Ranking Large Language Models' Knowledge in 26 Academic Fields

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# Abstract

*Keywords*: keywords, lower case, except proper nouns

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# Chapter 1: Introduction

Chapter 1 – Introduction

Background of the Study

Large language models (LLMs) such as GPT-4, Claude 3 Opus, and Llama 3 have achieved near–human–level performance on many single-domain benchmarks (Bubeck et al., 2023; Touvron et al., 2023). Yet, practitioners, educators, and researchers increasingly rely on these systems to answer questions drawn from a wide breadth of disciplines—from molecular biology to macroeconomics. Early cross-domain evaluations (e.g., MMLU; Hendrycks et al., 2021) reveal steep performance gradients across subjects, indicating that a model’s advertised “general intelligence” can mask critical blind spots that only emerge in less-publicized fields.

Recent work has begun to investigate discipline-specific capabilities: CS-Bench targets 26 sub-fields of computer science (Song et al., 2024); BrainBench measures neuroscience forecasting accuracy (Luo et al., 2024); and MaScQA probes metallurgical engineering knowledge (Bajan & Lambard, 2025).Bibliography. However, no empirical study has yet provided a systematic, statistically rigorous comparison of leading LLMs across the full span of all 26 academic fields defined by Scopus. The absence of such evidence leaves universities, enterprises, and government agencies without clear guidance when selecting or governing models for high-stakes, domain-specific tasks.

Statement of the Problem

The problem to be addressed in this study is that current large-language models exhibit uneven and insufficiently quantified knowledge across the 26 major academic fields, and stakeholders lack reliable, field-level rankings to inform critical adoption and governance decisions. Preliminary leaderboard data indicate that GPT-4 can achieve over 90% accuracy on business school exams, yet fall below passing thresholds on pharmacist licensing questions (Wang et al., 2023; Terwiesch, 2023). Without a statistically validated, cross-field evaluation, organizations risk deploying models that underperform in specialized contexts, potentially compromising research integrity, educational outcomes, and public trust.

Purpose of the Study

The purpose of this quantitative, comparative evaluation study is to rank the domain knowledge of state-of-the-art LLMs across 26 academic fields by administering a balanced corpus of 1,000 multiple-choice items per field and statistically analyzing differences in mean accuracy. Results will produce an Elo-style leaderboard (cf. LMSYS Chatbot Arena) that highlights strengths and weaknesses at the field level while controlling for item difficulty and chance performance.

Nature of the Study

A between-models quasi-experimental design will be employed. Each model (e.g., GPT-4, Claude 3 Opus, Gemini 1.5 Pro, Llama 3 70 B, Phi-3 mini) will answer the identical 26 × 1,000-item test set under deterministic temperature-0 settings. Correct answers earn +0.1, incorrect answers –0.1, and “unknown/abstain” 0, mirroring recent best practices for calibrated scoring. One-way repeated-measures ANOVA followed by Tukey HSD will test field-level performance differences, while Levene’s test will assess homogeneity of variance.

Research Questions and Hypotheses

Conceptual Framework

This study is grounded in the Holistic Evaluation of Language Models (HELM) framework (Liang et al., 2022), which posits that trustworthy assessment must encompass accuracy, calibration, robustness, and fairness. Bibliography Our focus on accuracy and robustness across subject domains aligns with HELM’s “scenario × metric” matrix. Additionally, Cognitive Load Theory suggests that domain-specific knowledge retrieval places varying demands on a model’s latent memory (Bommasani et al., 2023), providing a theoretical lens for interpreting inter-field variance.

Significance of the Study

By producing the first field-granular leaderboard, the study will:

Advance scholarship by extending single-domain benchmarks (e.g., MMLU) into a comprehensive cross-disciplinary scale.

Guide practitioners—universities, publishers, and R&D labs—on model selection for subject-matter-expert tasks.

Inform policy by supplying regulators with empirical evidence of domain gaps that could amplify misinformation or inequity (Bommasani et al., 2023).

Definitions of Key Terms

Elo Ranking. A rating system that updates a competitor’s score based on pairwise outcomes, adapted here to aggregate win-loss probabilities between LLMs (Originality.ai, 2024).

Large-Language Model (LLM). A neural network with ≥ 1 billion parameters trained on massive text corpora to predict the following tokens and generate coherent language (Brown et al., 2020).Bibliography

MMLU Benchmark. A 57-subject multiple-choice test used to measure multitask language understanding (Hendrycks et al., 2021).

Assumptions

Publicly released model checkpoints evaluated offline behave comparably to proprietary API versions.

Multiple-choice items sampled from prior exams faithfully represent field knowledge distributions.

Scope, Limitations, and Delimitations

The scope includes English-language questions at an undergraduate level. Limitations involve potential prompt-format bias and exclusion of multimodal reasoning. Delimitations restrict the study to seven widely used transformer-based language models (LLMs) available as of the data collection cut-off (April 2025).

Chapter Summary

Chapter 1 introduced the pervasive yet uneven adoption of LLMs and articulated the need for a systematic ranking across 26 academic fields. The problem, purpose, research questions, and HELM-based framework establish a foundation for the mixed-methodology approach detailed in Chapter 3. Chapter 2 will now survey prior evaluations of LLM knowledge and identify documented performance gaps at the field level.

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# Chapter 2: Literature Review

Chapter 2: Literature Review

This chapter presents a comprehensive literature review relevant to the proposed study. The purpose of this dissertation is to systematically evaluate and rank the domain knowledge of state-of-the-art large language models (LLMs) across 26 academic fields. While prior research has highlighted impressive LLM performance in specific contexts, evidence consistently demonstrates uneven results across domains. Universities, enterprises, and policymakers lack reliable field-level benchmarks to guide adoption and governance.   
  
The review is organized by the 26 academic fields defined by Scopus, following the prescribed order. Each subsection synthesizes existing research, identifies strengths and weaknesses, and highlights gaps in the literature. The chapter begins with the theoretical and conceptual framework underpinning LLM evaluation, followed by a review of the cross-domain benchmark. It then examines the literature field by field, culminating in a synthesis of convergence, divergence, and remaining gaps that justify the present study.

Theoretical and Conceptual Framework

Evaluating large language models (LLMs) necessitates a structured framework that considers both the technical and cognitive dimensions of performance. Two frameworks dominate recent discussions: the Holistic Evaluation of Language Models (HELM) and Cognitive Load Theory (CLT). HELM emphasizes accuracy, calibration, robustness, and fairness, while CLT helps explain uneven inter-field performance by considering the load on model memory during domain-specific tasks. Together, these frameworks guide the present study.

Cross-Domain Benchmarks

Cross-domain benchmarks, such as the Massive Multitask Language Understanding (MMLU) dataset and crowdsourced leaderboards like Chatbot Arena, demonstrate the broad potential of LLMs but reveal uneven accuracy across different disciplines. Studies show that while GPT-4 may excel in economics or general reasoning, it underperforms in specialized fields like pharmacology. Domain-specific benchmarks (e.g., CS-Bench, BrainBench, MaScQA) further highlight this fragmentation. Despite significant progress, no empirical study has yet provided a comprehensive, validated ranking of LLMs across all 26 fields — a gap that this dissertation aims to address.

Agricultural and biological sciences highlight both the promise and risks of LLMs. Tzachor et al. (2023) demonstrated that GPT models can enhance agrarian extension services by simplifying complex research outputs, but also cautioned about the dangers of misinformation. Lam, Ong, and Mutwil (2024) found that LLMs facilitate modeling of DNA and protein sequences, although general-purpose models often lack biological precision. Specialized models, such as PLLaMa (Yang et al., 2024) and IPM-AgriGPT (Wang, Li, & Zhang, 2024), outperform general-purpose baselines. However, De Clercq et al. (2024) warn against over-reliance without governance structures. Despite advances, no empirical comparison situates agricultural performance relative to other academic fields, a gap addressed in this dissertation.

Agricultural sciences show promise in extension services, genomics, and pest management, with models like PLLaMa and IPM-AgriGPT outperforming general-purpose LLMs. Yet, risks of misinformation and lack of cross-field ranking remain.

In the arts and humanities, LLMs demonstrate potential in supporting interpretation and research, but they remain limited in depth and reliability. Doe and Brown (2023) found that models could identify literary themes but struggled with symbolic analysis. Gonzalez Garcia and Weilbach (2023) demonstrated that LLMs aid historians in analyzing primary and secondary documents, although the factual reliability of these tools is questionable. Gu et al. (2025) demonstrated the strong performance of DeepSeek-R1 in student writing, while Liu, Wang, Xie, and Pei (2024) highlighted transformations in digital humanities, including the preservation of cultural heritage. However, no quantitative evaluation ranks LLMs across humanities fields, reinforcing the need for comparative benchmarks.

Studies demonstrate the utility of LLMs in literary analysis, history, and digital humanities. While helpful in annotation and interpretation, reliability and depth remain limited, with no cross-field benchmarks.

LLMs are increasingly applied in biochemistry, genetics, and molecular biology to accelerate research and discovery. Liu et al. (2024) reviewed bioinformatics applications, finding that models can process complex datasets in genomics, proteomics, and transcriptomics. Tripathi and Gabriel (2024) argued that LLMs are reshaping molecular biology by supporting the discovery of biomarkers and drug development. Feng, Zhang, and Liu (2024) emphasized that fine-tuning and prompt engineering enable LLMs to handle protein structure prediction and molecular property analysis. Zhang et al. (2024) surveyed scientific LLMs across biology and chemistry, identifying a lack of standardized benchmarks, while Yin et al. (2024) showed that LLMs excel at entity recognition but struggle in tasks such as antimicrobial peptide prediction and molecular optimization. Reliability remains a barrier, as Mugaanyi et al. (2024) documented hallucinated citations in biomedical writing. Despite promising research applications, no systematic evaluation compares LLM performance in molecular biology against other disciplines, underscoring the importance of this dissertation.

Applications span genomics, proteomics, and drug discovery. LLMs aid in biomolecular modeling, but challenges related to hallucination and reproducibility persist. Cross-field comparisons are absent.

Business-related fields illustrate LLM strengths in conceptual reasoning and weaknesses in quantitative problem-solving. Wood et al. (2023) evaluated ChatGPT on 25,000 accounting questions from 186 universities, finding that it consistently underperformed students, especially in calculation-heavy tasks. Conversely, Geerling, Mateer, and Damodaran (2023) reported that ChatGPT scored in the 91st percentile in microeconomics and the 99th percentile in macroeconomics, demonstrating strength in conceptual reasoning. Fatouros et al. (2023) showed that ChatGPT performed well in sentiment analysis for finance, although reliability issues arose due to hallucinations. Rahimikia and Drinkall (2024) noted that domain-specific financial models outperformed general-purpose LLMs in return prediction tasks. Yoo (2024) further warned that LLMs’ self-reported confidence scores do not reliably indicate accuracy, raising concerns for accounting and finance research. While LLMs hold value in economics and finance applications, their uneven performance across business fields highlights the need for cross-disciplinary benchmarking.

LLMs excel in economic reasoning (with 99th percentile performance) but struggle with accounting and quantitative tasks. Reliability concerns in finance remain unresolved without integrated evaluations.

Chemical engineering highlights the integration of LLMs in process optimization and autonomous experimentation. Nguyen and Zhao (2024) showed that LLMs can optimize reaction conditions and catalyst selection, improving efficiency. Gomes et al. (2023) introduced 'Coscientist,' an AI system that integrates LLMs with laboratory automation to design and execute chemical experiments, marking progress toward autonomous research. Zhou et al. (2025) combined chain-of-thought reasoning models with traditional surrogate models to improve prediction accuracy in chemical engineering tasks. Bran et al. (2024) emphasized that ChemCrow, which integrates LLMs with chemistry tools, enhances chemical reasoning, though hallucinations remain an issue. While the results are promising, datasets in chemical engineering remain small, which limits their generalizability. No study currently benchmarks chemical engineering alongside other academic domains, reinforcing the need for the present research.

LLMs support process optimization and autonomous chemical research. While tools like ChemCrow enhance performance, benchmarks remain fragmented and lack cross-field integration.

In chemistry, LLMs have been tested in symbolic reasoning, synthesis planning, and the interpretation of chemical data. Guo et al. (2023) benchmarked LLMs across eight chemistry-related tasks and found competence in conceptual descriptions but significant weaknesses in multi-step calculations and symbolic manipulation. Tool-augmented approaches show improvement: Bran et al. (2024) introduced ChemCrow, an integration of LLM reasoning with chemistry toolkits, which enhances performance in synthesis and research workflows. Liao, Yu, Mei, and Wei (2024) conducted a survey emphasizing the importance of tool-augmented workflows for reliability in chemistry applications. Clinical applications illustrate similar issues: Giannakopoulos et al. (2023) tested ChatGPT, Bard, and Bing in evidence-based dentistry tasks involving chemical-biological reasoning, finding that all models produced vague or incorrect outputs in some cases. These findings underscore the fragility of general-purpose LLMs in applied chemistry. Despite progress, no systematic evaluation situates chemistry alongside other disciplines, highlighting the importance of this dissertation.

LLMs demonstrate utility in tasks involving symbolic reasoning and synthesis. Tool-augmented approaches (e.g., ChemCrow) improve outcomes, but symbolic manipulation remains weak. No integrated comparisons exist.

Computer science serves as both the foundation for LLM development and a key testing ground for their performance. Song et al. (2024) introduced CS-Bench, which evaluates 26 subfields of computer science, yielding strong results in theoretical topics such as algorithms but weaker results in applied coding and debugging. Hou et al. (2023) reviewed 395 papers on the use of LLMs in software engineering, concluding that models are valuable for code generation and documentation, but struggle with scalability and debugging. Ellis and Slade (2023) demonstrated how LLMs can automate coding and teaching tasks, but still require human oversight to ensure accuracy. Vaswani et al. (2017) introduced the Transformer architecture, which underpins all modern LLMs, while the GPT-4 technical report (OpenAI, 2023) outlined strengths and safety concerns. Despite domain-specific benchmarks, no study has yet compared computer science outcomes against those in other fields, leaving a gap that this dissertation addresses.

CS-Bench shows strong theoretical performance but weaknesses in debugging and applied coding. Reviews emphasize productivity gains with continued reliance on human oversight. Comparative cross-field evaluations are absent.

Decision sciences emphasize reasoning under uncertainty and explainability. LLMs have been augmented with frameworks to improve contestability and transparency. Liu, Fu, Yogatama, and Neiswanger (2024) introduced DeLLMa, integrating decision theory and utility theory into LLMs, achieving up to a 40% improvement in uncertain tasks. Freedman et al. (2024) proposed ArgLLMs, which embed argumentative reasoning to produce more transparent and contestable decisions. Zhang, Liu, Jiang, Luo, and Zhang (2024) presented a 'Learning then Using' approach that improved decision-making in e-commerce optimization tasks. Klissarov et al. (2024) explored sequential decision-making, finding benefits from reinforcement learning combined with LLMs. While promising, these studies remain limited to experimental settings, and no comparative evaluation situates decision sciences within a broader academic context. This gap motivates the current study’s multi-field benchmarking.

Framework-augmented models, such as DeLLMa and ArgLLMs, improve reasoning under uncertainty and contestability. Applications remain experimental, highlighting the need for integration into multi-domain evaluations.

Earth and planetary sciences have adopted LLMs for multimodal data analysis and geoscience modeling. Zhang, Xu, Cui, Li, Yang, and Tang (2023) introduced Geoscience Foundation Models that integrate multimodal Earth system data. Deng et al. (2023) developed K2, a geoscience-specific LLM fine-tuned on geoscience literature and evaluated with GeoBench, showing stronger representation than general-purpose models. Wang, Hu, and Xiao (2024) reviewed GPT applications in geospatial science, demonstrating utility in hazard recognition and energy infrastructure planning. Zhang et al. (2024) applied generative AI to the Earth sciences, highlighting opportunities for multimodal integration. Jost, Koldunov, and Boers (2025) explored multi-agent systems powered by LLMs to enhance cross-disciplinary collaboration in geoscience. Despite these advances, challenges include limited datasets and interpretability issues. No comparative study situates geoscience performance relative to other academic fields, a gap this dissertation addresses.

Geoscience-specific models (e.g., K2) enhance multimodal integration and hazard forecasting. Reproducibility and interpretability remain challenges, and no comparative benchmarks exist.

Economics and finance have provided fertile ground for evaluating LLMs due to the availability of standardized datasets and tests. Geerling, Mateer, and Damodaran (2023) reported that GPT-4 scored in the 91st percentile for microeconomics and 99th percentile for macroeconomics. Carriero, Pettenuzzo, and Shekhar (2025) benchmarked LLMs for macroeconomic forecasting, finding mixed results compared to traditional time-series models. Ludwig, Mullainathan, and Rambachan (2024) proposed an econometric framework for integrating LLMs, emphasizing the risk of data leakage and the need for validation. Kim, Muhn, and Nikolaev (2024) demonstrated that LLMs outperformed human analysts in predicting firm earnings from financial statements. Li, Wang, Ding, and Chen (2023) provided a comprehensive survey of LLM applications in finance, highlighting their potential but warning of hallucinations. Yoo (2024) argued that LLM confidence scores are unreliable indicators of accuracy. Despite strong results in economic reasoning, no study situates economic and financial outcomes in relation to those of other disciplines, a gap this dissertation addresses.

GPT-4 excels in economics exams and financial analysis tasks. Specialized financial models outperform GPT in return prediction, yet reliability issues (e.g., self-confidence) persist. Comparative evaluations are lacking.

Energy research highlights the growing use of LLMs in forecasting, regulatory analysis, and energy management. Buster (2023) introduced the Energy Language Model (ELM), which automates the extraction of renewable energy siting ordinances from legal documents, outperforming humans in parsing complex regulatory texts. Majumder et al. (2024) evaluated LLMs on seven energy-related tasks, including load forecasting and hazard recognition, finding value but also hallucination risks. Qiu et al. (2024) developed EF-LLM, an approach that integrates sparse prediction and hallucination detection, resulting in improved load and renewable generation forecasting. Ren, Lai, Taylor, and Guo (2025) demonstrated that LLM agents, when combined with stochastic optimization, enhanced energy system balancing by reducing costs and curtailing energy. Despite progress, datasets remain proprietary, and reproducibility is limited. No study situates energy results across academic fields, a gap addressed in this dissertation.

Models like EF-LLM enhance forecasting by detecting hallucinations. Applications in regulation and grid balancing show promise, though reproducibility is constrained.

Engineering fields, especially software engineering, have integrated LLMs in automation, debugging, and modeling. Hou et al. (2023) reviewed 395 papers, concluding that LLMs facilitate code generation and documentation but encounter challenges related to scalability and adherence to best practices. Di Rocco, Di Ruscio, Di Sipio, Nguyen, and Rubei (2024) explored Model-Driven Engineering (MDE) tasks, where LLMs supported classification and recommendation but struggled with reasoning depth. Gao et al. (2024) surveyed agent-based modeling with LLMs, showing gains in simulating engineering decision-making. Ellis and Slade (2023) highlighted practical applications in coding and teaching, though oversight remains necessary. While evidence shows productivity improvements, no comparative evaluation benchmarks engineering outcomes against those of other disciplines, which this study aims to provide.

LLMs automate code and simulation tasks but struggle with applied reasoning and validation. Systematic cross-field evaluations are needed.

Environmental science has applied LLMs to climate research, hydrology, and carbon capture and sequestration. An article in Environmental Science & Technology (2024) highlighted benefits in streamlining writing, especially for non-native English speakers, while warning of risks such as undervaluing human expertise. A study in Science of the Total Environment (2024) demonstrated that LLMs can identify emerging research opportunities through large-scale data analysis. EnviroExam (2024) provided a benchmark of LLM knowledge in environmental sciences, noting uneven results across subfields like water treatment and life-cycle analysis. A Princeton report (2024) found GPTs could answer expert-level ecological questions, but reliability was variable. Scientific Reports (2024) highlighted the environmental costs of LLMs, including carbon emissions from training. Despite these insights, no comparative evaluation situates ecological sciences relative to other domains, leaving a critical gap.

Benchmarks such as EnviroExam highlight potential in QA and research acceleration. Risks include uneven accuracy and environmental costs. Comparative benchmarks are lacking.

In immunology and microbiology, LLMs have been tested in infectious disease education and protein modeling. Kaneda (2023) assessed GPT-3.5 and GPT-4 on infectious disease board exams, finding that even GPT-4 fell short of human pass rates. Dounas, Cotet, and Yermanos (2024) demonstrated the value of protein language models (PLMs) in representing immune receptors, suggesting cross-disciplinary benefits for immunology research. Wang, Wang, and Liu (2024) reviewed microbiology applications, noting that LLMs support taxonomic profiling and microbiome analysis but suffer from issues related to interpretability and reproducibility. Despite these efforts, no study has compared immunology and microbiology results with those from other fields, underscoring the contribution of this dissertation.

LLMs underperform on infectious disease exams, but PLMs improve immune receptor modeling. Reliability and interpretability remain concerns.

Materials science has emerged as a rapidly advancing application of LLMs, especially in property prediction and crystallography. Bajan and Lambard (2025) benchmarked 15 models on MaScQA, showing proprietary models outperformed open-source systems in metallurgical tasks. Mishra et al. (2024) developed LLaMat, pretrained on crystallographic data, which excelled in property extraction. Liu, Wen, Ye, Li, and Srolovitz (2024) developed ElaTBot, which is capable of predicting elastic constant tensors and suggesting new materials. Rubinggo et al. (2024) introduced LLM4Mat-Bench, the most significant benchmark for materials prediction, which highlighted the general-purpose limitations of LLMs. Schilling-Wilhelmi et al. (2024) discussed LLMs in structured data extraction, advocating for frameworks that combine AI and domain expertise. Despite advances, no study benchmarks materials science performance relative to other academic domains, a gap that this dissertation aims to address.

Proprietary models excel in the MaScQA benchmark. Domain-specific models, such as LLaMat and ElaTBot, improve predictive performance; however, open-source models often lag. Cross-field integration is absent.

Mathematics provides one of the most rigorous tests for LLMs, requiring precise symbolic reasoning and logical inference. Frieder, Pinchetti, and Chevalier et al. (2023) found ChatGPT performed inconsistently across mathematics problems, excelling in basic arithmetic but struggling in algebraic manipulation. Yuan, Li, Chen, Cui, and Ding (2024) surveyed mathematical reasoning in LLMs, noting that performance depends heavily on tokenization, pretraining corpora, and prompting. Azerbayev, Schoelkopf, Paster, and colleagues (2023) introduced Llemma, a model fine-tuned on mathematics corpora, which surpassed open baselines in theorem proving. Gou, Shao, Gong, Shen, and Yang (2023) developed ToRA, a tool-integrated reasoning agent that combines natural language reasoning with external solvers, significantly improving accuracy. Despite such advances, symbolic reasoning remains a weakness compared to pattern recognition. No cross-field evaluation currently situates mathematics alongside other disciplines, a gap this dissertation addresses.

LLMs demonstrate emergent reasoning but struggle with symbolic proofs. Specialized models (Llemma, ToRA) improve outcomes but lack cross-field comparisons.

Medicine is one of the most closely studied fields for LLM evaluation, with assessments ranging from licensing exams to clinical text summarization. Kung, Cheatham, Medenilla, Sillos, De Leon, Elepaño, and colleagues (2023) tested ChatGPT on the USMLE and found scores near the passing threshold, suggesting potential utility in medical education. Workum, Volkers, van de Sande, Arora, Goeijenbier, and colleagues (2025) benchmarked five LLMs on 1,181 critical care questions, finding that GPT-4 outperformed human physicians, scoring 93% compared to the human average of 62%. Croxford, Gao, Pellegrino, Wong, Wills, and Afshar (2025) reviewed medical summarization methods, noting gaps between automated metrics and expert judgments. Zhou, Liu, Gu, Zou, Huang, Wu, and colleagues (2023) surveyed LLMs in medicine, emphasizing both the diagnostic promise and ethical risks. Mugaanyi, Cai, Cheng, Lu, and Huang (2024) highlighted the dangers of hallucinated citations in a biomedical context. Despite advances, no comparative evaluation situates medicine alongside other domains, underscoring the significance of this dissertation's contribution.

GPT-4 surpasses physicians in critical care benchmarks, yet hallucination and ethical issues persist. Integration with other fields is lacking.

Neuroscience illustrates both applications of LLMs and parallels with brain function. Luo, Zhang, Ren, Li, Wang, Zhao, and Kording (2024) introduced BrainBench, finding that LLMs outperformed human experts in forecasting neuroscience research results. Google Research (2025) demonstrated similarities between LLM prediction mechanisms and human brain processing of language, highlighting convergent predictive dynamics. Nakagi, Schoelkopf, and colleagues (2025) proposed 'triple phase transitions' to align LLM learning stages with neural dynamics, linking model training to biological processes. While models contribute predictive insights and neuroscientific analogies, they often lack interpretability. No cross-disciplinary benchmark currently situates neuroscience outcomes in relation to other fields, a gap that this dissertation will address.

BrainBench shows models outperform human experts in predicting experimental results. Research also explores parallels with brain cognition. Cross-field positioning is missing.

Nursing studies highlight both progress and limitations in LLM adoption. Taira, Itaya, and Hanada (2023) evaluated ChatGPT on Japan’s National Nurse Examinations, finding scores close to passing but weaker in pharmacology and regulations. Mitchell et al. (2024) summarized potential nursing applications, including education, documentation, and care planning, while emphasizing the need for more empirical evaluation. Wang, Li, and colleagues (2024) tested LLMs for personalized nursing diagnoses and care plans, demonstrating utility but also identifying integration challenges. While LLMs support efficiency, unreliability in clinical contexts highlights risks. No comparative evaluation situates nursing performance within the broader set of academic fields, justifying its inclusion in this dissertation.

ChatGPT nears passing thresholds on nurse exams but struggles in pharmacology. Applications in care planning show utility, though reliability is limited.

Pharmacology, toxicology, and pharmaceutics are among the most demanding biomedical domains for LLMs. Wang, Shen, and Chen (2023) tested ChatGPT on Taiwan’s Pharmacist Licensing Exam and found an accuracy rate between 54% and 57%, which is below the 60% passing threshold. The results further showed weaker outcomes in Chinese-language exams compared to the English versions. Zheng, Koh, Yang, and colleagues (2024) surveyed drug discovery applications, noting potential in clinical trial analysis. Gu, Zhang, Usuyama, and others (2023) fine-tuned LLMs to extract adverse drug events, enhancing pharmacovigilance. Gao, Huang, Liu, and colleagues (2025) introduced PharmAgents, a multi-agent LLM framework simulating full drug discovery pipelines. Despite innovations, pharmacology remains an area where LLMs consistently underperform, especially in applied reasoning. No comparative study situates pharmacology alongside other domains, a gap this dissertation addresses.

ChatGPT underperforms on licensing exams. Domain-specific multi-agent models (PharmAgents) show progress. Cross-field benchmarking is needed.

Physics and astronomy remain complex domains for LLMs due to their reliance on quantitative reasoning and mathematical concepts. Dahlkemper, Lahme, and Klein (2023) studied student evaluations of ChatGPT’s responses to physics questions, finding that while students sometimes rated answers highly, they often contained scientific inaccuracies. Revalde, Zholdakhmet, Abola, and Murzagaliyeva (2025) evaluated ChatGPT-3.5 on 400 high school physics problems in multiple languages, showing competence in conceptual multiple-choice questions but poor accuracy on calculation-heavy tasks. Anand, Prasad, and Kirtani et al. (2024) introduced reinforcement learning with human-AI feedback (RLHAIF), which improved LLM reasoning for complex physics problems. Xu, Xu, Xiao, Chen, Yan, Zhang, and colleagues (2025) developed UGPhysics, a benchmark of 5,520 undergraduate physics questions, and found LLMs performed better in theoretical reasoning than in symbolic derivations. Despite these efforts, no comparative evaluation situates physics performance across academic domains, a gap this dissertation addresses.

LLMs offer plausible conceptual explanations but struggle with quantitative problem-solving. Specialized reinforcement approaches improve accuracy. However, cross-field benchmarks are absent.

Psychology research explores whether LLMs can replicate aspects of cognition and decision-making. Kosinski (2024) tested 11 LLMs on classic theory-of-mind tasks, finding that GPT-3.5 solved 20% of the functions, while GPT-4 achieved 75%, comparable to that of a six-year-old child. Binz and Schulz (2023) evaluated LLMs fine-tuned as cognitive models, showing they outperformed traditional cognitive models in simulating human decision-making. Lin (2024) argued that LLMs can act as simulators of human cognition but cannot replace human participants. These findings highlight emergent reasoning abilities but also reveal brittleness and reliance on linguistic pattern recognition. No comparative benchmark currently situates psychology performance against other fields, which this dissertation will address.

LLMs exhibit emergent theory-of-mind reasoning. Fine-tuned models outperform traditional cognitive models but remain vulnerable to brittleness. Comparative studies are lacking.

The social sciences have tested LLMs in annotation, text analysis, and social simulation. Ziems, Held, Shaikh, Chen, Zhang, and Yang (2023) found that LLMs approximated human performance across 25 social science benchmarks but lacked reliability in nuanced classification tasks. Piao, Yan, Zhang, and colleagues (2025) introduced AgentSociety, which simulates the interactions of over 10,000 generative agents to model social dynamics, such as polarization. Lin and Zhang (2025) examined risks in text annotation, arguing that validity and transparency remain challenges. While these studies show potential, no comparative evaluation situates social science performance relative to other domains, a gap addressed here.

LLMs scale annotation and simulate social dynamics (e.g., AgentSociety). Risks include epistemic validity and transparency gaps.

Medicine is one of the most closely studied fields for LLM evaluation, with assessments ranging from licensing exams to clinical text summarization. Kung, Cheatham, Medenilla, Sillos, De Leon, Elepaño, and colleagues (2023) tested ChatGPT on the USMLE and found scores near the passing threshold, suggesting potential utility in medical education. Workum, Volkers, van de Sande, Arora, Goeijenbier, and colleagues (2025) benchmarked five LLMs on 1,181 critical care questions, finding that GPT-4 outperformed human physicians, scoring 93% compared to the human average of 62%. Croxford, Gao, Pellegrino, Wong, Wills, and Afshar (2025) reviewed medical summarization methods, noting gaps between automated metrics and expert judgments. Zhou, Liu, Gu, Zou, Huang, Wu, and colleagues (2023) surveyed LLMs in medicine, emphasizing both diagnostic promise and ethical risks. Mugaanyi, Cai, Cheng, Lu, and Huang (2024) highlighted the dangers of hallucinated citations in biomedical contexts. Despite advances, no comparative evaluation situates medicine alongside other domains, underscoring the contribution of this dissertation.

VetLLM improves diagnostic coding, and fine-tuning enhances record interoperability. Validation across broader contexts is limited.

Dentistry provides another applied health context where LLMs have been evaluated. Giannakopoulos, Kavadella, Salim, Stamatopoulos, and Kaklamanos (2023) found that GPT-4 outperformed Bard and Bing on dentistry question-answering tasks, although all models sometimes produced vague or inaccurate responses. Huang, Zheng, Wang, Yin, Ding, and colleagues (2023) highlighted multimodal models for dentistry, integrating textual and imaging data for diagnostic tasks. Farhadi Nia, Ahmadi, and Irankhah (2024) explored the use of ChatGPT for dental diagnostics, demonstrating its applications in patient communication and workflow efficiency. Although useful as aids, reliability concerns remain, and no study benchmarks dentistry alongside other health domains, a gap this dissertation addresses.

GPT-4 outperforms Bard and Bing in dentistry QA but remains vague and sometimes inaccurate. Multimodal models show promise for diagnostics.

The broader health professions literature highlights both the opportunities and the ethical risks associated with the adoption of LLMs. Ng and Kuper (2023) critiqued the implications of AI authorship and authority in health education research, emphasizing ethical challenges. Sun, Wang, and colleagues (2024) proposed AI-driven frameworks for nursing and elderly care, showing potential for monitoring and decision support. Zhang and Feng (2023) examined open-source LLMs in medicine and healthcare, reporting applications in diagnostics, project management, and medical writing. Despite broad utility, ethical concerns and governance issues remain unresolved. No study situates health professions outcomes relative to other fields, reinforcing the need for this dissertation’s comprehensive benchmarking.

LLMs support education and diagnostics across professions. Governance and ethical issues remain unresolved. Cross-field comparisons are absent.

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Areas of Convergence and Divergence

Across the 26 academic fields, several converging trends are evident. First, specialized or fine-tuned models consistently outperform general-purpose LLMs, whether in agriculture (Yang et al., 2024), medicine (Workum et al., 2025), or materials science (Bajan & Lambard, 2025). Second, models perform best in conceptual reasoning tasks (e.g., economics, computer science theory) and weakest in applied, quantitative, or high-stakes decision-making contexts (e.g., pharmacology, nursing, physics problem-solving). Third, tool-augmented or hybrid architectures (e.g., ChemCrow, ToRA, EF-LLM) markedly improve accuracy and reliability, suggesting a trajectory toward human-AI collaboration. Divergences include variability in reliability, with some fields (e.g., neuroscience, economics) reporting near-human or above-human performance, while others remain below professional thresholds (e.g., pharmacy licensing, infectious diseases). These divergences underscore the fragmentation of current benchmarking efforts.

Gaps in the Literature

While benchmarks exist across many domains, no comprehensive study has systematically evaluated and ranked LLM knowledge across all 26 academic fields. Existing approaches remain fragmented: broad benchmarks, such as MMLU, emphasize generality but lack field-specific granularity, while domain-specific benchmarks (e.g., CS-Bench, BrainBench, MaScQA) provide depth but lack comparability across different domains. Reliability and reproducibility challenges further undermine trust in current results. This dissertation fills the gap by designing a quasi-experimental evaluation across 26 fields, applying rigorous statistical analysis, and producing the first Elo-style leaderboard to guide research, education, and governance.

Chapter Summary

This chapter reviewed the literature on LLM evaluation across 26 academic fields, beginning with theoretical frameworks and cross-domain benchmarks before examining field-specific studies. Converging themes show that while LLMs exhibit impressive capabilities, they remain uneven across domains. Divergences reveal critical weaknesses in high-stakes contexts and highlight the need for systematic, comparative evaluation. The identified gaps justify the purpose of the present study: to provide the first comprehensive, field-level ranking of LLM knowledge across all academic domains. The next chapter will outline the methodology used to achieve this aim.

# Chapter 3: Methodology

Chapter 3: Methodology

Introduction

This chapter outlines the methodology employed in the study. The problem addressed is that current large language models (LLMs) demonstrate uneven and insufficiently quantified knowledge across the 26 major academic fields, leaving stakeholders without validated benchmarks for adoption and governance The purpose of this quantitative, comparative evaluation study is to rank the domain knowledge of state-of-the-art LLMs across 26 academic fields by administering a balanced corpus of multiple-choice items and statistically analyzing differences in mean accurac. This chapter describes the research design, population and sample, instruments, procedures, data analysis, and ethical considerations, providing a roadmap for replication.

Research Design

A quasi-experimental, between-models design will be employed to compare the performance of multiple LLMs across 26 fields. Each model (e.g., GPT-4, Claude 3 Opus, Gemini 1.5 Pro, LLaMA 3 70B, Phi-3 Mini) will complete the identical test set of 1,000 multiple-choice items per field. The independent variable is the LLM used, while the dependent variable is the accuracy score. Alternative designs, such as case studies or qualitative interviews, were deemed less appropriate due to their inability to provide statistically rigorous, field-level comparisons.

Population and Sample

The population of interest includes the 26 academic fields defined by Scopus. The sample will consist of 1,000 multiple-choice items per field, drawn from prior exams, validated question banks, and peer-reviewed sources. This results in a total sample of 26,000 items. The models selected represent widely used, state-of-the-art transformer-based architectures available as of April 2025. This sampling approach ensures coverage of both breadth and depth of domain knowledge while maintaining replicability.

Materials and Instrumentation

The instrument used is a balanced corpus of multiple-choice items, standardized to undergraduate-level knowledge. Each item has one correct answer and three incorrect options, known as distractors. Correct responses will be scored as +0.1, incorrect responses as -0.1, and abstentions as 0, adapting best practices for calibrated scoring. Deterministic evaluation (temperature = 0) will be applied to eliminate randomness. Items were selected to represent domain knowledge faithfully, and pilot testing will be conducted to ensure fairness across models.

Operational Definitions of Variables

Independent Variable: The LLM evaluated (GPT-4, Claude 3, Gemini 1.5, etc.).  
Dependent Variable: Mean accuracy scores per academic field.  
Measurement: Accuracy will be calculated as the percentage of correct responses across 1,000 items per field, adjusted by the scoring schema.

Study Procedures

. Assemble a balanced test corpus (1,000 questions per field).  
2. Standardize item formatting to ensure consistency.  
3. Configure deterministic evaluation for each model.  
4 Administer the test corpus to each LLM under identical conditions.  
 . Record and score results using the calibrated scoring system. 6. Compile accuracy scores per field and model for analysis.

Data Analysis

Data will be analyzed using one-way repeated measures ANOVA to test for differences in model performance across fields. Tukey’s HSD will be applied for post-hoc comparisons. Levene’s test will check the homogeneity of variance. Reliability will be assessed using bootstrap and split-half validation methods. Statistical significance will be set at p < 0.05. Analyses will be conducted using statistical software (e.g., SPSS, R).

Validity and Credibility Issues

Validity will be supported by constructing the test corpus from validated sources and piloting items before deployment. Credibility is enhanced through deterministic evaluation to remove stochastic noise. Reliability will be examined via multiple validation strategies. Researcher bias is minimized by automating model evaluation and scoring.

Assumptions

1. Publicly available model checkpoints behave comparably to their proprietary API versions.  
2. Multiple-choice items adequately represent domain knowledge in each field. Deterministic evaluation settings ensure replicable results.

Limitations

This study is limited by its focus on English-language items at an undergraduate level, excluding multimodal and higher-order reasoning. Prompt-format bias and differences in pretraining corpora may influence outcomes. The study is restricted to transformer-based models released by April 2025.

Delimitations

Delimitations include limiting the scope to 26 Scopus fields, a multiple-choice question format, and deterministic evaluation conditions. These decisions enhance comparability but restrict generalization to other tasks or languages.

Ethical Assurances

This study involves no human subjects and therefore qualifies as exempt from IRB oversight. All data will be sourced from publicly available sources and securely stored in accordance with institutional guidelines and regulations. The researcher acknowledges the potential for bias due to prior experience with LLM evaluation but will employ strategies such as blind scoring and external replication to mitigate this risk.

Summary

This chapter detailed the methodology for systematically evaluating LLM knowledge across 26 academic fields. The design, population, instruments, and procedures were described in detail, along with statistical analysis, validity strategies, assumptions, and limitations. By applying a rigorous and replicable methodology, the study aims to produce the first comprehensive leaderboard of LLM performance across academic disciplines. The next chapter will present the results of this analysis.

# Chapter 4: Analysis and Results

This chapter will present the analysis and results of the study.

# Chapter 5: Findings and Recommendations

This chapter will interpret findings and provide recommendations.

# References

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# Appendix A: Instruments and Protocols

Include instruments, surveys, or protocols.

# Appendix B: Supplementary Data

Include supplementary tables, figures, or data.