40.59	43.56	72.28
Sports, Media & Finance Linkages	44.44	53.33	68.89
Taxation & Regulatory Compliance	56.13	38.71	74.84
BBK			
Agri-Environmental & Allied Disciplines	43.75	43.18	75.57
Agricultural Biotechnology	55.34	51.15	91.6
Agricultural Chemistry & Biochemistry	44.48	38.43	83.63
Agricultural Economics & Policy	46.41	43.38	73.21
Agricultural Engineering & Technology	41.39	37.3	67.21
Agricultural Extension Education	46.25	42.51	72.87
Agricultural Microbiology	54.05	43.24	90.99
Agriculture Communication	44.49	44.49	78.35
Agriculture Information Technology	52.63	54.21	74.74
Agronomy	41.73	38.89	71.92
Animal Sciences	47.97	46.62	77.7
Crop Sciences	42.08	36.79	67.4
Dairy & Poultry Science	52.81	46.07	75.28
Entomology	39.94	39.66	77.44
Fisheries and Aquaculture	38.24	50	79.41
General Knowledge & Reasoning	44.48	41.6	73.22
Genetics and Plant Breeding	43.44	44.22	76.86
Horticulture	37.25	35.41	64.98
Natural Resource Management	37.82	37.31	65.8
Nematology	33.15	39.13	63.04
Plant Pathology	40.55	36.52	78.34
Plant Sciences & Physiology	45.74	48.06	86.82
Seed Science and Technology	42.08	34.65	66.34
Soil Science	42	39.35	72.37
Veterinary Sciences	45.83	50	87.5
BBL			
Civil Litigation & Procedure	38.65	35.31	72.12

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Table 16 – Continued from previous page

Subject Domain	2.5-3B	2.5-3B-it	3-235B-A22B-it-2507
Constitutional & Administrative Law	43.67	37.93	82.65
Consumer & Competition Law	36	46.67	82.67
Corporate & Commercial Law	40.74	37.7	77.11
Criminal Law & Justice	38.21	34.45	75.44
Employment & Labour Law	39.43	37.14	71.43
Environmental & Energy Law	44.65	38.84	76.74
Family & Personal Law	38.35	32.8	74.37
General Academic Subjects	53.82	45.44	85.82
Healthcare & Medical Law	56	40	88
Human Rights & Social Justice	47.37	31.58	73.68
Intellectual Property Law	60.44	54.95	87.91
Interdisciplinary Studies	49.31	44.08	84.85
International & Comparative Law	47.51	43.76	83.89
Legal Skills & Communication	32.35	31.74	61.27
Legal Theory & Jurisprudence	46.45	40.04	79.38
Media & Entertainment Law	42.59	33.33	79.63
Real Estate & Property Law	36.09	33.55	71.7
Tax & Revenue Law	39.83	37.66	74.03
Technology & Cyber Law	58.54	59.35	86.18

Table 17 Performance of GPT model family across sub-domains in BhashaBench v1, comparing different model sizes (20B, 120B, GPT-4o)

Subject Domain	gpt-oss-20b	gpt-oss-120b	gpt-4o
BBA			
Administration, AYUSH & Miscellaneous	53.78	79.83	75.63
Agad Tantra & Forensic Medicine	39.52	60.14	63.54
Ayurvedic Literature & History	33.82	51.47	59.31
Dravyaguna & Bhaishajya	30.75	44.48	54.78
Kaumarbhritya & Pediatrics	35.99	51.4	56.58
Kayachikitsa (General Medicine & Internal Medicine in Ayurveda)	39.06	54.69	60.69
Panchakarma & Rasayana	28.36	41.44	50.76
Research & Statistics	70.95	86.67	90
Roga Vigyana (Diagnostics & Pathology)	66.25	82.5	81.25
Samhita & Siddhanta (Fundamentals)	30.63	46.07	53.41
Shalakya Tantra (ENT, Eye, Dentistry)	38.15	54.9	62.4
Shalya Tantra (Surgery)	35.36	55.13	61.41
Sharir (Anatomy & Physiology)	39.75	57.06	62.7
Stri Roga & Prasuti Tantra (Gynecology & Obstetrics)	35.18	59.03	64.82
Swasthavritta & Public Health	56.51	76.6	81.02
Yoga & Psychology	41.49	70.74	73.94
BBF			
Accounting	35.45	73.61	49.55
Banking Services	42.53	67.29	68.57
Behavioral Finance	50.75	77.61	76.12
Business Management	53.01	87.95	81.93
Commerce	37.89	69.76	54.46
Corporate Finance & Investment	37.25	73.63	61.43
Data & Analytics in Finance	34.65	51.97	44.09
Economics & Development Studies	46.72	69.34	71.53
Energy, Infrastructure & Finance	39.02	64.63	67.07

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Table 17 – Continued from previous page

Subject Domain	gpt-oss-20b	gpt-oss-120b	gpt-4o
Environmental Finance	55.95	73.21	77.98
Finance Education	46.61	73.73	74.58
Financial Markets	61.7	59.57	72.34
Financial Technology	47.83	73.91	78.26
General Knowledge	48.42	77.18	77.18
Governance & Policy	39.85	69.36	78.29
Healthcare Economics	49.12	78.07	80.7
History, Sociology & Cultural Studies of Finance	48.03	68.5	87.4
Information Technology Finance	76.94	90.82	92.04
Insurance & Risk Management	47.62	57.14	64.29
Interdisciplinary Finance	45.1	73.2	75.82
International Finance & Trade	54.22	75.9	85.54
Language & Communication	47.57	74.42	77.48
Legal Finance	41.18	64.71	76.47
Marketing Finance	61.9	85.71	78.57
Mathematics for Finance	30.05	76.16	41.28
Problem Solving	26.63	64.14	42.65
Rural Economics	47.89	75.86	82.76
Science and Technology in Finance	45.54	77.23	73.27
Sports, Media & Finance Linkages	46.67	75.56	73.33
Taxation & Regulatory Compliance	44.52	68.39	73.55
BBK			
Agri-Environmental & Allied Disciplines	41.48	73.86	74.43
Agricultural Biotechnology	65.27	89.69	89.31
Agricultural Chemistry & Biochemistry	54.8	80.43	81.14
Agricultural Economics & Policy	46.57	71.77	73.68
Agricultural Engineering & Technology	39.75	62.7	66.8
Agricultural Extension Education	43.93	69.25	75.19
Agricultural Microbiology	53.15	89.19	94.59
Agriculture Communication	42.91	73.23	81.1
Agriculture Information Technology	51.58	75.26	68.42
Agronomy	44.1	68	72.43
Animal Sciences	53.38	69.59	76.35
Crop Sciences	41.71	64.66	68.85
Dairy & Poultry Science	52.81	75.28	78.65
Entomology	48.28	72.84	77.87
Fisheries and Aquaculture	50	64.71	73.53
General Knowledge & Reasoning	42.81	69.59	68.38
Genetics and Plant Breeding	44.47	74.04	75.84
Horticulture	41.26	61.88	70.14
Natural Resource Management	41.97	64.77	65.8
Nematology	42.93	64.13	64.67
Plant Pathology	41.56	71.03	78.34
Plant Sciences & Physiology	51.94	82.17	88.37
Seed Science and Technology	35.15	64.85	65.84
Soil Science	42.45	70.67	73.18
Veterinary Sciences	56.25	87.5	93.75
BBL			
Civil Litigation & Procedure	34.63	59.01	71.91
Constitutional & Administrative Law	41.06	75.56	83.15
Consumer & Competition Law	33.33	72	81.33
Corporate & Commercial Law	37.48	69.59	78.93
Criminal Law & Justice	35.14	65.11	75.95
Employment & Labour Law	33.14	62.86	73.14

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Table 17 – *Continued from previous page*

Subject Domain	gpt-oss-20b	gpt-oss-120b	gpt-4o
Environmental & Energy Law	41.4	69.3	73.26
Family & Personal Law	37.03	63.87	72.86
General Academic Subjects	56.49	83.14	84.79
Healthcare & Medical Law	60	92	92
Human Rights & Social Justice	15.79	73.68	68.42
Intellectual Property Law	53.85	85.71	90.11
Interdisciplinary Studies	43.25	82.64	83.75
International & Comparative Law	48.86	79.42	81.7
Legal Skills & Communication	32.84	69.12	53.43
Legal Theory & Jurisprudence	42.08	75.16	81.21
Media & Entertainment Law	50	83.33	85.19
Real Estate & Property Law	32.59	59.62	71.7
Tax & Revenue Law	42.86	67.53	69.26
Technology & Cyber Law	56.91	86.18	86.99