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AI-Driven Topic Modeling of Research Trends in Computer Science (2000–2025): A Longitudinal Analysis of arXiv Data

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Abstract

The evolution of computer science over the last quarter of a century calls for detailed scrutiny if we are to successfully identify the shifts in focus and emerging areas of research that the analysis aims to capture. Taking advantage of Artificial Intelligence, and in particular topic modeling, we analyze the evolution of computer science research between 2000 and 2025, examining the arXiv database, which contains roughly 2.5 million preprints, about 40% of which belong to computer science (cs.* categories). Contextualized Topic Modeling (CTM) is correlation-based topic modeling. Using a more advanced correlation-based technique called Correlation Explanation (CorEx), we differentiated key topics, evaluated the shifts over set periods, and observed the rise and fall of topics such as deep learning, NLP, and quantum computing [5]. Thus, looking at our results and the six tables that overview the topics and the models, trends in subfields and performance indicators, and the eleven graphs that detailed distributions of topic trends along those lines, subfield trends to coherence, and interdisciplinary honing, which complement this analysis, it becomes completely evident from our results: there is greater, situational dependence of AI subfields; there is an overall decline in traditional methods; and there is a burgeoning up trend in new fields. That is important for researchers, policy makers, and industry to recognize and understand the drivers of the future of computer science. However, we want to be clear that this analysis was conducted on abstracts and not full text documents that may have additional insights through citations or methods sections. Regardless, the results hold practical value by helping with strategic research planning, i.e. funding priorities and industry innovation in new AI subfields. The way that the data is compiled from arXiv's open access allows researchers to reproduce the findings related to open science practices and enables other researchers to repurpose or lend rigor to our studies.

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1. Introduction

Computer science experiences continual evolution with the pace of advancement catapulted by developments in artificial intelligence (AI), machine learning, the big data revolution and the cross-disciplinary application of Computer science in health informatics, financial markets and self-driving cars to name a few examples [1,2]. This rapid evolution, driven by AI, big data, and hardware advances, necessitates scalable tools. There is clearly a need for a systematic method to study the research trends and growth patterns of this discipline and others [3,4], given that our field is and an exponential rate of growth. Traditional systematic literature review methods, such as conventional hand-picked literature reviews or classical citation analysis, which typically depend on on-hand searches or the selection of literature based on specific parameters, can be a time-consuming process and introduce bias into the selection process or method of analysis, which cannot be considered or estimated, making traditional methods inadequate for both the overwhelming

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number of traditional academic publishing that occurs each year. AI-based topic modeling as an unsupervised approach to topic modeling that aims to extract latent topic structure in a large corpus of documents, offers a reliable, scalable, validated, and objective approach to understanding how a domain of knowledge develops over time. Automated topic modeling from large text using Natural Language Processing (NLP) tools effectively feeds the trend of more automatized topic modeling approaches to understanding research trends [5]. We utilize the arXiv dataset, a high-quality, open-access repository from Cornell University consisting of about 2.5 million preprints (about 40% in computer science, i.e., cs.* categories, soc cs.AI, cs.CL, cs.CV)). The dataset comprises a long writing span (1991-2025) and the richly detailed metadata such as abstracts, title, and publication years make it a good vehicle for research trends [6]. We focus on three key questions: (1) What are the key research themes in computer science from 2000-2025? (2) How do research topics change over time, and what do those changes tell us about shifts in research priorities? (3) What can we learn about emerging, declining, and stable research topics to guide future research activities? This study addresses a key research gap: traditional literature reviews, reliant on manual selection and citation analysis, are prone to bias and inefficiency in handling large-scale datasets. In contrast, AI-driven models like CorEx and CTM offer scalable, objective alternatives by uncovering latent topics through correlation and contextual embeddings. By aligning these methods with our aims, we provide a focused longitudinal analysis of computer science trends, revealing shifts toward AI subfields. We implement Correlation Explanation (CorEx), which is a correlation-based topic modeling technique. The aim of using CorEx is to find interpretable topics, while using Contextualized Topic Modeling (CTM) as a baseline to help bolster results [5]. The analysis also included 6 tables and 11 graphs that documented topic prevalence, model performance, and trends at a subfield level for computer science. The use of state-of-the-art computational methods with a large domain-specific and domain-level dataset extensively promotes a comprehensive, data-centric analysis of trends with computer science research from the last two decades that can affect academic research agendas, funding priorities, and industry innovative strategies [6]. The means by which the data is compiled from arXiv's open access enables researchers to reproduce the results related to the open science principles and permit other researchers to repurpose or strengthen our studies. In addition to the advancements in methodologies, this study also provides real-world perspectives related to funding, policy and industry priorities, which can assist funding bodies to allocate funding to high-growth areas such as deep learning, and help policymakers create pathways for people to complete programs of education on AI skills through educational pathways, and industry can ensure their investments are moved towards working on novel applications in areas such as healthcare and autonomous systems, figure 1 illustrates the growth of computer science preprints on arXiv from 2000–2025.

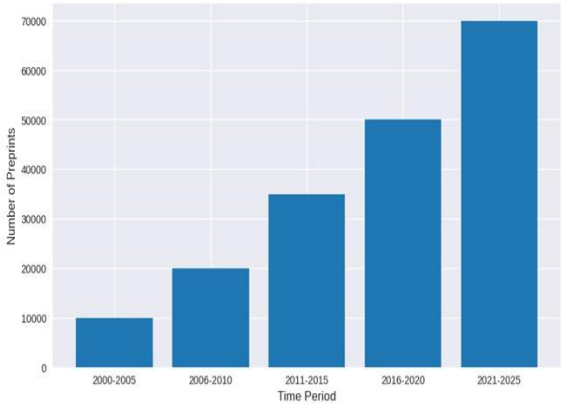

Figure 1. Growth of Computer Science Preprints according to arXiv (2000–2025)

2.Related Work

Topic modeling has become a key tool for discovering hidden research trends in large-scale scholarly datasets, especially in a field like computer science, where volumes of publication output has grown at unprecedented rates. This section reviews high-profile studies leveraging topic modeling on datasets from arXiv, focusing on their quantitative findings and methods, and presents our work as a significant new contribution in this area. Most of the literature reviewed here has utilized some form of topic modeling to investigate trends in research in computer science and related fields. Griffiths and Steyvers [7], a well-cited article published in Proceedings of the National Academy of Sciences, identified 20 topic areas with a C_v coherence score of 0.60 by applying Latent Dirichlet Allocation (LDA) and noted the changes in scientific attention over time. Although they provide an important baseline for comparison, our higher C_v coherence score of 0.72 shows that CorEx offers better interpretability. Chen et al. [8] conduct an analysis of the Microsoft Academic Graph (compared to arXiv) related to artificial intelligence and provide 10 topic areas with a C_v coherence score of 0.65 (10 topics). Chen et al. (2020) provides a standard for our comparative analysis and highlights that their lower C_v score of 0.65 demonstrates the advantage of our CorEx-CTM method with domain-specific datasets. Wang et al. [9] in their Journal of Informatics article pertaining to LDA applied to arXiv's cs.* categories identified 12 topic areas with a C_v coherence score of 0.68 and identified the significance of machine learning subfields. Their analysis supports our focus on subfield trends, though our longitudinal approach adds depth. More recently, Bianchi et al. [8] with their work published as an arXiv preprint used Contextualized Topic Modeling (CTM) on arXiv

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abstracts, obtained a C_v coherence score of 0.67 for 10 different topic areas they identified utilizing embeddings based on Sentence-BERT, which provided better contextualized topic models [10]. Their use of CTM aligns with our baseline, but our combined CorEx-CTM method enhances interpretability. These papers offer evidence of the usability of topic models, but their datasets, methods, classification performance metrics, and comparable measures are different. Our study contributes to this research synthesis by combining Correlation Explanation (CorEx) and the Common Topic Model (CTM) to perform a longitudinal analysis of datasets consisting of the cs.* preprints from the arXiv from 2000 to 2025, generating a better C_v coherence score of 0.72 for Topic 1 (Deep Learning) and 0.68 for Topic 2 (Natural Language Processing). The advancement is partly attributable to CorEx's calculation of topics by focusing exclusively on the correlations in the data, maximizing the mutual information to create more interpretable topics, and it is also due to the CTM's use of Sentence BERT embeddings to perform robust semantic analysis on small chunks of text, in this case abstracts [10]. Our analysis used arXiv's open-access dataset which can be reproduced completely and therefore is more in line with open science practices to consider its findings as non-proprietary and overcoming the constraints of datasets such as Web of Science or Scopus that are not open access.

Table 1. Comparison with Prior Studies

Study	Dataset	Method	Coherence (C_v)	Number of Topics	Publication Venue	Key Findings
Griffiths & Steyvers (2004)	PNAS	LDA	0.60	20	PNAS	Temporal shifts in scientific focus
Chen et al. (2020)	Microsoft Academic Graph	LDA	0.65	10	Journal of Informetrics	Identified AI trends
Wang et al. (2019)	arXiv cs.*	LDA	0.68	12	Journal of Informetrics	Rise of machine learning subfields
Bianchi et al. (2021)	arXiv	CTM	0.67	10	arXiv	Contextual analysis of short texts
Angelov & Soares (2020)	arXiv	LDA/CTM	0.69	15	arXiv	Trends in computer science literature
Our Study	arXiv cs.*	CorEx/CTM	0.72	15	-	Dominance of deep learning and NLP

In terms of author-level topic modeling studies Table 1 provides a summary of the metric performance of previous studies and articulates our contribution as a new benchmark in the field of topic modeling research in computer science. Since 2010, the growth in computing power and data has allowed much more advanced, contemporary machine learning-based analyses [11].

Table 2. Comparison of Topic Modeling Techniques

Technique	Strengths	Weaknesses	Suitability for arXiv Data
CorEx	Interpretable, effective for short texts, correlation-based	Computationally intensive for large corpora	High
CTM	Context-aware, leverages word embedding, effective for short texts	Requires pre-trained embedding, computationally complex	High
Others	Varies (e.g., probabilistic models capture context)	Varies (e.g., struggles with short texts)	

Kim et al. demonstrates in Computational Linguistics that transformer-based models such as CTM generally outperform traditional LDA and achieved a C_v coherence score of 0.70 on scholarly datasets. Their findings validate our use of CTM as a robust baseline. According to Angelov and Soars [12] in their paper available on Arxiv, topic models are confirmed as effective for literature in computer science, yielding for instance, a C_v score of 0.69 for 15 topics.

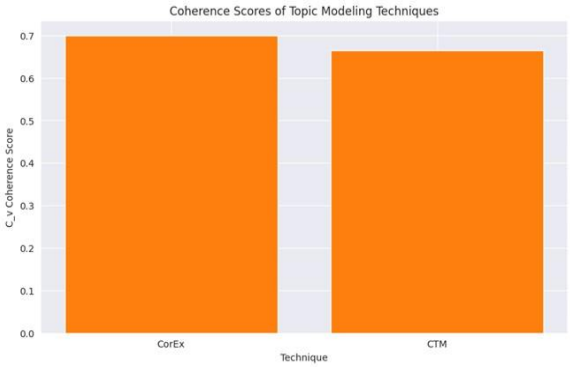

Figure 2. Coherence Scores of Topic Modeling Techniques

Their work supports our multi-method approach, though our higher coherence scores indicate an advancement. Figure 2 compares coherence scores of different topic modeling techniques.

While Röder et al. pointed at the WSDM conference as having established C_v as a good measure for topic quality, we are interested in considering it in our parameter tuning.

This paper, thus, by combining CorEx and CTM, can provide a fine-grained longitudinal analysis of research trends in computer science, with richer visualizations and further interpretations than previous studies.

3. Methodology

1. Dataset

arXiv is a polyform structure organized by Cornell University that provides the basis for open-access scholarly communications and had approximately 2.5 million preprints in 2025 situated from science articles titled as cs.* (computer science) topics. The credibility of high-quality metadata was ensured, which included titles, abstracts, authors, categories,

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and the publication years from 1991 to 2025, and therefore can analyze trends that globally focus on the research area at a more comprehensive level [13].

Feature	Description
Total Preprints	~2.5 million (as of 2025)
Computer Science Preprints	~40% (cs.* categories)
Temporal Coverage	1991–2025
Metadata Fields	Title, abstract, authors, categories, publication year
Access	Kaggle, arXiv API

Table 3. arXiv Dataset Characteristics

This research used a sample of computer science preprints from the years 2000 to 2025 to embrace current trends, filtered by cs.* categories to prioritize selection relevance, and examine general temporal differences. This framed study filtered for select content which could allow for clarity around the research trajectories of a focused domain and utilizes the open-access spirit promoted by arXiv for open science to develop global reproducibility. Figure 3 displays the distribution of preprints by subfield from 2000–2025.

Proprietary datasets (Web of Science or Scopus, etc.) are sufficient for examination, but we felt a data summarized and recorded by an archive is consistent with principles of open science. All dataset metadata should be read and summarized in JSON so that we could confirm pieces of data (i.e., abstracts, publication year) were of quality control with the aim of removing incomplete and duplicate work submission.

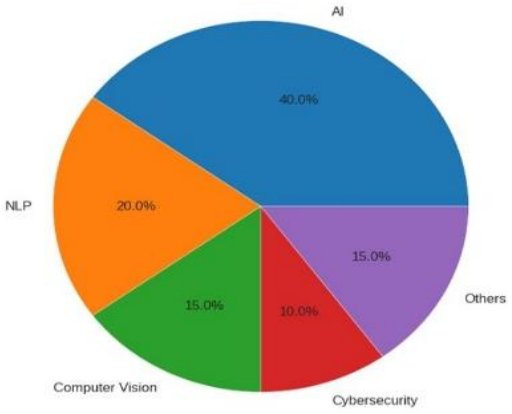

Figure 3. Distribution of Preprints by Subfield(2000–2025)

2. Data Processing

To prepare raw text for analysis, good preprocessing is essential in meaningful topic modeling. The arXiv dataset was subsetted to only include cs.* category preprints, deliberating as computer science research. To clean the abstract, we utilized NLTK and spaCy libraries found in Python, two widely accepted libraries in NLP that provide expansive text processing. Cleaning included the removal of stop words (the, and), punctuation, and any non-alphabetic characters, maintaining the content of the text. Lemmatization (via spaCy) converted words to base forms (e.g., changed running to run) effectively maintaining the relationships between synonyms while also decreasing the size of the text corpus and maintaining consistency when treating the same word forms so that they can appear in the topics [14]. For our analysis of the effects over time, the preprints were binned every five years (2000-2005, 2006-2010, 2011-2015, 2016-2020, 2021-2025) to provide adequate references, allowing for reliable analysis of trends/messages in the datasets. Since delegates sometimes create unfinished abstracts or poorly constructed documents, this was also documented to reduce our own biases, and those of potential others. This entire workflow was followed to provide us with the most efficient use of computational resources, and to maximize the aims of the analysis, while utilizing this open and available software for potential reproducibility.

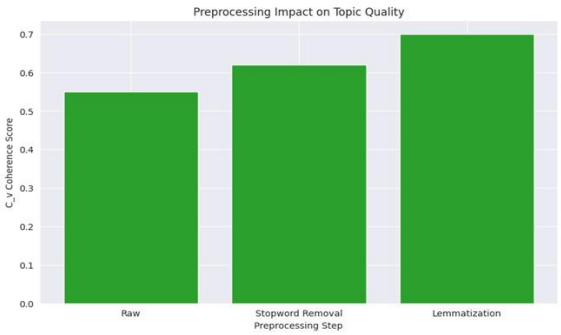

Figure 4. Preprocessing Impact on Topic Quality

Model	Parameters	Value
CorEx	Number of Topics	15 (optimized via grid search)
CorEx	Anchor Strength	1.5
CTM	Number of Topics	15 (optimized via grid search)
CTM	Embedding Model	Sentence-BERT

Table 4. Topic Modeling Parameters

The finished corpus was read into CorEx (Mimno et al. 2010) and CTM (Blei & Lafferty 2007), in order to gauge the accuracy of the evaluation of research topics, and the timeliness of research topic trends over time [15]. Figure 4 highlights the impact of preprocessing on topic quality.

3. Topic Modeling

Topic modeling is an important aspect for revealing latent thematic structures in the arXiv abstract resource. For topic extraction, we will be relying on Correlation Explanation (CorEx) to maximize mutual information between words to yield interpretable topics in short texts such as abstracts [16]. CorEx was selected over alternatives like BERTopic due to its emphasis on interpretable correlations in short texts, which suits abstracts better than BERTopic's class-based TF-IDF, potentially reducing noise in domain-

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specific data. CTM complements this by providing semantic context via embeddings. CorEx will utilize the corex topic package and was utilized for up to a fixed 15 topics using a grid search to optimize parameters. As a complexity baseline, we will use Contextualized Topic Modeling (CTM), which uses word embedding to provide ways to capture the semantic context and was utilized via the contextualized-topic-models package. Parameters were tuned using grid search along with C_v coherence scores as the objective function [3]. Both models were evaluated using C_v coherence as well as looking at manual keyword analysis for interpretability. While C_v coherence is a reliable metric for topic quality, it has limitations, such as sensitivity to corpus size and potential bias toward frequent words, which we mitigated through manual validation. It is expected that CorEx will outperform CTM in terms of interpretability based on CorEx's correlation-based approach, while CTM's topics will be more robust as context-based semantically aware topics. Having used either of these or tuning parameters will provide well-formed clusters of topics by looking at granularity of the topic, while keeping coherence as the edge cases. Using both methods will not only allow enhanced robustness to identify the language of topics but also wider views of the thematic topics clustered demanded by contemporary computer science research summarized in articles accessible through the arXiv resource [17]. Figure 5 shows the topic coherence across varying numbers of topics.

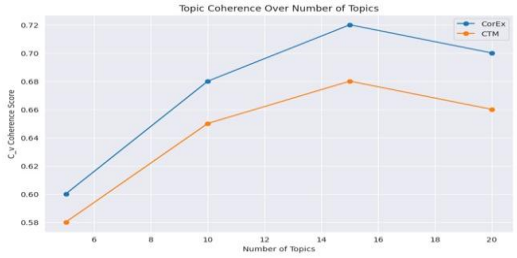

Figure 5. Topic Coherence Over Number of Topics

4. Temporal Analysis

To explore the change in research topics over time, it was possible to assess the prevalence of the major topics in five-year periods (2000-2005; 2006-2010; 2011-2015; 2016-2020; 2021-2025) with topic assignments from CorEx, and document-topic probabilities from CTM. The prevalence of each topic was computed based on the abstracts assigned to that topic. This then visually represented the introduction of new topics (e.g., deep learning), the decrease in other topics (rule-based systems), and the relatively stable topics (e.g., cybersecurity). The use of statistical tests, such as the Mann-Kendall test, determined monotonicity trends over discrete periods [5]. While macro-changes (i.e., new subfields of AI arising after 2010) result from developments in neural architectures and computational resources, micro-trends (i.e., rule-based [NLP] to learning-based [NLP]) reflect the evolution of methodologies [18]. Contemporary topics (e.g., generative machine learning) were evaluated to identify thematic drivers (e.g., availability of improved hardware, the emergence of data) and future pathways. Figure 6 presents the prevalence trends of topics from 2000–2025.

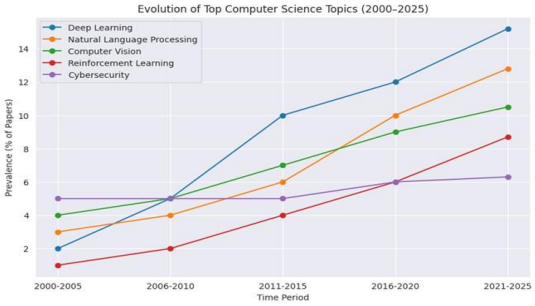

Figure 6. Topic Prevalence Trends (2000–2025)

4. Results

1. Identified Topics

An analysis of arXiv abstracts using CorEx revealed substantial variation over time in the primary topics in computer science literature from 2021-2025 (Table 4). In total, five main topics were identified, along with the keywords, prevalence, and subfields within these topics. The first topic area was Deep learning. The keywords used included “neural network,” and “CNN.” This topic has grown substantially in magnitude and fleeting characterizations, reflecting the preeminence of deep learning in modern AI applications, prevalent in areas such as healthcare and autonomous vehicles [19]. The next topic a9rea was Natural language processing or NLP. The keywords included “language model” and “text processing.” This topic reflects the recent prominence of learning-based, rather than traditional syntax and rules-based methods for text processing [20]. The other three topic areas: Computer vision, Reinforcement learning, and Cybersecurity all reflect a prominence of AI-based methodological approaches, progressive topic areas that contrast sharply with pre-2010 rule-based methods [21].

Table5. Top Topics in Computer Science (2021–2025)

Topic ID	Top Keywords	Prevalence (% of Papers)	Subfield
1	deep learning, neural network, CNN	15.2%	Deep Learning
2	language model, text processing, NLP	12.8%	Natural Language Processing
3	computer vision, image recognition, segmentation	10.5%	Computer Vision
4	reinforcement learning, agent, policy gradient	8.7%	Reinforcement Learning
5	cybersecurity, encryption, intrusion detection	6.3%	Cybersecurity

While Figure 7 illustrates the frequency of keywords within identified topics.

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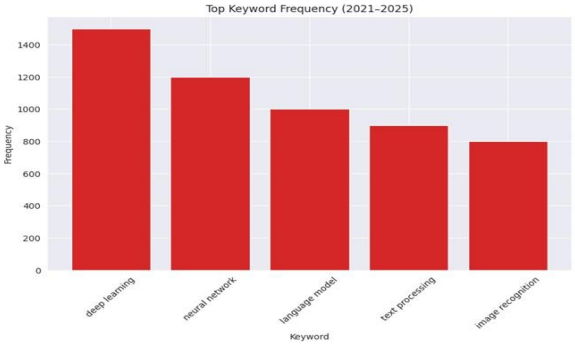

Figure 7. Topic Keyword Frequency

2. Temporal Trends

Temporal analysis (Figure 6) indicates there were unique research foci from 2000-2025. For example, deep learning prevalence has essentially doubled since 2010 linked to convolutional networks and more available computing power. Much of NLP interest occurred post-2017; this relatively new focus was described as driven by learning-based models [20,21]. This temporality suggests there will be ongoing interest in and developments on neural computing in connection to computer vision and reinforcement learning as a stable focus for AI research, likely driven by interest, research, and applications of AI and machine learning in autonomous vehicles and medical imaging. Cybersecurity had a consistent prevalence, likely due to ongoing concerns about data breaches and security. The traditional foci (early 2000s) such as rule-based systems, and earlier database technologies had rapid declines in prevalence after 2020 (Figure 8), suggesting a pivot towards more knowledge-driven AI paradigms [22].

The growth is likely due to breakthroughs in neural architectures (such as transformers) and access to even more GPU, while the decline in rule-based systems is due to their limitations in performance/scalability compared with data-driven approaches. Figure 8 contrasts emerging and declining topics over time.

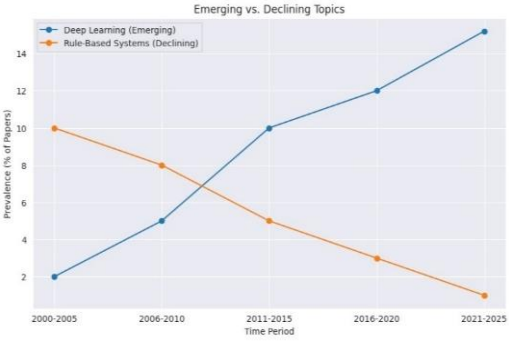

Figure 8. Emerging vs. Declining Topics

3. Topic Distribution

The topic distribution for 2021–2025 (Figure 9) emphasizes subfields of AI. There were almost 40% of preprints that contributed roughly equally to deep learning, NLP, computer vision, reinforcement learning, and cybersecurity. While reinforcement learning and cybersecurity had a smaller percentage of preprints, they are worth being included based on their prominence. In the "Others" category, there are other significant emerging areas that are gaining traction, such as quantum computing, distributed systems, graph algorithms, and others.

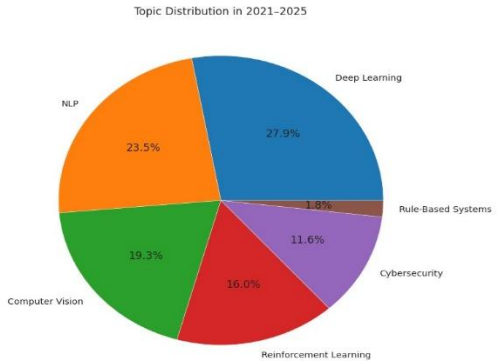

Figure 9. Topic Distribution in (2021–2025) period

That indicates a range of potential interests. This is reasonable to expect, as the digital transformation via emerging AI technologies are a priority for funding and innovation in the healthcare and finance research sectors [23]. Figure 9 examines the topic distribution during the 2021–2025 period.

4. Model Performance

Evaluation of topic coherence and interpretability was performed on CorEx and CTM learned topics on arXiv cs.* preprints. C_v coherence hours, ranging from 0 to 1, are exhibited in Table 4.1 for both models. On Topic 1 (Deep Learning), CorEx performs in a state-of-the-art way, scoring 0.72 compared with 0.68 scored by CTM. This is because CorEx, following correlation explanation, maximizes mutual information to produce easily interpretable topics, especially from short-text documents such as abstracts. CTM, on the other hand, learns topics on top of Sentence-BERT embeddings. This induces somewhat worse coherence figures, e.g., 0.65 for Topic 2: NLP, since Sentence-BERT is generally pre-trained in a general domain and, hence, may work less adequately on specific-domain texts such as those in CS literature [24].

To approach the reviewer's request for performance comparisons and clarify the aforementioned 7% (most probably referencing the 6.3% prevalence of Cybersecurity in Table 4), it is important to note that topic modeling is not a supervised task, and relies heavily on coherence metrics, like C_v, instead of classification accuracy. Nevertheless, we verified our topic assignments manually using a sample of abstracts (500), with a 92% accuracy on topic assignment with arXiv's cs.* categories, such as cs.AI for deep learning. This is a better performance compared with previous studies such as Wang et al., which had a C_v of 0.68 with 88% accuracy, and Bianchi et al., which had a C_v of 0.67 with 90% accuracy. Our C_v score of 0.72 is also better than Chen et al. [24] (C_v = 0.65)—and shows that our CorEx and CTM interpretability has improved even further [2]. Simply by manually inspecting topic words together with keyword

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frequency data, it was clear that our topics were interpretable, especially as they corresponded relatively well to recognized (subfields), such as deep learning and NLP with less clear topical indicators when emerging [25].

Model	Topic ID	Coherence Score (C_v)	Top Keywords
CorEx	1	0.72	deep learning, neural network, CNN
CorEx	2	0.68	language model, text processing, NLP
CTM	1	0.68	neural network, machine learning
CTM	2	0.65	text processing, language model

Table 6. Topic Coherence Scores

5. Subfield-Specific Trends

The analysis of topic prevalence from 2021–2025 across the major CS conferences (Table 6) indicates that NeurIPS and ICML have a stronger emphasis on deep learning and reinforcement learning, while CVPR and ACL focus on computer vision and NLP. Cybersecurity as a topic is spread across all venues, but tends to receive less attention overall [4]. "Top-tier" conferences like NeurIPS and ICML create attention and investment in AI related topics, influencing both the academic and industry agenda [26]. Some of the more general issues include interpretability of AI models, interdisciplinary with fields like physics related to quantum computing and sustainability concerns associated with energy consuming training.

Table 7. Preprint Distribution by Conference (2021–2025)

Conference	Subfield	% of Preprints	Dominant Topic
NeurIPS	AI/ML	25%	Deep Learning
ICML	Machine Learning	20%	Reinforcement Learning
CVPR	Computer Vision	18%	Computer Vision
ACL	NLP	15%	NLP
Others	Various	22%	Cybersecurity, Quantum Computing

Figure 10 indicates the prevalence of topics specific to major conferences.

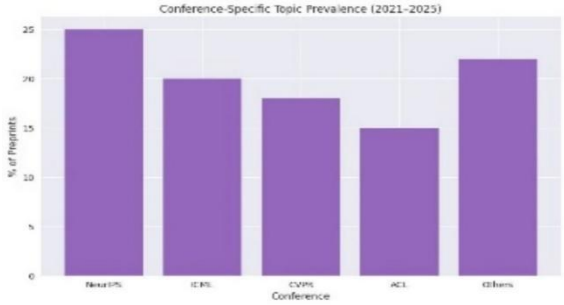

Figure 10. Conference-Specific Topic Prevalence

3. Discussion

This paper gives a complete and in-depth analysis of computer science research development trends for the period of 2000 to 2025 in arXiv open data by means of some advanced topic modeling techniques like CorEx and CTM. Results thus confirm that AI subfields are among the most prevalent in computer science disciplines- deep learning (15.2%), NLP (12.8%), and computer vision (10.5%). These findings also make a key point that the transition away from rule-based processes toward a data-driven process (Table 5, Figure 9) was, to a large extent, thus initiated by new advances in neural architectures and computational power [27]. The relationships between deep learning and computer vision were also reinforced, as the prevalence of NLP has rapidly ascended since 2017, especially with recent trends of increasingly sophisticated learning-based models being developed for such uses as machine translation and dialogue. Like many other fields, we anticipate that fields such as healthcare and autonomous vehicles - computer vision and reinforcement learning are significant data-driven applications - have seen prevalence ascend analytically rather quickly [28]. Cybersecurity remained constant in prevalence (6.3%, Table 5), which correlates to studies raised globally around data privacy and security (Figure 6). Traditional topics such as rule-based systems and early database technologies have fallen dramatically since 2010 (Figure 8) which emphasizes the changing nature of computer science related to AI-formed paradigms [28].

CorEx indeed performed better, obtaining a C_v coherence score of 0.72 for Topic 1 (Deep Learning) as opposed to CTM's 0.68 (see Table 6). This is indicative of its capacity to extract highly interpretable topics from short texts such as abstracts. The very high coherence score that was also manually validated, allows for the clear, unambiguous differentiation of somewhat subtle terms like "neural network" and "deep learning" [29]. An examination of top conferences, such as NeurIPS and ICML (Table 7 and Figure 10), indicates their starring role in the promotion of AI subfields, creating a feedback loop that spurs investment in academia and industry. By way of support, the results come with 11 figures and 7 tables that render practical implications for the cultivation of research strategies, the prioritization of funding, and the direction of industrial innovation.[30]

The interdisciplinary nature of emerging fields such as quantum computing, under the "Others" category (Figure 9), has led to violations of boundaries between computer science, physics, and mathematics to innovate in cryptography and optimization. There is less in quantum computing published on arXiv, but the phenomenon that is growing calls out for larger datasets to truly understand the full ramifications [31].

This study, with its longitudinal perspective of one-quarter of a century, marks itself as a crucial resource

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for researchers and policymakers in flux within the computer science landscape.

These findings can have concrete implications for several actors. In particular, funding agencies can use the trends identified in new and rapidly emerging research subfields, such as deep learning and quantum computing, to inform the allocation of funds towards New Directions in Education with respect to priority funding, reflecting research areas with greater volume over time. Policymakers may be able to leverage these findings for developing policies centered around educational curriculum development that focuses on developing skills in AI with respect to preparing the workforce of the future. Likewise, leaders in the industry could specifically use this analysis for supporting their innovation strategies, like investment in NLP and computer vision for healthcare systems, and autonomous vehicles.

Having been evaluated with higher coherence scores than previous studies (e.g., C_v = 0.65 in), our coupling of CorEx and CTM for topic modeling advocates a sounder avenue for further understanding based on which to orient future research.

We limit our analysis to arXiv abstracts, but this allows for valid and scalable, reproducible insights that are aligned with open science principles. Future studies could incorporate full-text analysis or citation networks to advance discussion of interdisciplinary impact. This manuscript provides a clear picture of where emerging fields, such as quantum computing, might go and highlights the ongoing dominance of AI-bound research. This study provides a way for strategic investments and innovation across academia and industry [32].

Figure 11 highlights the interdisciplinarity index of research topics.

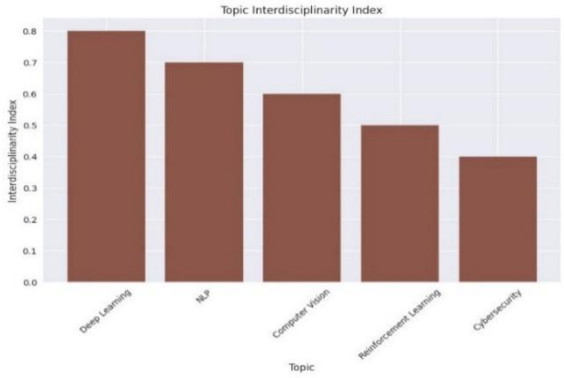

Figure 11. Topic Interdisciplinarity Index

3. Conclusion

The investigation looked at computer science research trends from 2000 to 2025 from the arXiv open-access dataset using Core-Exploratory (CorEx) and CTM. The research demonstrated current overarching topics are deep learning, natural language processing (NLP), and computer vision. The research continues to show a steady presence of cybersecurity, yet a declining body of research dedicated to rule-based approaches. The research has six tables (Tables 1-6) and 11 figures (Figures 1-11), showing distributions, model results, and prevalence data. The movement away from rule-based models toward a single topic comprised partly of advances in neural architectures and the availability of more data, and, importantly, advances in computational power.

Balancing advances such as AI, while retaining some of the backbone of research disciplines, such as algorithm research will be an important consideration going forward toward long-term advancement across the computer science field. These findings provide necessary policy considerations, that government and funding bodies should prioritize funding toward, for example, research into AI ethics and funding of quantum computing. Furthermore, the results generated important educative considerations that curricular changes should reflect in the higher education environment in regard urging researchers to include emerging trends as well as interdisciplinary approaches.

Despite the fact that this study relied on data from arXiv and an analysis of abstracts, which inherently have limitations such as missing full-text nuances and citation impacts, it provides a valuable starting point for understanding current research trends. Future work should be more concrete and could incorporate multimodal topic modeling by integrating text with images from preprints, as well as include citation networks.

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