

From Hypothesis to Publication: A Comprehensive Survey of AI-Driven Research Support Systems

Anonymous ACL submission

Abstract

Research is a fundamental process driving the advancement of human civilization, yet it demands substantial time and effort from researchers. In recent years, the rapid development of artificial intelligence (AI) technologies has inspired researchers to explore how AI can accelerate and enhance research. To monitor relevant advancements, this paper presents a systematic review of the progress in this domain. Specifically, we organize the relevant studies into three main categories: hypothesis formulation, hypothesis validation, and manuscript publication. Hypothesis formulation involves knowledge synthesis and hypothesis generation. Hypothesis validation includes the verification of scientific claims, theorem proving, and experimental validation. Manuscript publication encompasses manuscript writing and the peer review process. Furthermore, we identify and discuss the current challenges faced in these areas, as well as potential future directions for research. Finally, we also offer a comprehensive overview of existing benchmarks and tools across various domains that support the integration of AI into the research process. We hope this paper serves as an introduction for beginners and fosters future research.

1 Introduction

Research is creative and systematic work aimed at expanding knowledge and driving civilization’s development (Eurostat, 2018). Researchers typically identify a topic, review relevant literature, synthesize existing knowledge, and formulate hypothesis, which are validated through theoretical and experimental methods. Findings are then documented in manuscripts that undergo peer review before publication (Benos et al., 2007; Boyko et al., 2023). However, this process is resource-intensive, requiring specialized expertise and posing entry barriers for researchers (Blaxter et al., 2010).

In recent years, artificial intelligence (AI) technologies, represented by large language models (LLMs), have experienced rapid development (Brown et al., 2020; OpenAI, 2023; Dubey et al., 2024; Yang et al., 2024a; DeepSeek-AI et al., 2024; Guo et al., 2025). These models exhibit exceptional capabilities in text understanding, reasoning, and generation (Schaeffer et al., 2023). In this context, AI is increasingly involving the entire research pipeline (Messerli and Crockett, 2024), sparking extensive discussion about its implications for research (Hutson, 2022; Williams et al., 2023; Morris, 2023; Fecher et al., 2023). Moreover, following the release of ChatGPT, approximately 20% of academic papers and peer-reviewed texts in certain fields have been modified by LLMs (Liang et al., 2024a,b). A study also reveals that 81% of researchers integrate LLMs into their workflows (Liao et al., 2024).

As the application of AI in research attracts increasing attention, a significant body of related studies has begun to emerge. To systematically synthesize existing research, we present comprehensive survey that emulates human researchers by using the research process as an organizing framework. Specifically, as depicted in Figure 1, the research process is divided into three key stages: (1) Hypothesis Formulation, involving knowledge synthesis and hypothesis generation; (2) Hypothesis Validation, encompassing scientific claim verification, theorem proving, and experimental validation; (3) Manuscript Publication, which focuses on academic publications and is further divided into manuscript writing and peer-review.

Comparing with Existing Surveys Although Luo et al. (2025) reviews the application of AI in research, it predominantly focuses on LLMs while neglecting the knowledge synthesis that precedes hypothesis generation and the theoretical validation of hypothesis. Other surveys concentrate on more specific areas, such as paper recom-

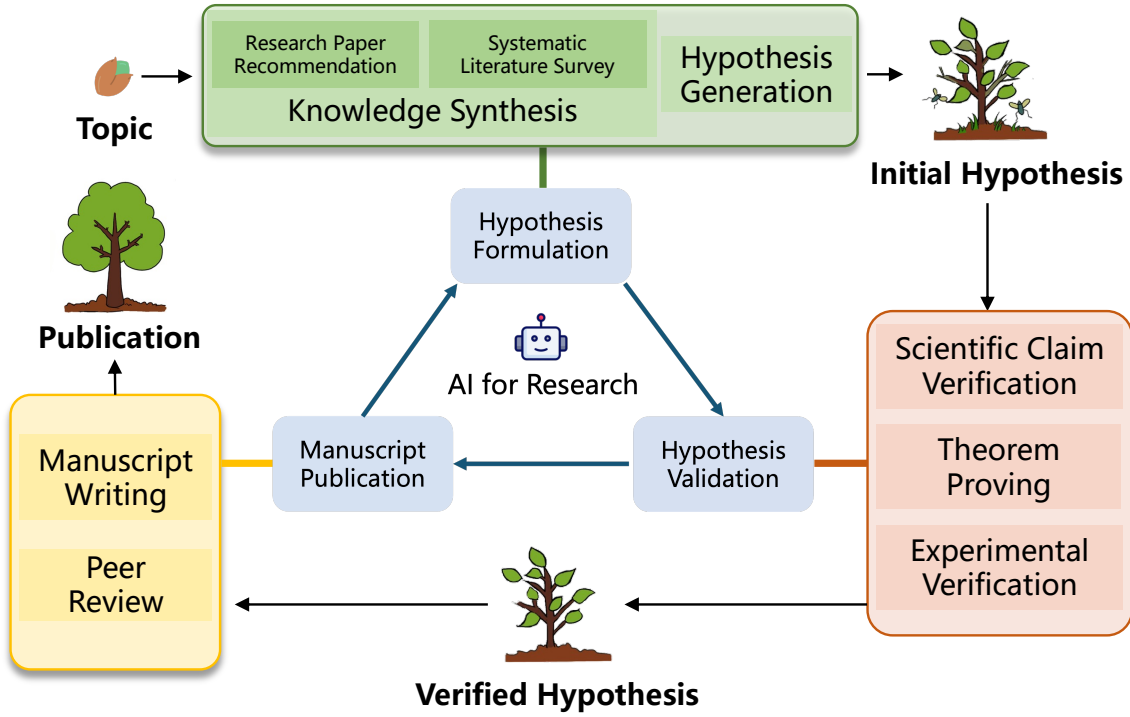


Figure 1: Overview of AI for research. The framework consists of three stages: hypothesis formulation, hypothesis validation, and manuscript publication. In the hypothesis formulation stage, knowledge integration leads to the proposal of an initial hypothesis after a topic is identified. The hypothesis validation stage involves verifying the hypothesis from three perspectives to ensure its correctness and validity. Finally, the manuscript publication stage focuses on drafting and publishing the validated hypothesis.

mendation (Beel et al., 2016; Bai et al., 2019; Kreutz and Schenkel, 2022), scientific literature review (Altmami and Menai, 2022), scientific claim verification (Vladika and Matthes, 2023; Dmonte et al., 2024), theorem proving (Li et al., 2024e), manuscript writing (Li and Ouyang, 2024), and peer review (Lin et al., 2023a; Kousha and Thelwall, 2024). Additionally, certain surveys emphasize the application of AI in scientific domains (Zheng et al., 2023; Zhang et al., 2024d).

Contributions Our contributions can be summarized as follows: (1) We align the relevant fields with the research process of human researchers, systematically integrating and extending these aspects while primarily focusing on the research process itself. (2) We introduce a meticulous taxonomy (shown in Figure 2). (3) We provide a summary of tools that can assist in the research process. (4) We formally define AI for research and clearly distinguish it from AI for science in §A.

Survey Organization We first elaborate Hypothesis Formulation (§2), followed by Hypothesis Validation (§3) and Manuscript Publication (§4). Additionally, we present benchmarks (§5), and tools (§6) that utilized in research. Finally, we outline chal-

lenges as well as future directions (§7) and give a further discussion about open questions (§A).

2 Hypothesis Formulation

This stage centers on the process of hypothesis formulation. As illustrated in Figure 3, it commences with developing a comprehensive understanding of the domain, followed by identifying a specific aspect and generating pertinent hypothesis. This section is further structured into two key components: Knowledge Synthesis and Hypothesis Generation.

2.1 Knowledge Synthesis

Knowledge synthesis constitutes the foundational step in the research process. During this phase, researchers are required to identify and critically evaluate existing literature to establish a thorough understanding of the field. This step is pivotal for uncovering new research directions, refining methodologies, and supporting evidence-based decision-making (Asai et al., 2024). In this section, the process of knowledge synthesis is divided into two modules: Research Paper Recommendation and Systematic Literature Review.

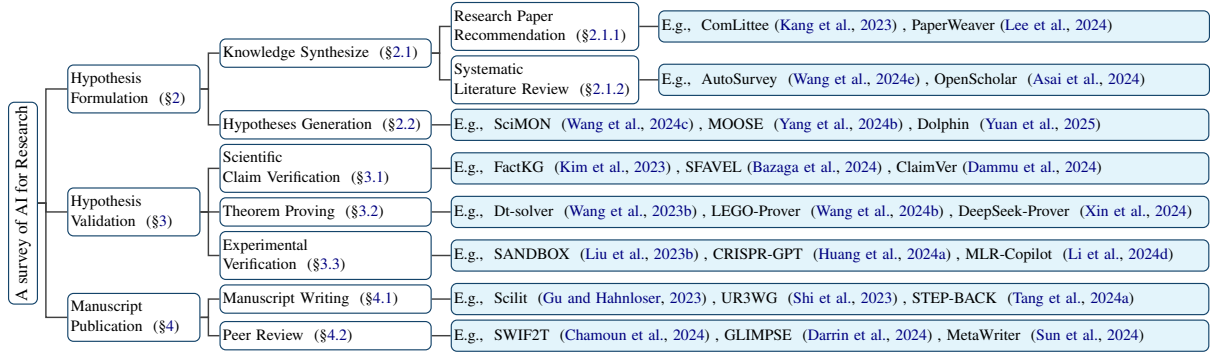


Figure 2: Taxonomy of Hypothesis Formulation, Hypothesis Validation and Manuscript Publication (This is a simplified version, full version in Figure 6).

2.1.1 Research Paper Recommendation

Research Paper Recommendation (RPR) identifies and recommends novel and seminal articles aligned with researchers’ interests. Prior studies have shown that recommendation systems outperform keyword-based search engines in terms of efficiency and reliability when extracting valuable insights from large-scale datasets (Bai et al., 2019). Existing methodologies are broadly categorized into four paradigms: content-based filtering, collaborative filtering, graph-based approaches, and hybrid systems (Beel et al., 2016; Li and Zou, 2019; Bai et al., 2019; Shahid et al., 2020). Recent advancements propose multi-dimensional classification frameworks based on data source utilization (Kreutz and Schenkel, 2022).

Recent trends in research suggest a decline in publication volumes related to RPR (Sharma et al., 2023), alongside an increasing focus on user-centric optimizations. Existing studies emphasize the limitations of traditional paper-centric interaction models and advocate for more effective utilization of author relationship graphs (Kang et al., 2023). Multi-stage recommendation architectures that integrate diverse methodologies have been shown to achieve superior performance (Pinedo et al., 2024; Stergiopoulos et al., 2024). Visualization techniques that link recommended papers to users’ publication histories via knowledge graphs (Kang et al., 2022) and LLMs-powered comparative analysis frameworks (Lee et al., 2024) represent emerging directions for enhancing interpretability and contextual relevance.

2.1.2 Systematic Literature Review

Systematic Literature Review (SLR) constitutes a rigorous and structured methodology for evaluating and integrating prior research on a specific topic

(Webster and Watson, 2002; Zhu et al., 2023; Bolaños et al., 2024). In contrast to single-document summaries, SLR entails synthesizing information across multiple related scientific documents (Altamimi and Menai, 2022). SLR can further be divided into two stages: outline generation and full-text generation (Shao et al., 2024; Agarwal et al., 2024b; Block and Kuckertz, 2024).

Outline generation, especially structured outline generation, is highlighted by recent studies as a pivotal factor in enhancing the quality of surveys. Zhu et al. (2023) demonstrated that hierarchical frameworks substantially enhance survey coherence. AutoSurvey (Wang et al., 2024e) extends conventional outline generation by recommending both sub-chapter titles and detailed content descriptions, ensuring comprehensive topic coverage. Additionally, multi-level topic generation via clustering methodologies has been proposed as an effective strategy for organizing survey structures (Katz et al., 2024). Advanced systems such as STORM (Shao et al., 2024) employ LLM-driven outline drafting combined with multi-agent discussion cycles to iteratively refine the generated outlines. Tree-based hierarchical architectures have gained increasing adoption in this domain. For instance, CHIME (Hsu et al., 2024) optimizes LLM-generated hierarchies through human-AI collaboration, while HiReview (Hu et al., 2024b) demonstrates the efficacy of multi-layer tree representations for systematic knowledge organization.

Full-text generation follows the outline generation stage. AutoSurvey and (Lai et al., 2024) utilized LLMs with carefully designed prompts to construct comprehensive literature reviews step-by-step. PaperQA2 (Skarlinski et al., 2024) introduced an iterative agent-based approach for generating reviews, while STORM employed multi-

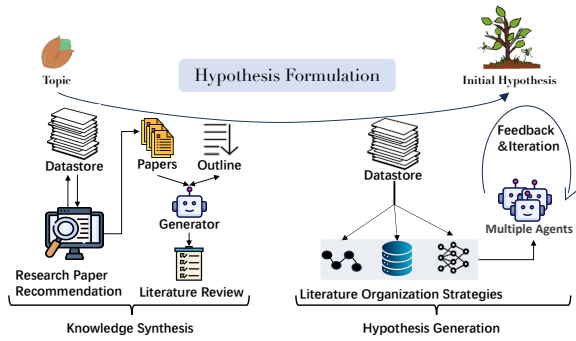


Figure 3: This figure illustrates the hypothesis formulation process, consisting of two stages: knowledge synthesis and hypothesis generation, which together produce an initial hypothesis related to a specific topic.

agent conversation data for this purpose. LitLLM (Agarwal et al., 2024a) and Agarwal et al. (2024b) adopted a plan-based search enhancement strategy. KGSum (Wang et al., 2022a) integrated knowledge graph information into paper encoding and used a two-stage decoder for summary generation. Bio-SIEVE (Robinson et al., 2023) and Susnjak et al. (2024) fine-tuned LLMs for automatic review generation. OpenScholar (Asai et al., 2024) developed a pipeline that trained a new model without relying on a dedicated survey-generation model.

2.2 Hypothesis Generation

Hypothesis Generation, known as Idea Generation, refers to the process of coming up with new concepts, solutions, or approaches. It is the most important step in driving the progress of the entire research (Qi et al., 2023).

Early work focused more on predicting relationships between concepts, because researchers believed that new concepts come from links with old concepts (Henry and McInnes, 2017; Krenn et al., 2022). As language models became more powerful (Zhao et al., 2023a), researchers are beginning to focus on open-ended idea generation (Girotra et al., 2023; Si et al., 2024; Kumar et al., 2024). Recent advancements in AI-driven hypothesis generation highlight diverse approaches to research conceptualization. For instance, MOOSE-Chem (Yang et al., 2024c) and IdeaSynth (Pu et al., 2024) use LLMs to bridge inspiration-to-hypothesis transformation via interactive frameworks. The remaining research can primarily be categorized into two areas: enhancing input data quality and improving the quality of generated hypothesis.

Input data quality improvement is demon-

strated by Majumder et al. (2024a); Liu et al. (2024a), who show that LLMs can generate comprehensive hypothesis from existing academic data. Literature organization strategies have evolved through various methodologies, including triplet representations (Wang et al., 2024c), chain-based architectures (Li et al., 2024a), and complex database systems (Wang et al., 2024d). Knowledge graphs emerge as critical infrastructure (Hogan et al., 2021), enabling semantic relationship mapping via subgraph identification (Buehler, 2024; Ghafarollahi and Buehler, 2024). Notably, SciMuse (Gu and Krenn, 2024) pioneers researcher-specific hypothesis generation by constructing personalized knowledge graphs.

Hypothesis quality improvement has been addressed through feedback and iteration, as proposed by HypoGeniC (Zhou et al., 2024) and MOOSE (Yang et al., 2024b). Feedback mechanisms include direct responses to hypothesis (Baek et al., 2024), experimental outcome evaluations (Ma et al., 2024; Yuan et al., 2025), and automated peer review comments (Lu et al., 2024). Beyond iterative feedback, collaborative efforts among researchers have also been recognized, leading to multi-agent hypothesis generation approaches (Nigam et al., 2024; Ghafarollahi and Buehler, 2024). VIRSCI (Su et al., 2024) further optimized this process by customizing knowledge for each agent. Additionally, the Nova framework (Hu et al., 2024a) was introduced to refine hypothesis by leveraging outputs from other research as input.

Knowledge Synthesis and Hypothesis Generation comprise the Hypothesis Formulation phase. Research Paper Recommendation supports knowledge acquisition, while Systematic Literature Review aids organization within Knowledge Synthesis. Recent advances integrate LLMs (de la Torre-López et al., 2023) to enhance knowledge integration (Huang and Tan, 2023; Gupta et al., 2023; Kacena et al., 2024; Tang et al., 2024b). By developing a deep understanding of a domain through Knowledge Synthesis, researchers can identify research directions and use hypothesis generation techniques to formulate hypothesis. Additionally, the distinction between scientific discovery and hypothesis generation is discussed in §A.

3 Hypothesis Validation

In scientific research, any proposed hypothesis must undergo rigorous validation to establish its

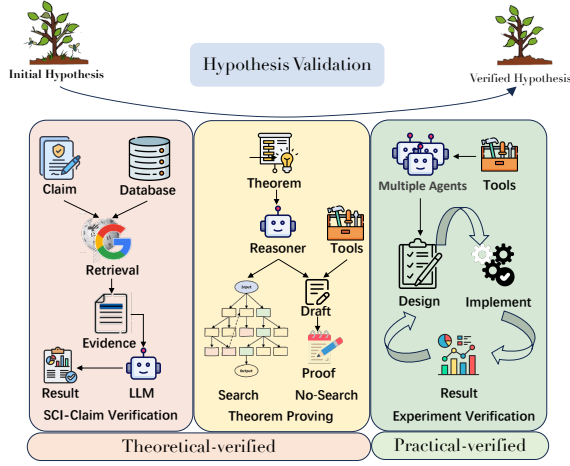


Figure 4: This figure illustrates the various perspectives for hypothesis validation during the hypothesis validation stage. A hypothesis is typically divided into scientific claims and theorems, with SCI-claim verification (scientific claim verification) and theorem proving ensuring theoretical correctness, while experiment validation assesses practical feasibility.

validity. As illustrated in Figure 4, this section explores the application of AI in verifying scientific hypothesis through three methodological components: Scientific Claim Verification, Theorem Proving, and Experiment Validation.

3.1 Scientific Claim Verification

Scientific Claim Verification, also referred to as Scientific Fact-Checking or Scientific Contradiction Detection, aims to assess the veracity of claims related to scientific knowledge. This process assists scientists in verifying research hypothesis, discovering evidence, and advancing scientific work (Wadden et al., 2020; Vladika and Matthes, 2023; Skarlinski et al., 2024). Research on scientific claim verification primarily focuses on three key elements: the claim, the evidence, and the validity of the claim (Dmonte et al., 2024).

Claim Studies have highlighted that certain claims lack supporting evidence (Wühl et al., 2024a), while others have demonstrated the ability to perform claim-evidence alignment without annotated data (Bazaga et al., 2024). Additionally, methods such as SFAVEL (Bazaga et al., 2024), HiSS (Zhang and Gao, 2023), and ProToCo (Zeng and Gao, 2023) propose generating multiple claim variants to enhance verification.

Evidence Existing research has explored various aspects related to evidence, including evidentiary

sources (Vladika and Matthes, 2024a), retrieval configurations (Vladika and Matthes, 2024b), strategies for identifying and mitigating flawed evidence (Glockner et al., 2022; Wühl et al., 2024b; Glockner et al., 2024a), and approaches for processing sentence-level (Pan et al., 2023b) versus document-level indicators (Wadden et al., 2022b).

Verification In the verification results generation phase, studies propose leveraging LLMs to synthesize evidence into comprehensive information (Kao and Yen, 2024; Cao et al., 2024b). FactKG (Kim et al., 2023) and Muharram and Purwarianti (2024) structure evidence into knowledge graphs, enabling claim attribution (Dammu et al., 2024; Wu et al., 2023). Furthermore, Atanasova et al. (2020); Krishna et al. (2022); Pan et al. (2023a); El-difrawi et al. (2024); Zhang et al. (2024b) advocate for generating explanatory annotations alongside experimental outcomes during the verification process. Meanwhile, Das et al. (2023); Altuncu et al. (2023) emphasize the critical role of domain expertise in ensuring accurate verification.

3.2 Theorem Proving

Theorem proving constitutes a subtask of logical reasoning, aimed at reinforcing the validity of the underlying theory within a hypothesis (Yang et al., 2023c; Li et al., 2024e).

Following the proposal of GPT-f (Polu and Sutskever, 2020) to utilize generative language models for theorem proving, researchers initially combined search algorithms with language models (Lample et al., 2022; Wang et al., 2023b). However, a limitation in search-based approaches was later identified by Wang et al. (2024a), who highlighted their tendency to explore insignificant intermediate conjectures. This led some teams to abandon search algorithms entirely. Subsequently, alternative methods emerged, such as the two-stage framework proposed by Jiang et al. (2023) and Lin et al. (2024), which prioritized informal conceptual generation before formal proof construction. Thor (Jiang et al., 2022a) introduced theorem libraries to accelerate proof generation, an approach enhanced by Logo-power (Wang et al., 2024b) through dynamic libraries. Studies like Baldur (First et al., 2023), Mustard (Huang et al., 2024c), and DeepSeek-Prover (Xin et al., 2024) demonstrated improvements via targeted data synthesis and fine-tuning, though COPRA (Thakur et al., 2024) questioned their generalizability and pro-

posed an environment-agnostic alternative. Complementary strategies included theoretical decomposition into sub-goals (Zhao et al., 2023b) and leveraging LLMs as collaborative assistants in interactive environments (Song et al., 2024).

3.3 Experiment Verification

Experiment verification involves designing and conducting experiments based on the hypothesis. The empirical validity of the hypothesis is then determined through analysis of the experimental results (Huang et al., 2024b).

Experiment verification represents a time-consuming component of scientific research. Recent advancements in LLMs have enhanced their ability to plan and reason about experimental tasks (Kambhampati et al., 2024), prompting researchers to use these models for designing and implementing experiments (Ruan et al., 2024b). To ensure accuracy, studies such as Zhang et al. (2023) and Arlt et al. (2024) imposed input/output constraints, though this reduced generalizability. To address this, Boiko et al. (2023); Bran et al. (2024); Huang et al. (2024a) integrated tools to expand model capabilities. Full automation was achieved by Ni and Buehler (2023); Li et al. (2024a); Lu et al. (2024) through prompt-guided multi-agent collaboration. Madaan et al. (2023); Yuan et al. (2025) further highlighted that the integration of feedback mechanisms demonstrated potential for enhancing design quality, while Zhang et al. (2024a); Liu et al. (2024c); Ni et al. (2024) employed experimental outcomes to refine hyperparameter configurations, and Szymanski et al. (2023); Li et al. (2024d); Baek et al. (2024) leveraged agent-generated analytical insights to facilitate iterative hypothesis refinement. In contrast, social science research often uses LLMs as experimental subjects to simulate human participants (Liu et al., 2023b; Manning et al., 2024; Mou et al., 2024).

A hypothesis can be conceptualized as consisting of two key components: claims and theorems. Scientific Claim Verification and Theorem Proving offer theoretical validation of hypothesis through formal reasoning and logical deduction, whereas Experimental Verification provides comprehensive practical validation via empirical testing.

4 Manuscript Publication

Upon validating a hypothesis as feasible, researchers generally progress to the publication

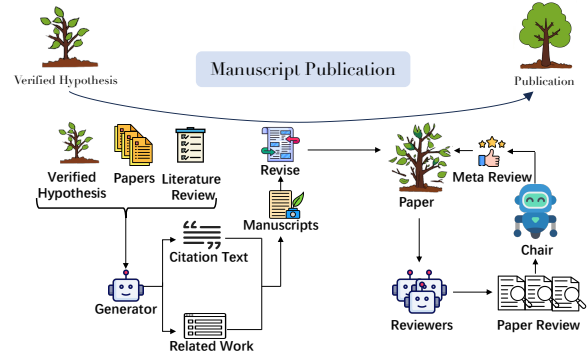


Figure 5: This figure shows the transformation of a validated hypothesis into a publication, leveraging outputs from the hypothesis formulation and validation stages.

stage. As depicted in Figure 5, this section categorizes Manuscript Publication into two primary components: Manuscript Writing and Peer Review.

4.1 Manuscript Writing

Manuscript writing, also referred to as scientific or research writing. At this stage, researchers articulate the hypothesis they have formulated and the results they have validated in the form of a scholarly paper. This process is crucial, as it not only disseminates findings but also deepens researchers’ understanding of their work (Colyar, 2009).

Citation Text Generation (Sentence Level) A subset of research on AI in scientific writing has focused on citation text generation, which addresses the academic need for referencing prior work while mitigating model inaccuracies (Gao et al., 2023b; Gu and Hahnloser, 2023). For instance, Wang et al. (2022b) developed an automated citation generation system by integrating manuscript content with citation graphs. However, its reliance on rigid template-based architectures led to inflexible citation formats. This limitation motivated subsequent studies to propose incorporating citation intent as a control parameter during text generation, aiming to improve contextual relevance and rhetorical adaptability (Yu et al., 2022; Jung et al., 2022; Gu and Hahnloser, 2024).

Related Work Generation (Paragraph Level) In contrast to citation text generation, several studies have focused on related work generation in scholarly writing, emphasizing the production of multiple citation texts and the systematic analysis of inter-citation relationships (Li and Ouyang, 2022, 2024). The ScholaCite framework (Martin-Boyle et al., 2024) leveraged GPT-4 to cluster ci-

tation sources and generate draft literature review sections, although it required manually provided reference lists. By contrast, the UR3WG system (Shi et al., 2023) adopted a retrieval-augmented architecture integrated with large language models to autonomously acquire relevant references. To improve the quality of generated related work sections, Yu et al. (2024b) utilized graph neural networks (GNNs) to model complex relational dynamics between target manuscripts and cited literature, while Nishimura et al. (2024) initiative advocated for explicit novelty assertions regarding referenced publications.

Complete Manuscripts Generation (Full-text Level) The aforementioned investigations primarily focused on specific components of scientific writing, while a study by Lai et al. (2024) explored the progressive generation of complete manuscripts via structured workflows. The AI-Scientist system (Lu et al., 2024) further introduced section-wise self-reflection mechanisms to enhance compositional coherence. Several studies emphasized human-AI collaborative frameworks for improving writing efficiency (Lin, 2024; Feng et al., 2024; Ifargan et al., 2024), whereas Tang et al. (2024a) concentrated on enabling personalized content generation in multi-author collaborative environments. Following initial manuscript drafting, subsequent text revision processes were systematically examined (Jourdan et al., 2023). The OREO system (Li et al., 2022) utilized attribute classification for iterative in-situ editing, while Du et al. (2022); Pividori and Greene (2024) incorporated researcher feedback loops for progressive text optimization. Notably, Chamoun et al. (2024); D’Arcy et al. (2024b) proposed replacing manual feedback with automated evaluation metrics.

4.2 Peer Review

Peer review serves as a critical mechanism for improving the quality of academic manuscripts through feedback and evaluation, forming the cornerstone of quality control in scientific research. However, the process is hindered by its slow pace, high time consumption, and increasing strain due to the growing academic workload (Lin et al., 2023a; Kousha and Thelwall, 2024; Thelwall and Yaghi, 2024). To address these challenges and enhance manuscript quality, researchers have investigated the application of AI in peer review (Yuan et al., 2022; Liu and Shah, 2023; Niu et al., 2023;

Kuznetsov et al., 2024). Peer review can be categorized into two main types: paper review generation and meta-review generation.

Paper Review Generation In paper review generation, reviewers provide both scores and evaluations for manuscripts. For instance, Setio and Tsuchiya (2022) formulated score prediction as a regression task, Muangkammuen et al. (2022) utilized semi-supervised learning, and Couto et al. (2024) treated the task as a classification problem to evaluate the alignment between manuscripts and review criteria. While these approaches focused on label prediction for paper reviews, Yuan and Liu (2022) extended the scope by directly generating reviews through the construction of a concept graph integrated with a citation graph.

Subsequently, a pilot study conducted by Robertson (2023) demonstrated the capability of GPT-4 to generate paper reviews. Further investigations, such as those by AI-Scientist (Lu et al., 2024) and Liang et al. (2023), evaluated its performance as a review agent. Additionally, systems like MARG (D’Arcy et al., 2024a) and SWIF2T (Chamoun et al., 2024) employed multi-agent frameworks to generate reviews via internal discussions and task decomposition. In contrast, AgentReview (Jin et al., 2024) and Tan et al. (2024) modeled the review process as a dynamic, multi-turn dialogue. Furthermore, CycleResearcher (Weng et al., 2024) and OpenReviewer (Idahl and Ahmadi, 2024) fine-tuned models for comparative reviews and structured outputs aligned with conference guidelines.

Meta-Review Generation In meta-review generation, chairs are tasked with identifying a paper’s core contributions, strengths, and weaknesses while synthesizing expert opinions on manuscript quality. Meta-reviews are conceptualized as abstractions of comments, discussions, and paper abstracts (Li et al., 2023). Santu et al. (2024) investigated the use of LLMs for automated meta-review generation, while Zeng et al. (2023) proposed a guided, iterative prompting approach. MetaWriter (Sun et al., 2024) utilized LLMs to extract key reviewer arguments, whereas GLIMPSE (Darrin et al., 2024) and Kumar et al. (2023) focused on reconciling conflicting statements to ensure fairness. Additionally, Li et al. (2024b) introduced a three-layer sentiment consolidation framework for meta-review generation, and PeerArg (Sukpanichnant et al., 2024) integrated LLMs with knowledge representation to address subjectivity and bias via

a multiparty argumentation framework (MPAF).

During the Manuscript Publication phase, researchers can leverage AI to systematically complete manuscript writing by incorporating validated hypothesis, related papers, and literature reviews. The manuscript is subsequently subjected to peer review, involving iterative revisions before culminating in its final publication.

5 Benchmarks

Given that AI for research spans multiple disciplines, the tasks addressed within each domain vary significantly. To facilitate cross-domain exploration, we provide a summary of benchmarks associated with various areas, including research paper recommendation, systematic literature review, hypothesis generation, scientific claim verification, theorem proving, experiment verification, manuscript writing, and peer review. An overview of these benchmarks is presented in Table 1.

6 Tools

To accelerate the research workflow, we have curated a collection of tools designed to support various stages of the research process, with their applicability specified for each stage. To ensure practical relevance, our selection criteria emphasize tools that are publicly accessible or demonstrate significant influence on GitHub. A comprehensive overview of these tools is presented in Table 2.

7 Challenges

We identify several intriguing and promising avenues for future research.

7.1 Integration of Diverse Research Tasks

Many existing studies on AI for research remain focused narrowly within their respective domains, often neglecting related technologies and potentially undermining overall outcomes. However, the research process is inherently an integrated pipeline comprising interdependent stages. Therefore, we propose that researchers strive to bridge diverse fields, either by combining technologies or harmonizing workflows. For instance, meta-review generation could be integrated with scientific claim verification, experiment verification could be linked with hypothesis formulation (Yuan et al., 2025), and research paper recommendation systems could be connected with manuscript writing processes (Gu and Hahnloser, 2023). Furthermore, some studies

have begun to emphasize the development of systems capable of spanning multiple stages of the research process (Jansen et al., 2024; Weng et al., 2024; Yu et al., 2024a).

7.2 Integration with Reasoning-Oriented Language Models

Research is a process that places significant emphasis on logic and reasoning. Theorem proving serves as a subtask within logical reasoning (Li et al., 2024e), while hypothesis generation is widely recognized as the primary form of reasoning employed by scientists when observing the world and proposing hypothesis to explain these observations (Yang et al., 2024b). Experiment verification, in turn, demands a high degree of planning capability from models (Kambhampati et al., 2024). Recent advancements in reasoning-oriented language models, such as OpenAI-o1 (Jaech et al., 2024) and DeepSeek-R1 (Guo et al., 2025), have substantially enhanced the reasoning abilities of these models. Consequently, we posit that integrating reasoning language models with reasoning tasks is a promising future direction. This prediction was validated by experiments conducted by Schmidgall et al. (2025) using o1-Preview.

Furthermore, in Appendix §B, we provide a summary of the challenges in hypothesis formulation, validation, and manuscript publication.

8 Conclusion

This paper provides a systematic survey of existing research on AI for research, offering a comprehensive review of the advancements in the field. Within each category, we offer detailed descriptions of the associated subfields. Furthermore, we analyze potential future research directions and address the challenges that remain unresolved. To facilitate researchers’ exploration of AI for research and enhance workflow efficiency, we provide a summary of relevant benchmarks and tools.

Furthermore, in the course of investigating various subfields within AI for research, we observed that this domain remains in its infancy. Research in numerous directions remains at an experimental stage, and substantial progress is necessary before these approaches can be effectively applied in practical scenarios. We hope that this survey serves as an introduction to the field for researchers and contributes to its continued advancement.

Limitation

This study presents a comprehensive survey of AI for research, based on the framework of the research process conducted by human researchers.

We have made our best effort, but there may still be some limitations. On one hand, due to page limitations, we can only provide a brief summary of each method without exhaustive technical details. On the other hand, given the widespread exploration by researchers across disciplines on applying AI to their work, and our focus on articles published after 2022, it is possible that some important contributions may have been overlooked. Additionally, to prioritize areas that closely simulate the human research process, we excluded certain domains that could also be classified under AI for research.

References

- Shubham Agarwal, Issam H. Laradji, Laurent Charlin, and Christopher Pal. 2024a. [Litlm: A toolkit for scientific literature review](#). *CoRR*, abs/2402.01788.
- Shubham Agarwal, Gaurav Sahu, Abhay Puri, Issam H Laradji, Krishnamurthy DJ Dvijotham, Jason Stanley, Laurent Charlin, and Christopher Pal. 2024b. Lms for literature review: Are we there yet? *arXiv preprint arXiv:2412.15249*.
- Microsoft Research AI4Science and Microsoft Azure Quantum. 2023. [The impact of large language models on scientific discovery: a preliminary study using GPT-4](#). *CoRR*, abs/2311.07361.
- Fadi Aljamaan, Mohamad-Hani Temsah, Ibraheem Altamimi, Ayman Al-Eyadhy, Amr Jamal, Khalid Alhasan, Tamer A Mesallam, Mohamed Farahat, Khalid H Malki, et al. 2024. Reference hallucination score for medical artificial intelligence chatbots: development and usability study. *JMIR Medical Informatics*, 12(1):e54345.
- Nouf Ibrahim Altmami and Mohamed El Bachir Menai. 2022. [Automatic summarization of scientific articles: A survey](#). *J. King Saud Univ. Comput. Inf. Sci.*, 34(4):1011–1028.
- Enes Altuncu, Jason R. C. Nurse, Meryem Bagriacik, Sophie Kaleba, Haiyue Yuan, Lisa Bonheme, and Shujun Li. 2023. [aedfact: Scientific fact-checking made easier via semi-automatic discovery of relevant expert opinions](#). *CoRR*, abs/2305.07796.
- Sören Arlt, Haonan Duan, Felix Li, Sang Michael Xie, Yuhuai Wu, and Mario Krenn. 2024. [Meta-designing quantum experiments with language models](#). *CoRR*, abs/2406.02470.
- Akari Asai, Jacqueline He, Rulin Shao, Weijia Shi, Amanpreet Singh, Joseph Chee Chang, Kyle Lo,

- Luca Soldaini, Sergey Feldman, Mike D’Arcy, David Wadden, Matt Latzke, Minyang Tian, Pan Ji, Shengyan Liu, Hao Tong, Bohao Wu, Yanyu Xiong, Luke Zettlemoyer, Graham Neubig, Daniel S. Weld, Doug Downey, Wen-tau Yih, Pang Wei Koh, and Hannaneh Hajishirzi. 2024. [Openscholar: Synthesizing scientific literature with retrieval-augmented lms](#). *CoRR*, abs/2411.14199.
- Pepa Atanasova, Jakob Grue Simonsen, Christina Lioma, and Isabelle Augenstein. 2020. [Generating fact checking explanations](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 7352–7364. Association for Computational Linguistics.
- Sai Anirudh Athaluri, Sandeep Varma Manthena, VSR Krishna Manoj Kesapragada, Vineel Yarlagadda, Tirth Dave, and Rama Tulasi Siri Duddumpudi. 2023. Exploring the boundaries of reality: investigating the phenomenon of artificial intelligence hallucination in scientific writing through chatgpt references. *Cureus*, 15(4).
- Jinheon Baek, Sujay Kumar Jauhar, Silviu Cucerzan, and Sung Ju Hwang. 2024. [Researchagent: Iterative research idea generation over scientific literature with large language models](#). *CoRR*, abs/2404.07738.
- Xiaomei Bai, Mengyang Wang, Ivan Lee, Zhuo Yang, Xiangjie Kong, and Feng Xia. 2019. [Scientific paper recommendation: A survey](#). *IEEE Access*, 7:9324–9339.
- Adrián Bazaga, Pietro Lio, and Gos Micklem. 2024. [Unsupervised pretraining for fact verification by language model distillation](#). In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. Open-Review.net.
- Joeran Beel, Bela Gipp, Stefan Langer, and Corinna Breiteringer. 2016. Paper recommender systems: a literature survey. *International Journal on Digital Libraries*, 17:305–338.
- Dale J Benos, Edlira Bashari, Jose M Chaves, Amit Gagar, Niren Kapoor, Martin LaFrance, Robert Mans, David Mayhew, Sara McGowan, Abigail Polter, et al. 2007. The ups and downs of peer review. *Advances in physiology education*, 31(2):145–152.
- Loraine Blaxter, Christina Hughes, and Malcolm Tight. 2010. *How to research*. McGraw-Hill Education (UK).
- Joern Block and Andreas Kuckertz. 2024. What is the future of human-generated systematic literature reviews in an age of artificial intelligence? *Management Review Quarterly*, pages 1–6.
- Ben Bogin, Kejuan Yang, Shashank Gupta, Kyle Richardson, Erin Bransom, Peter Clark, Ashish Sabharwal, and Tushar Khot. 2024. [SUPER: evaluating](#)

754	agents on setting up and executing tasks from re-	2024, Bangkok, Thailand and virtual meeting, Au-	811
755	search repositories. In <i>Proceedings of the 2024 Con-</i>	gust 11-16, 2024, pages 9742–9763. Association for	812
756	<i>ference on Empirical Methods in Natural Language</i>	Computational Linguistics.	813
757	<i>Processing, EMNLP 2024, Miami, FL, USA, Novem-</i>		
758	<i>ber 12-16, 2024</i> , pages 12622–12645. Association	Tzeng-Ji Chen. 2023. Chatgpt and other artificial intel-	814
759	for Computational Linguistics.	ligence applications speed up scientific writing. <i>Jour-</i>	815
		<i>nal of the Chinese Medical Association</i> , 86(4):351–	816
760	Daniil A. Boiko, Robert MacKnight, Ben Kline, and	353.	817
761	Gabe Gomes. 2023. Autonomous chemical research		
762	with large language models . <i>Nat.</i> , 624(7992):570–	Gautam Choudhary, Natwar Modani, and Nitish Mau-	818
763	578.	rya. 2021. React: A review comment dataset for	819
		actionability (and more) . In <i>Web Information Sys-</i>	820
764	Francisco Bolaños, Angelo A. Salatino, Francesco Os-	<i>tems Engineering - WISE 2021 - 22nd International</i>	821
765	borne, and Enrico Motta. 2024. Artificial intelligence	<i>Conference on Web Information Systems Engineer-</i>	822
766	for literature reviews: opportunities and challenges .	<i>ing, WISE 2021, Melbourne, VIC, Australia, October</i>	823
767	<i>Artif. Intell. Rev.</i> , 57(9):259.	<i>26-29, 2021, Proceedings, Part II</i> , volume 13081 of	824
		<i>Lecture Notes in Computer Science</i> , pages 336–343.	825
768	James Boyko, Joseph Cohen, Nathan Fox, Maria Han	Springer.	826
769	Veiga, Jennifer I-Hsiu Li, Jing Liu, Bernardo Mod-		
770	enesi, Andreas H. Rauch, Kenneth N. Reid, Soumi	Julia Colyar. 2009. Becoming writing, becoming writ-	827
771	Tribedi, Anastasia Visheratina, and Xin Xie. 2023.	ers. <i>Qualitative Inquiry</i> , 15(2):421–436.	828
772	An interdisciplinary outlook on large language mod-		
773	els for scientific research . <i>CoRR</i> , abs/2311.04929.	Paulo Henrique Couto, Quang Phuoc Ho, Nageeta Ku-	829
		mari, Benedictus Kent Rachmat, Thanh Gia Hieu	830
774	Andres M. Bran, Sam Cox, Oliver Schilter, Carlo Bal-	Khuong, Ihsan Ullah, and Lisheng Sun-Hosoya. 2024.	831
775	dassari, Andrew D. White, and Philippe Schwaller.	Relevai-reviewer: A benchmark on AI reviewers for	832
776	2024. Augmenting large language models with chem-	survey paper relevance . <i>CoRR</i> , abs/2406.10294.	833
777	istry tools . <i>Nat. Mac. Intell.</i> , 6(5):525–535.		
		Preetam Prabhu Srikar Dammu, Himanshu Naidu,	834
778	Tom Brown, Benjamin Mann, Nick Ryder, Melanie	Mouly Dewan, YoungMin Kim, Tanya Roosta, Aman	835
779	Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind	Chadha, and Chirag Shah. 2024. Claimver: Explain-	836
780	Neelakantan, Pranav Shyam, Girish Sastry, Amanda	able claim-level verification and evidence attribution	837
781	Askell, et al. 2020. Language models are few-shot	of text through knowledge graphs . In <i>Findings of the</i>	838
782	learners. <i>Advances in neural information processing</i>	<i>Association for Computational Linguistics: EMNLP</i>	839
783	<i>systems</i> , 33:1877–1901.	<i>2024, Miami, Florida, USA, November 12-16, 2024</i> ,	840
		pages 13613–13627. Association for Computational	841
784	Markus J. Buehler. 2024. Accelerating scientific	Linguistics.	842
785	discovery with generative knowledge extraction,		
786	graph-based representation, and multimodal intelli-	Mike D’Arcy, Tom Hope, Larry Birnbaum, and Doug	843
787	gent graph reasoning . <i>Mach. Learn. Sci. Technol.</i> ,	Downey. 2024a. MARG: multi-agent review genera-	844
788	5(3):35083.	tion for scientific papers . <i>CoRR</i> , abs/2401.04259.	845
789	Ruisheng Cao, Fangyu Lei, Haoyuan Wu, Jixuan Chen,	Mike D’Arcy, Alexis Ross, Erin Bransom, Bailey Kuehl,	846
790	Yeqiao Fu, Hongcheng Gao, Xinzhuang Xiong, Han-	Jonathan Bragg, Tom Hope, and Doug Downey.	847
791	chong Zhang, Wenjing Hu, Yuchen Mao, Tianbao	2024b. ARIES: A corpus of scientific paper edits	848
792	Xie, Hongshen Xu, Danyang Zhang, Sida I. Wang,	made in response to peer reviews . In <i>Proceedings</i>	849
793	Ruoxi Sun, Pengcheng Yin, Caiming Xiong, Ansong	<i>of the 62nd Annual Meeting of the Association for</i>	850
794	Ni, Qian Liu, Victor Zhong, Lu Chen, Kai Yu, and	<i>Computational Linguistics (Volume 1: Long Papers)</i> ,	851
795	Tao Yu. 2024a. Spider2-v: How far are multimodal	<i>ACL 2024, Bangkok, Thailand, August 11-16, 2024</i> ,	852
796	agents from automating data science and engineering	pages 6985–7001. Association for Computational	853
797	workflows? In <i>Advances in Neural Information Pro-</i>	Linguistics.	854
798	<i>cessing Systems 38: Annual Conference on Neural</i>		
799	<i>Information Processing Systems 2024, NeurIPS 2024,</i>	Maxime Darrin, Ines Arous, Pablo Piantanida, and	855
800	<i>Vancouver, BC, Canada, December 10 - 15, 2024</i> .	Jackie Chi Kit Cheung. 2024. GLIMPSE: prag-	856
		matically informative multi-document summariza-	857
801	Yupeng Cao, Aishwarya Muralidharan Nair, Elyon Ey-	tion for scholarly reviews . In <i>Proceedings of the</i>	858
802	imife, Nastaran Jamalipour Soofi, K. P. Subbalak-	<i>62nd Annual Meeting of the Association for Compu-</i>	859
803	shmi, John R. Wullert II, Chumki Basu, and David	<i>tational Linguistics (Volume 1: Long Papers)</i> , <i>ACL</i>	860
804	Shallcross. 2024b. Can large language models detect	<i>2024, Bangkok, Thailand, August 11-16, 2024</i> , pages	861
805	misinformation in scientific news reporting? <i>CoRR</i> ,	12737–12752. Association for Computational Lin-	862
806	abs/2402.14268.	guistics.	863
807	Eric Chamoun, Michael Sejr Schlichtkrull, and Andreas	Anubrata Das, Houjiang Liu, Venelin Kovatchev, and	864
808	Vlachos. 2024. Automated focused feedback genera-	Matthew Lease. 2023. The state of human-centered	865
809	tion for scientific writing assistance . In <i>Findings of</i>	NLP technology for fact-checking . <i>Inf. Process.</i>	866
810	<i>the Association for Computational Linguistics, ACL</i>	<i>Manag.</i> , 60(2):103219.	867

868	José de la Torre-López, Aurora Ramírez, and José Raúl	927
869	Romero. 2023. Artificial intelligence to automate the	928
870	systematic review of scientific literature . <i>Computing</i> ,	929
871	105(10):2171–2194.	930
872	DeepSeek-AI, Aixin Liu, Bei Feng, Bing Xue, Bingx-	931
873	uan Wang, Bochao Wu, Chengda Lu, Chenggang	932
874	Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan,	933
875	Damai Dai, Daya Guo, Dejian Yang, Deli Chen,	934
876	Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai,	935
877	Fuli Luo, Guangbo Hao, Guanting Chen, Guowei	936
878	Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng	937
879	Wang, Haowei Zhang, Honghui Ding, Huajian Xin,	938
880	Huazuo Gao, Hui Li, Hui Qu, J. L. Cai, Jian Liang,	939
881	Jianzhong Guo, Jiaqi Ni, Jiashi Li, Jiawei Wang,	940
882	Jin Chen, Jingchang Chen, Jingyang Yuan, Junjie	941
883	Qiu, Junlong Li, Junxiao Song, Kai Dong, Kai Hu,	942
884	Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean	943
885	Wang, Lecong Zhang, Lei Xu, Leyi Xia, Liang Zhao,	944
886	Litong Wang, Liyue Zhang, Meng Li, Miaojun Wang,	945
887	Mingchuan Zhang, Minghua Zhang, Minghui Tang,	946
888	Mingming Li, Ning Tian, Panpan Huang, Peiyi Wang,	947
889	Peng Zhang, Qiancheng Wang, Qihao Zhu, Qinyu	948
890	Chen, Qiushi Du, R. J. Chen, R. L. Jin, Ruiqi Ge,	949
891	Ruisong Zhang, Ruizhe Pan, Runji Wang, Runxin	950
892	Xu, Ruoyu Zhang, Ruyi Chen, S. S. Li, Shanghao	951
893	Lu, Shangyan Zhou, Shanhuang Chen, Shaoqing Wu,	952
894	Shengfeng Ye, Shengfeng Ye, Shirong Ma, Shiyu	953
895	Wang, Shuang Zhou, Shuiping Yu, Shunfeng Zhou,	954
896	Shuting Pan, T. Wang, Tao Yun, Tian Pei, Tianyu Sun,	955
897	W. L. Xiao, and Wangding Zeng. 2024. Deepseek-v3	956
898	technical report . <i>CoRR</i> , abs/2412.19437.	957
899	Alphaeus Dmonte, Roland Oruche, Marcos Zampieri,	958
900	Prasad Calyam, and Isabelle Augenstein. 2024.	959
901	Claim verification in the age of large language mod-	960
902	els: A survey . <i>CoRR</i> , abs/2408.14317.	961
903	Iddo Drori and Dov Te’eni. 2024. Human-in-the-loop	962
904	AI reviewing: Feasibility, opportunities, and risks . <i>J.</i>	963
905	<i>Assoc. Inf. Syst.</i> , 25(1):7.	964
906	Wanyu Du, Zae Myung Kim, Vipul Raheja, Dhruv Ku-	965
907	mar, and Dongyeop Kang. 2022. Read, revise, repeat:	966
908	A system demonstration for human-in-the-loop iter-	967
909	ative text revision . <i>CoRR</i> , abs/2204.03685.	968
910	Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey,	969
911	Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman,	970
912	Akhil Mathur, Alan Schelten, Amy Yang, Angela	971
913	Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang,	972
914	Archi Mitra, Archie Sravankumar, Artem Korenev,	973
915	Arthur Hinsvark, Arun Rao, Aston Zhang, Aurélien	974
916	Rodriguez, Austen Gregerson, Ava Spataru, Bap-	975
917	tiste Rozière, Bethany Biron, Binh Tang, Bobbie	976
918	Chern, Charlotte Caucheteux, Chaya Nayak, Chloe	977
919	Bi, Chris Marra, Chris McConnell, Christian Keller,	978
920	Christophe Touret, Chunyang Wu, Corinne Wong,	979
921	Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Al-	980
922	lonsius, Daniel Song, Danielle Pintz, Danny Livshits,	981
923	David Esiobu, Dhruv Choudhary, Dhruv Mahajan,	982
924	Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes,	983
925	Egor Lakomkin, Ehab AlBadawy, Elina Lobanova,	984
926	Emily Dinan, Eric Michael Smith, Filip Radenovic,	985
	Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Geor-	
	gia Lewis Anderson, Graeme Nail, Grégoire Mialon,	
	Guan Pang, Guillem Cucurell, Hailey Nguyen, Han-	
	nah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov,	
	Imanol Arrieta Ibarra, Isabel M. Kloumann, Ishan	
	Misra, Ivan Evtimov, Jade Copet, Jaewon Lee, Jan	
	Geffert, Jana Vranes, Jason Park, Jay Mahadeokar,	
	Jeet Shah, Jelmer van der Linde, Jennifer Billock,	
	Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi,	
	Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu,	
	Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph	
	Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia,	
	Kalyan Vasuden Alwala, Kartikeya Upasani, Kate	
	Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, and	
	et al. 2024. The llama 3 herd of models . <i>CoRR</i> ,	
	abs/2407.21783.	
	Nils Dycke, Ilia Kuznetsov, and Iryna Gurevych. 2023.	
	Nlpeer: A unified resource for the computational	
	study of peer review . In <i>Proceedings of the 61st An-</i>	
	<i>annual Meeting of the Association for Computational</i>	
	<i>Linguistics (Volume 1: Long Papers), ACL 2023,</i>	
	<i>Toronto, Canada, July 9-14, 2023</i> , pages 5049–5073.	
	Association for Computational Linguistics.	
	Islam Eldifrawi, Shengrui Wang, and Amine Trabelsi.	
	2024. Automated justification production for claim	
	veracity in fact checking: A survey on architectures	
	and approaches . In <i>Proceedings of the 62nd An-</i>	
	<i>annual Meeting of the Association for Computational</i>	
	<i>Linguistics (Volume 1: Long Papers), ACL 2024,</i>	
	<i>Bangkok, Thailand, August 11-16, 2024</i> , pages 6679–	
	6692. Association for Computational Linguistics.	
	Eurostat. 2018. <i>The measurement of scientific, techno-</i>	
	<i>logical and innovation activities Oslo manual 2018</i>	
	<i>guidelines for collecting, reporting and using data</i>	
	<i>on innovation</i> . OECD publishing.	
	Benedikt Fecher, Marcel Hebing, Melissa Laufer, Jörg	
	Pohle, and Fabian Sofsky. 2023. Friend or foe? ex-	
	ploring the implications of large language models on	
	the science system . <i>CoRR</i> , abs/2306.09928.	
	K. J. Kevin Feng, Kevin Pu, Matt Latzke, Tal August,	
	Pao Siangliulue, Jonathan Bragg, Daniel S. Weld,	
	Amy X. Zhang, and Joseph Chee Chang. 2024. Co-	
	coa: Co-planning and co-execution with AI agents .	
	<i>CoRR</i> , abs/2412.10999.	
	Emily First, Markus N. Rabe, Talia Ringer, and Yuriy	
	Brun. 2023. Baldur: Whole-proof generation and	
	repair with large language models . In <i>Proceedings of</i>	
	<i>the 31st ACM Joint European Software Engineering</i>	
	<i>Conference and Symposium on the Foundations of</i>	
	<i>Software Engineering, ESEC/FSE 2023, San Fran-</i>	
	<i>cisco, CA, USA, December 3-9, 2023</i> , pages 1229–	
	1241. ACM.	
	Martin Funkquist, Ilia Kuznetsov, Yufang Hou, and	
	Iryna Gurevych. 2023. Citebench: A benchmark for	
	scientific citation text generation . In <i>Proceedings of</i>	
	<i>the 2023 Conference on Empirical Methods in Natu-</i>	
	<i>ral Language Processing, EMNLP 2023, Singapore,</i>	
	<i>December 6-10, 2023</i> , pages 7337–7353. Association	
	for Computational Linguistics.	

1097	Xinyu Hua, Mitko Nikolov, Nikhil Badugu, and	Andy Applebaum, Angela Jiang, Ashvin Nair, Bar-	1153
1098	Lu Wang. 2019. Argument mining for understanding	ret Zoph, Behrooz Ghorbani, Ben Rossen, Benjamin	1154
1099	peer reviews . In <i>Proceedings of the 2019 Conference</i>	Sokolowsky, Boaz Barak, Bob McGrew, Borys Mi-	1155
1100	<i>of the North American Chapter of the Association for</i>	naiev, Botao Hao, Bowen Baker, Brandon Houghton,	1156
1101	<i>Computational Linguistics: Human Language Tech-</i>	Brandon McKinzie, Brydon Eastman, Camillo Lu-	1157
1102	<i>nologies, NAACL-HLT 2019, Minneapolis, MN, USA,</i>	garesi, Cary Bassin, Cary Hudson, Chak Ming Li,	1158
1103	<i>June 2-7, 2019, Volume 1 (Long and Short Papers),</i>	Charles de Bourcy, Chelsea Voss, Chen Shen, Chong	1159
1104	<i>pages 2131–2137. Association for Computational</i>	Zhang, Chris Koch, Chris Orsinger, Christopher	1160
1105	<i>Linguistics.</i>	Hesse, Claudia Fischer, Clive Chan, Dan Roberts,	1161
1106	Jingshan Huang and Ming Tan. 2023. The role of chat-	Daniel Kappler, Daniel Levy, Daniel Selsam, David	1162
1107	gpt in scientific communication: writing better sci-	Dohan, David Farhi, David Mely, David Robinson,	1163
1108	entific review articles. <i>American journal of cancer</i>	Dimitris Tsipras, Doug Li, Dragos Oprica, Eben Free-	1164
1109	<i>research</i> , 13(4):1148.	man, Eddie Zhang, Edmund Wong, Elizabeth Proehl,	1165
1110	Kaixuan Huang, Yuanhao Qu, Henry Cousins,	Enoch Cheung, Eric Mitchell, Eric Wallace, Erik	1166
1111	William A. Johnson, Di Yin, Mihir Shah, Denny	Ritter, Evan Mays, Fan Wang, Felipe Petroski Such,	1167
1112	Zhou, Russ B. Altman, Mengdi Wang, and Le Cong.	Filippo Raso, Florencia Leoni, Foivos Tsimplouras,	1168
1113	2024a. CRISPR-GPT: an LLM agent for auto-	Francis Song, Fred von Lohmann, Freddie Sulit,	1169
1114	mated design of gene-editing experiments . <i>CoRR</i> ,	Geoff Salmon, Giambattista Parascandolo, Gildas	1170
1115	abs/2404.18021 .	Chabot, Grace Zhao, Greg Brockman, Guillaume	1171
1116	Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong,	Leclerc, Hadi Salman, Haiming Bao, Hao Sheng,	1172
1117	Zhangyin Feng, Haotian Wang, Qianglong Chen,	Hart Andrin, Hessam Bagherinezhad, Hongyu Ren,	1173
1118	Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting	Hunter Lightman, Hyung Won Chung, Ian Kivlichan,	1174
1119	Liu. 2023. A survey on hallucination in large lan-	Ian O’Connell, Ian Osband, Ignasi Clavera Gilaberte,	1175
1120	guage models: Principles, taxonomy, challenges, and	and Ilge Akkaya. 2024. Openai o1 system card .	1176
1121	open questions . <i>CoRR</i> , abs/2311.05232 .	<i>CoRR</i> , abs/2412.16720 .	1177
1122	Qian Huang, Jian Vora, Percy Liang, and Jure Leskovec.	Peter A. Jansen, Marc-Alexandre Côté, Tushar	1178
1123	2024b. Mlagentbench: Evaluating language agents	Khot, Erin Bransom, Bhavana Dalvi Mishra, Bod-	1179
1124	on machine learning experimentation . In <i>Forty-</i>	hisattwa Prasad Majumder, Oyvind Tafjord, and Peter	1180
1125	<i>first International Conference on Machine Learning,</i>	Clark. 2024. Discoveryworld: A virtual environment	1181
1126	<i>ICML 2024, Vienna, Austria, July 21-27, 2024. Open-</i>	for developing and evaluating automated scientific	1182
1127	<i>Review.net.</i>	discovery agents . In <i>Advances in Neural Information</i>	1183
1128	Yinya Huang, Xiaohan Lin, Zhengying Liu, Qingxing	<i>Processing Systems 38: Annual Conference on Neu-</i>	1184
1129	Cao, Huajian Xin, Haiming Wang, Zhenguo Li, Linqi	<i>ral Information Processing Systems 2024, NeurIPS</i>	1185
1130	Song, and Xiaodan Liang. 2024c. MUSTARD: mas-	2024, Vancouver, BC, Canada, December 10 - 15,	1186
1131	tering uniform synthesis of theorem and proof data .	2024.	1187
1132	In <i>The Twelfth International Conference on Learning</i>	Albert Qiaochu Jiang, Wenda Li, Szymon Tworkowski,	1188
1133	<i>Representations, ICLR 2024, Vienna, Austria, May</i>	Konrad Czechowski, Tomasz Odrzygóźdź, Piotr Mi-	1189
1134	<i>7-11, 2024. OpenReview.net.</i>	los, Yuhuai Wu, and Mateja Jamnik. 2022a. Thor:	1190
1135	Matthew Hutson. 2022. Could ai help you to write your	Wielding hammers to integrate language models and	1191
1136	next paper? <i>Nature</i> , 611(7934):192–193.	automated theorem provers . In <i>Advances in Neural</i>	1192
1137	Maximilian Idahl and Zahra Ahmadi. 2024. Open-	<i>Information Processing Systems 35: Annual Confer-</i>	1193
1138	reviewer: A specialized large language model for	<i>ence on Neural Information Processing Systems 2022,</i>	1194
1139	generating critical scientific paper reviews . <i>CoRR</i> ,	<i>NeurIPS 2022, New Orleans, LA, USA, November 28</i>	1195
1140	abs/2412.11948 .	<i>- December 9, 2022.</i>	1196
1141	Tal Ifargan, Lukas Hafner, Maor Kern, Ori Alcalay,	Albert Qiaochu Jiang, Sean Welleck, Jin Peng Zhou,	1197
1142	and Roy Kishony. 2024. Autonomous llm-driven re-	Timothée Lacroix, Jiacheng Liu, Wenda Li, Mateja	1198
1143	search from data to human-verifiable research papers .	Jamnik, Guillaume Lample, and Yuhuai Wu. 2023.	1199
1144	<i>CoRR</i> , abs/2404.17605 .	Draft, sketch, and prove: Guiding formal theorem	1200
1145	Aaron Jaech, Adam Kalai, Adam Lerer, Adam Richard-	provers with informal proofs . In <i>The Eleventh In-</i>	1201
1146	son, Ahmed El-Kishky, Aiden Low, Alec Hel-	<i>ternational Conference on Learning Representations,</i>	1202
1147	yar, Aleksander Madry, Alex Beutel, Alex Carney,	<i>ICLR 2023, Kigali, Rwanda, May 1-5, 2023. Open-</i>	1203
1148	Alex Iftimie, Alex Karpenko, Alex Tachard Pas-	<i>Review.net.</i>	1204
1149	sos, Alexander Neitz, Alexander Prokofiev, Alexan-	Chao Jiang, Wei Xu, and Samuel Stevens. 2022b. arx-	1205
1150	der Wei, Allison Tam, Ally Bennett, Ananya Ku-	ivedits: Understanding the human revision process in	1206
1151	mar, Andre Saraiva, Andrea Vallone, Andrew Du-	scientific writing . In <i>Proceedings of the 2022 Con-</i>	1207
1152	berstein, Andrew Kondrich, Andrey Mishchenko,	<i>ference on Empirical Methods in Natural Language</i>	1208
		<i>Processing, EMNLP 2022, Abu Dhabi, United Arab</i>	1209
		<i>Emirates, December 7-11, 2022, pages 9420–9435.</i>	1210
		Association for Computational Linguistics.	1211

1326	review of recent publications. <i>Int. J. Digit. Libr.</i> ,	1383
1327	23(4):335–369.	1384
1328	Amrith Krishna, Sebastian Riedel, and Andreas Vlachos.	1385
1329	2022. Proofver: Natural logic theorem proving for	1386
1330	fact verification . <i>Trans. Assoc. Comput. Linguistics</i> ,	
1331	10:1013–1030.	
1332	Sandeep Kumar, Tirthankar Ghosal, and Asif Ekbal.	
1333	2023. When reviewers lock horns: Finding disagree-	
1334	ments in scientific peer reviews . In <i>Proceedings of</i>	
1335	<i>the 2023 Conference on Empirical Methods in Natu-</i>	
1336	<i>ral Language Processing, EMNLP 2023, Singapore,</i>	
1337	<i>December 6-10, 2023</i> , pages 16693–16704. Associa-	
1338	tion for Computational Linguistics.	
1339	Sandeep Kumar, Tirthankar Ghosal, Vinayak Goyal,	
1340	and Asif Ekbal. 2024. Can large language mod-	
1341	els unlock novel scientific research ideas? <i>CoRR</i> ,	
1342	abs/2409.06185.	
1343	Ilia Kuznetsov, Osama Mohammed Afzal, Koen Der-	
1344	cksen, Nils Dycke, Alexander Goldberg, Tom Hope,	
1345	Dirk Hovy, Jonathan K. Kummerfeld, Anne Lauscher,	
1346	Kevin Leyton-Brown, Sheng Lu, Mausam, Margot	
1347	Mieskes, Aurélie Névéol, Danish Pruthi, Lizhen	
1348	Qu, Roy Schwartz, Noah A. Smith, Thamar Solorio,	
1349	Jingyan Wang, Xiaodan Zhu, Anna Rogers, Nihar B.	
1350	Shah, and Iryna Gurevych. 2024. What can natu-	
1351	ral language processing do for peer review? <i>CoRR</i> ,	
1352	abs/2405.06563.	
1353	Yuxuan Lai, Yupeng Wu, Yidan Wang, Wenpeng Hu,	
1354	and Chen Zheng. 2024. Instruct large language mod-	
1355	els to generate scientific literature survey step by step .	
1356	In <i>Natural Language Processing and Chinese Com-</i>	
1357	<i>puting - 13th National CCF Conference, NLPCC</i>	
1358	<i>2024, Hangzhou, China, November 1-3, 2024, Pro-</i>	
1359	<i>ceedings, Part V</i> , volume 15363 of <i>Lecture Notes in</i>	
1360	<i>Computer Science</i> , pages 484–496. Springer.	
1361	Guillaume Lample, Timothée Lacroix, Marie-Anne	
1362	Lachaux, Aurélien Rodriguez, Amaury Hayat,	
1363	Thibaut Lavril, Gabriel Ebner, and Xavier Martinet.	
1364	2022. Hypertree proof search for neural theorem	
1365	proving . In <i>Advances in Neural Information Pro-</i>	
1366	<i>cessing Systems 35: Annual Conference on Neural</i>	
1367	<i>Information Processing Systems 2022, NeurIPS 2022,</i>	
1368	<i>New Orleans, LA, USA, November 28 - December 9,</i>	
1369	<i>2022</i> .	
1370	Jon M. Laurent, Joseph D. Janizek, Michael Ruzo,	
1371	Michaela M. Hinks, Michael J. Hammerling, Sid-	
1372	dharth Narayanan, Manvitha Ponnampati, Andrew D.	
1373	White, and Samuel G. Rodrigues. 2024. Lab-bench:	
1374	Measuring capabilities of language models for biol-	
1375	ogy research . <i>CoRR</i> , abs/2407.10362.	
1376	Ju Yoen Lee. 2023. Can an artificial intelligence chat-	
1377	bot be the author of a scholarly article? <i>Journal of</i>	
1378	<i>educational evaluation for health professions</i> , 20.	
1379	Yoonjoo Lee, Hyeonsu B. Kang, Matt Latzke, Juho	
1380	Kim, Jonathan Bragg, Joseph Chee Chang, and Pao	
1381	Siangliulue. 2024. Paperweaver: Enriching topical	
1382	paper alerts by contextualizing recommended papers	
	with user-collected papers . In <i>Proceedings of the</i>	
	<i>CHI Conference on Human Factors in Computing</i>	
	<i>Systems, CHI 2024, Honolulu, HI, USA, May 11-16,</i>	
	<i>2024</i> , pages 19:1–19:19. ACM.	
	Jingjing Li, Zichao Li, Tao Ge, Irwin King, and	
	Michael R. Lyu. 2022. Text revision by on-the-fly	
	representation optimization . In <i>Thirty-Sixth AAAI</i>	
	<i>Conference on Artificial Intelligence, AAAI 2022,</i>	
	<i>Thirty-Fourth Conference on Innovative Applications</i>	
	<i>of Artificial Intelligence, IAAI 2022, The Twelveth</i>	
	<i>Symposium on Educational Advances in Artificial In-</i>	
	<i>telligence, EAAI 2022 Virtual Event, February 22 -</i>	
	<i>March 1, 2022</i> , pages 10956–10964. AAAI Press.	
	Long Li, Weiwen Xu, Jiayan Guo, Ruochen Zhao,	
	Xingxuan Li, Yuqian Yuan, Boqiang Zhang, Yuming	
	Jiang, Yifei Xin, Ronghao Dang, Deli Zhao, Yu Rong,	
	Tian Feng, and Lidong Bing. 2024a. Chain of ideas:	
	Revolutionizing research via novel idea development	
	with LLM agents . <i>CoRR</i> , abs/2410.13185.	
	Miao Li, Eduard H. Hovy, and Jey Han Lau. 2023. Sum-	
	marizing multiple documents with conversational	
	structure for meta-review generation . In <i>Findings</i>	
	<i>of the Association for Computational Linguistics:</i>	
	<i>EMNLP 2023, Singapore, December 6-10, 2023,</i>	
	<i>pages 7089–7112</i> . Association for Computational	
	Linguistics.	
	Miao Li, Jey Han Lau, and Eduard H. Hovy. 2024b. A	
	sentiment consolidation framework for meta-review	
	generation . In <i>Proceedings of the 62nd Annual Meet-</i>	
	<i>ing of the Association for Computational Linguis-</i>	
	<i>tics (Volume 1: Long Papers), ACL 2024, Bangkok,</i>	
	<i>Thailand, August 11-16, 2024</i> , pages 10158–10177.	
	Association for Computational Linguistics.	
	Ruochen Li, Liqiang Jing, Chi Han, Jiawei Zhou, and	
	Xinya Du. 2024c. Learning to generate research idea	
	with dynamic control . <i>CoRR</i> , abs/2412.14626.	
	Ruochen Li, Teerth Patel, Qingyun Wang, and Xinya	
	Du. 2024d. Mlr-copilot: Autonomous machine learn-	
	ing research based on large language models agents .	
	<i>CoRR</i> , abs/2408.14033.	
	Weisheng Li, Chao Chang, Chaobo He, Zhengyang	
	Wu, Jiongsheng Guo, and Bo Peng. 2020. Academic	
	paper recommendation method combining hetero-	
	geneous network and temporal attributes . In <i>Com-</i>	
	<i>puter Supported Cooperative Work and Social Com-</i>	
	<i>puting - 15th CCF Conference, ChineseCSCW 2020,</i>	
	<i>Shenzhen, China, November 7-9, 2020, Revised Se-</i>	
	<i>lected Papers</i> , volume 1330 of <i>Communications in</i>	
	<i>Computer and Information Science</i> , pages 456–468.	
	Springer.	
	Xiangci Li and Jessica Ouyang. 2022. Automatic	
	related work generation: A meta study . <i>CoRR</i> ,	
	abs/2201.01880.	
	Xiangci Li and Jessica Ouyang. 2024. Related work and	
	citation text generation: A survey . In <i>Proceedings of</i>	
	<i>the 2024 Conference on Empirical Methods in Natu-</i>	
	<i>ral Language Processing, EMNLP 2024, Miami, FL,</i>	

1440	USA, November 12-16, 2024, pages 13846–13864.	Haokun Liu, Yangqiaoyu Zhou, Mingxuan Li, Chenfei	1495
1441	Association for Computational Linguistics.	Yuan, and Chenhao Tan. 2024a. Literature meets data: A synergistic approach to hypothesis generation . <i>CoRR</i> , abs/2410.17309.	1496
1442	Zhaoyu Li, Jialiang Sun, Logan Murphy, Qidong Su,		1497
1443	Zenan Li, Xian Zhang, Kaiyu Yang, and Xujie Si.		1498
1444	2024e. A survey on deep learning for theorem proving . <i>CoRR</i> , abs/2404.09939.	Ruibo Liu, Ruixin Yang, Chenyan Jia, Ge Zhang, Denny	1499
1445		Zhou, Andrew M. Dai, Diyi Yang, and Soroush	1500
1446	Zhi Li and Xiaozhu Zou. 2019. A review on personal-	Vosoughi. 2023b. Training socially aligned lan-	1501
1447	alized academic paper recommendation . <i>Comput. Inf.</i>	guage models in simulated human society . <i>CoRR</i> ,	1502
1448	<i>Sci.</i> , 12(1):33–43.	abs/2305.16960.	1503
1449	Weixin Liang, Zachary Izzo, Yaohui Zhang, Haley Lepp,	Ryan Liu and Nihar B. Shah. 2023. Reviewergpt? an	1504
1450	Hancheng Cao, Xuandong Zhao, Lingjiao Chen, Hao-	exploratory study on using large language models for	1505
1451	tian Ye, Sheng Liu, Zhi Huang, Daniel A. McFarland,	paper reviewing . <i>CoRR</i> , abs/2306.00622.	1506
1452	and James Y. Zou. 2024a. Monitoring ai-modified	Shengchao Liu, Jiong Xiao Wang, Yijin Yang, Cheng-	1507
1453	content at scale: A case study on the impact of chat-	peng Wang, Ling Liu, Hongyu Guo, and Chaowei	1508
1454	gpt on AI conference peer reviews . In <i>Forty-first In-</i>	Xiao. 2024b. Conversational drug editing using re-	1509
1455	<i>ternational Conference on Machine Learning, ICML</i>	trieval and domain feedback . In <i>The Twelfth Inter-</i>	1510
1456	<i>2024, Vienna, Austria, July 21-27, 2024</i> . OpenRe-	<i>national Conference on Learning Representations,</i>	1511
1457	<i>view.net</i> .	<i>ICLR 2024, Vienna, Austria, May 7-11, 2024</i> . Open-	1512
1458	Weixin Liang, Yaohui Zhang, Zhengxuan Wu, Haley	<i>Review.net</i> .	1513
1459	Lepp, Wenlong Ji, Xuandong Zhao, Hancheng Cao,	Shuaiqi Liu, Jiannong Cao, Ruosong Yang, and Zhiyuan	1514
1460	Sheng Liu, Siyu He, Zhi Huang, Diyi Yang, Christo-	Wen. 2022. Generating a structured summary of	1515
1461	pher Potts, Christopher D. Manning, and James Y.	numerous academic papers: Dataset and method . In	1516
1462	Zou. 2024b. Mapping the increasing use of llms in	<i>Proceedings of the Thirty-First International Joint</i>	1517
1463	scientific papers . <i>CoRR</i> , abs/2404.01268.	<i>Conference on Artificial Intelligence, IJCAI 2022,</i>	1518
1464	Weixin Liang, Yuhui Zhang, Hancheng Cao, Binglu	<i>Vienna, Austria, 23-29 July 2022</i> , pages 4259–4265.	1519
1465	Wang, Daisy Ding, Xinyu Yang, Kailas Vodrahalli,	<i>ijcai.org</i> .	1520
1466	Siyu He, Daniel Scott Smith, Yian Yin, Daniel A.	Siyi Liu, Chen Gao, and Yong Li. 2024c. Large lan-	1521
1467	McFarland, and James Zou. 2023. Can large lan-	guage model agent for hyper-parameter optimization .	1522
1468	guage models provide useful feedback on research	<i>CoRR</i> , abs/2402.01881.	1523
1469	papers? A large-scale empirical analysis . <i>CoRR</i> ,	Renze Lou, Hanzhi Xu, Sijia Wang, Jiangshu Du,	1524
1470	abs/2310.01783.	Ryo Kamoi, Xiaoxin Lu, Jian Xie, Yuxuan Sun,	1525
1471	Zhehui Liao, Maria Antoniak, Inyoung Cheong,	Yusen Zhang, Jihyun Janice Ahn, Hongchao Fang,	1526
1472	Evie Yu-Yen Cheng, Ai-Heng Lee, Kyle Lo,	Zhuoyang Zou, Wenchao Ma, Xi Li, Kai Zhang, Con-	1527
1473	Joseph Chee Chang, and Amy X. Zhang. 2024. Llms	gying Xia, Lifu Huang, and Wenpeng Yin. 2024.	1528
1474	as research tools: A large scale survey of researchers’	AAAR-1.0: assessing ai’s potential to assist research .	1529
1475	usage and perceptions . <i>CoRR</i> , abs/2411.05025.	<i>CoRR</i> , abs/2410.22394.	1530
1476	Haohan Lin, Zhiqing Sun, Yiming Yang, and Sean	Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foer-	1531
1477	Welleck. 2024. Lean-star: Learning to interleave	ster, Jeff Clune, and David Ha. 2024. The AI scien-	1532
1478	thinking and proving . <i>CoRR</i> , abs/2407.10040.	tist: Towards fully automated open-ended scientific	1533
1479	Jialiang Lin, Jiabin Song, Zhangping Zhou, Yidong	discovery . <i>CoRR</i> , abs/2408.06292.	1534
1480	Chen, and Xiaodong Shi. 2023a. Automated schol-	Xinyuan Lu, Liangming Pan, Qian Liu, Preslav Nakov,	1535
1481	arly paper review: Concepts, technologies, and chal-	and Min-Yen Kan. 2023. SCITAB: A challenging	1536
1482	lenges . <i>Inf. Fusion</i> , 98:101830.	benchmark for compositional reasoning and claim	1537
1483	Jialiang Lin, Jiabin Song, Zhangping Zhou, Yidong	verification on scientific tables . In <i>Proceedings of the</i>	1538
1484	Chen, and Xiaodong Shi. 2023b. MOPRD: A multi-	<i>2023 Conference on Empirical Methods in Natural</i>	1539
1485	disciplinary open peer review dataset . <i>Neural Com-</i>	<i>Language Processing, EMNLP 2023, Singapore, De-</i>	1540
1486	<i>put. Appl.</i> , 35(34):24191–24206.	<i>cember 6-10, 2023</i> , pages 7787–7813. Association	1541
1487	Zhicheng Lin. 2024. Techniques for supercharging aca-	for Computational Linguistics.	1542
1488	demic writing with generative ai . <i>Nature Biomedical</i>	Ziming Luo, Zonglin Yang, Zexin Xu, Wei Yang, and	1543
1489	<i>Engineering</i> , pages 1–6.	Xinya Du. 2025. LLM4sr: A survey on large lan-	1544
1490	Chengwu Liu, Jianhao Shen, Huajian Xin, Zhengying	guage models for scientific research . <i>arXiv preprint</i>	1545
1491	Liu, Ye Yuan, Haiming Wang, Wei Ju, Chuanyang	<i>arXiv:2501.04306</i> .	1546
1492	Zheng, Yichun Yin, Lin Li, Ming Zhang, and Qun	Pingchuan Ma, Tsun-Hsuan Wang, Minghao Guo,	1547
1493	Liu. 2023a. FIMO: A challenge formal dataset for	Zhiqing Sun, Joshua B. Tenenbaum, Daniela Rus,	1548
1494	automated theorem proving . <i>CoRR</i> , abs/2309.04295.	Chuang Gan, and Wojciech Matusik. 2024. LLM and	1549
		simulation as bilevel optimizers: A new paradigm	1550

1551	to advance physical scientific discovery. In <i>Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024</i> . OpenReview.net.	
1552		
1553		
1554		
1555	Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegrefe, Uri Alon,	
1556	Nouha Dziri, Shrimai Prabhumoye, Yiming Yang,	
1557	Shashank Gupta, Bodhisattwa Prasad Majumder,	
1558	Katherine Hermann, Sean Welleck, Amir Yazdanbakhsh, and Peter Clark. 2023. Self-refine: Iterative refinement with self-feedback . In <i>Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023</i> .	
1559		
1560		
1561		
1562		
1563		
1564		
1565		
1566	Bodhisattwa Prasad Majumder, Harshit Surana, Dhruv Agarwal, Sanchaita Hazra, Ashish Sabharwal, and Peter Clark. 2024a. Position: Data-driven discovery with large generative models . In <i>Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024</i> . OpenReview.net.	
1567		
1568		
1569		
1570		
1571		
1572	Bodhisattwa Prasad Majumder, Harshit Surana, Dhruv Agarwal, Bhavana Dalvi Mishra, Abhijeetsingh Meena, Aryan Prakhar, Tirth Vora, Tushar Khot, Ashish Sabharwal, and Peter Clark. 2024b. Discoverybench: Towards data-driven discovery with large language models . <i>CoRR</i> , abs/2407.01725.	
1573		
1574		
1575		
1576		
1577		
1578	Benjamin S Manning, Kehang Zhu, and John J Horton. 2024. Automated social science: Language models as scientist and subjects. Technical report, National Bureau of Economic Research.	
1579		
1580		
1581		
1582	Anna Martin-Boyle, Aahan Tyagi, Marti A. Hearst, and Dongyeop Kang. 2024. Shallow synthesis of knowledge in gpt-generated texts: A case study in automatic related work composition . <i>CoRR</i> , abs/2402.12255.	
1583		
1584		
1585		
1586		
1587	Rui Meng, Khushboo Thaker, Lei Zhang, Yue Dong, Xingdi Yuan, Tong Wang, and Daqing He. 2021. Bringing structure into summaries: a faceted summarization dataset for long scientific documents . In <i>Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 2: Short Papers), Virtual Event, August 1-6, 2021</i> , pages 1080–1089. Association for Computational Linguistics.	
1588		
1589		
1590		
1591		
1592		
1593		
1594		
1595		
1596		
1597	Lisa Messeri and MJ Crockett. 2024. Artificial intelligence and illusions of understanding in scientific research. <i>Nature</i> , 627(8002):49–58.	
1598		
1599		
1600	Meredith Ringel Morris. 2023. Scientists’ perspectives on the potential for generative AI in their fields . <i>CoRR</i> , abs/2304.01420.	
1601		
1602		
1603	Xinyi Mou, Xuanwen Ding, Qi He, Liang Wang, Jingcong Liang, Xinnong Zhang, Libo Sun, Jiayu Lin, Jie Zhou, Xuanjing Huang, and Zhongyu Wei. 2024. From individual to society: A survey on social simulation driven by large language model-based agents . <i>CoRR</i> , abs/2412.03563.	
1604		
1605		
1606		
1607		
1608		
	Panitan Muangkammuen, Fumiyo Fukumoto, Jiyi Li, and Yoshimi Suzuki. 2022. Exploiting labeled and unlabeled data via transformer fine-tuning for peer-review score prediction . In <i>Findings of the Association for Computational Linguistics: EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022</i> , pages 2233–2240. Association for Computational Linguistics.	1609 1610 1611 1612 1613 1614 1615 1616
	Arief Purnama Muharram and Ayu Purwarianti. 2024. Enhancing natural language inference performance with knowledge graph for COVID-19 automated fact-checking in indonesian language . <i>CoRR</i> , abs/2409.00061.	1617 1618 1619 1620 1621
	Bo Ni and Markus J. Buehler. 2023. Mechagents: Large language model multi-agent collaborations can solve mechanics problems, generate new data, and integrate knowledge . <i>CoRR</i> , abs/2311.08166.	1622 1623 1624 1625
	Ziqi Ni, Yahao Li, Kaijia Hu, Kunyuan Han, Ming Xu, Xingyu Chen, Fengqi Liu, Yicong Ye, and Shuxin Bai. 2024. Matpilot: an llm-enabled AI materials scientist under the framework of human-machine collaboration . <i>CoRR</i> , abs/2411.08063.	1626 1627 1628 1629 1630
	Harshit Nigam, Manasi Patwardhan, Lovekesh Vig, and Gautam Shroff. 2024. Acceleron: A tool to accelerate research ideation . <i>CoRR</i> , abs/2403.04382.	1631 1632 1633
	Kazuya Nishimura, Kuniaki Saito, Tosho Hirasawa, and Yoshitaka Ushiku. 2024. Toward related work generation with structure and novelty statement. In <i>Proceedings of the Fourth Workshop on Scholarly Document Processing (SDP 2024)</i> , pages 38–57.	1634 1635 1636 1637 1638
	Liang Niu, Nian Xue, and Christina Pöpper. 2023. Unveiling the sentinels: Assessing AI performance in cybersecurity peer review . <i>CoRR</i> , abs/2309.05457.	1639 1640 1641
	OpenAI. 2023. GPT-4 technical report . <i>CoRR</i> , abs/2303.08774.	1642 1643
	Liangming Pan, Xiaobao Wu, Xinyuan Lu, Anh Tuan Luu, William Yang Wang, Min-Yen Kan, and Preslav Nakov. 2023a. Fact-checking complex claims with program-guided reasoning . In <i>Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023</i> , pages 6981–7004. Association for Computational Linguistics.	1644 1645 1646 1647 1648 1649 1650 1651
	Liangming Pan, Yunxiang Zhang, and Min-Yen Kan. 2023b. Investigating zero- and few-shot generalization in fact verification . In <i>Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics, IJCNLP 2023 - Volume 1: Long Papers, Nusa Dua, Bali, November 1 - 4, 2023</i> , pages 511–524. Association for Computational Linguistics.	1652 1653 1654 1655 1656 1657 1658 1659 1660
	Iratxe Pinedo, Mikel Larrañaga, and Ana Arruarte. 2024. Arzigo: A recommendation system for scientific articles . <i>Inf. Syst.</i> , 122:102367.	1661 1662 1663

- Milton Pividori and Casey S. Greene. 2024. [A publishing infrastructure for artificial intelligence \(ai\)-assisted academic authoring](#). *J. Am. Medical Informatics Assoc.*, 31(9):2103–2113.
- Stanislas Polu and Ilya Sutskever. 2020. [Generative language modeling for automated theorem proving](#). *CoRR*, abs/2009.03393.
- Kevin Pu, K. J. Kevin Feng, Tovi Grossman, Tom Hope, Bhavana Dalvi Mishra, Matt Latzke, Jonathan Bragg, Joseph Chee Chang, and Pao Siangliulue. 2024. [Ideasynth: Iterative research idea development through evolving and composing idea facets with literature-grounded feedback](#). *CoRR*, abs/2410.04025.
- Biqing Qi, Kaiyan Zhang, Haoxiang Li, Kai Tian, Si-hang Zeng, Zhang-Ren Chen, and Bowen Zhou. 2023. [Large language models are zero shot hypothesis proposers](#). *CoRR*, abs/2311.05965.
- Dragomir R. Radev, Pradeep Muthukrishnan, Vahed Qazvinian, and Amjad Abu-Jbara. 2013. [The ACL anthology network corpus](#). *Lang. Resour. Evaluation*, 47(4):919–944.
- Zachary Robertson. 2023. [GPT4 is slightly helpful for peer-review assistance: A pilot study](#). *CoRR*, abs/2307.05492.
- Ambrose Robinson, William Thorne, Ben P. Wu, Abdullah Pandor, Munira Essat, Mark Stevenson, and Xingyi Song. 2023. [Bio-sieve: Exploring instruction tuning large language models for systematic review automation](#). *CoRR*, abs/2308.06610.
- Kai Ruan, Xuan Wang, Jixiang Hong, and Hao Sun. 2024a. [Liveideabench: Evaluating llms’ scientific creativity and idea generation with minimal context](#). *CoRR*, abs/2412.17596.
- Yixiang Ruan, Chenyin Lu, Ning Xu, Yuchen He, Yixin Chen, Jian Zhang, Jun Xuan, Jianzhang Pan, Qun Fang, Hanyu Gao, et al. 2024b. [An automatic end-to-end chemical synthesis development platform powered by large language models](#). *Nature communications*, 15(1):10160.
- Michele Salvagno, Fabio Silvio Taccone, and Alberto Giovanni Gerli. 2023. Can artificial intelligence help for scientific writing? *Critical care*, 27(1):75.
- Shubhra Kanti Karmaker Santu, Sanjeev Kumar Sinha, Naman Bansal, Alex Knipper, Souvika Sarkar, John Salvador, Yash Mahajan, Sri Guttikonda, Mousumi Akter, Matthew Freestone, and Matthew C. Williams Jr. 2024. [Prompting llms to compose meta-review drafts from peer-review narratives of scholarly manuscripts](#). *CoRR*, abs/2402.15589.
- Mourad Sarrouiti, Asma Ben Abacha, Yassine Mrabet, and Dina Demner-Fushman. 2021. [Evidence-based fact-checking of health-related claims](#). In *Findings of the Association for Computational Linguistics: EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 16-20 November, 2021*, pages 3499–3512. Association for Computational Linguistics.
- Rylan Schaeffer, Brando Miranda, and Sanmi Koyejo. 2023. [Are emergent abilities of large language models a mirage?](#) In *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*.
- Samuel Schmidgall, Yusheng Su, Ze Wang, Ximeng Sun, Jialian Wu, Xiaodong Yu, Jiang Liu, Zicheng Liu, and Emad Barsoum. 2025. [Agent laboratory: Using llm agents as research assistants](#). *arXiv preprint arXiv:2501.04227*.
- Yakub Sebastian, Eu-Gen Siew, and Sylvester O. Ori-maye. 2017. [Emerging approaches in literature-based discovery: techniques and performance review](#). *The Knowledge Engineering Review*, 32:e12.
- Basuki Setio and Masatoshi Tsuchiya. 2022. [The quality assist: A technology-assisted peer review based on citation functions to predict the paper quality](#). *IEEE Access*, 10:126815–126831.
- Abdul Shahid, Muhammad Tanvir Afzal, Moloud Abdar, Mohammad Ehsan Basiri, Xujuan Zhou, Neil Y Yen, and Jia-Wei Chang. 2020. Insights into relevant knowledge extraction techniques: a comprehensive review. *The Journal of Supercomputing*, 76:1695–1733.
- Yijia Shao, Yucheng Jiang, Theodore A. Kanell, Peter Xu, Omar Khattab, and Monica S. Lam. 2024. [Assisting in writing wikipedia-like articles from scratch with large language models](#). In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), NAACL 2024, Mexico City, Mexico, June 16-21, 2024*, pages 6252–6278. Association for Computational Linguistics.
- Ritu Sharma, Dinesh Gopalani, and Yogesh Kumar Meena. 2023. [An anatomization of research paper recommender system: Overview, approaches and challenges](#). *Eng. Appl. Artif. Intell.*, 118:105641.
- Chenhui Shen, Liying Cheng, Ran Zhou, Lidong Bing, Yang You, and Luo Si. 2022. [Mred: A meta-review dataset for structure-controllable text generation](#). In *Findings of the Association for Computational Linguistics: ACL 2022, Dublin, Ireland, May 22-27, 2022*, pages 2521–2535. Association for Computational Linguistics.
- Yongliang Shen, Kaitao Song, Xu Tan, Wenqi Zhang, Kan Ren, Siyu Yuan, Weiming Lu, Dongsheng Li, and Yueting Zhuang. 2024. [Taskbench: Benchmarking large language models for task automation](#). In *Advances in Neural Information Processing Systems 38: Annual Conference on Neural Information Processing Systems 2024, NeurIPS 2024, Vancouver, BC, Canada, December 10 - 15, 2024*.

1777	Zhengliang Shi, Shen Gao, Zhen Zhang, Xiuying Chen,	Cheng Tan, Dongxin Lyu, Siyuan Li, Zhangyang Gao,	1833
1778	Zhumin Chen, Pengjie Ren, and Zhaochun Ren. 2023.	Jingxuan Wei, Siqu Ma, Zicheng Liu, and Stan Z.	1834
1779	Towards a unified framework for reference retrieval	Li. 2024. Peer review as A multi-turn and long-	1835
1780	and related work generation . In <i>Findings of the Asso-</i>	context dialogue with role-based interactions . <i>CoRR</i> ,	1836
1781	<i>ciation for Computational Linguistics: EMNLP 2023</i> ,	abs/2406.05688.	1837
1782	<i>Singapore, December 6-10, 2023</i> , pages 5785–5799.		
1783	Association for Computational Linguistics.		
1784	Chenglei Si, Diyi Yang, and Tatsunori Hashimoto. 2024.	Xiangru Tang, Xingyao Zhang, Yanjun Shao, Jie Wu,	1838
1785	Can llms generate novel research ideas? A large-scale	Yilun Zhao, Arman Cohan, Ming Gong, Dongmei	1839
1786	human study with 100+ NLP researchers . <i>CoRR</i> ,	Zhang, and Mark Gerstein. 2024a. Step-back profil-	1840
1787	abs/2409.04109.	ing: Distilling user history for personalized scientific	1841
1788		writing . <i>CoRR</i> , abs/2406.14275.	1842
1789	Zachary S. Siegel, Sayash Kapoor, Nitya Nagdir,		
1790	Benedikt Stroebl, and Arvind Narayanan. 2024.	Xuemei Tang, Xufeng Duan, and Zhenguang G Cai.	1843
1791	Core-bench: Fostering the credibility of published re-	2024b. Are llms good literature review writers? eval-	1844
1792	search through a computational reproducibility agent	uating the literature review writing ability of large	1845
1793	benchmark . <i>CoRR</i> , abs/2409.11363.	language models. <i>arXiv preprint arXiv:2412.13612</i> .	1846
1794	Michael D. Skarlinski, Sam Cox, Jon M. Laurent,		
1795	James D. Braza, Michaela M. Hinks, Michael J.	Min Tao, Xinmin Yang, Gao Gu, and Bohan Li. 2020.	1847
1796	Hammerling, Manvitha Ponnampati, Samuel G. Ro-	Paper recommend based on lda and pagerank. In	1848
1797	driques, and Andrew D. White. 2024. Language	<i>Artificial Intelligence and Security: 6th International</i>	1849
1798	agents achieve superhuman synthesis of scientific	<i>Conference, ICAIS 2020, Hohhot, China, July 17–</i>	1850
1799	knowledge . <i>CoRR</i> , abs/2409.13740.	<i>20, 2020, Proceedings, Part III</i> 6, pages 571–584.	1851
1800		Springer.	1852
1801	Peiyang Song, Kaiyu Yang, and Anima Anandkumar.		
1802	2024. Towards large language models as copilots for	Amitayush Thakur, George Tsoukalas, Yeming Wen,	1853
1803	theorem proving in lean . <i>CoRR</i> , abs/2404.12534.	Jimmy Xin, and Swarat Chaudhuri. 2024. An in-	1854
1804		context learning agent for formal theorem-proving.	1855
1805	Vaios Stergiopoulos, Michael Vassilakopoulos, Eleni	In <i>First Conference on Language Modeling</i> .	1856
1806	Tousidou, and Antonio Corral. 2024. An academic		
1807	recommender system on large citation data based on	Mike Thelwall and Abdullah Yaghi. 2024. Evaluating	1857
1808	clustering, graph modeling and deep learning . <i>Knowl.</i>	the predictive capacity of chatgpt for academic peer	1858
1809	<i>Inf. Syst.</i> , 66(8):4463–4496.	review outcomes across multiple platforms . <i>CoRR</i> ,	1859
1810		abs/2411.09763.	1860
1811	Haoyang Su, Renqi Chen, Shixiang Tang, Xinzhe		
1812	Zheng, Jingzhe Li, Zhenfei Yin, Wanli Ouyang, and	James Thorne, Andreas Vlachos, Christos	1861
1813	Nanqing Dong. 2024. Two heads are better than one:	Christodoulopoulos, and Arpit Mittal. 2018.	1862
1814	A multi-agent system has the potential to improve	FEVER: a large-scale dataset for fact extraction	1863
1815	scientific idea generation . <i>CoRR</i> , abs/2410.09403.	and verification . In <i>Proceedings of the 2018</i>	1864
1816		<i>Conference of the North American Chapter of the</i>	1865
1817	Purin Sukpanichnant, Anna Rapberger, and Francesca	<i>Association for Computational Linguistics: Human</i>	1866
1818	Toni. 2024. Peerarg: Argumentative peer review with	<i>Language Technologies, NAACL-HLT 2018, New</i>	1867
1819	llms . <i>CoRR</i> , abs/2409.16813.	<i>Orleans, Louisiana, USA, June 1-6, 2018, Volume</i>	1868
1820		<i>1 (Long Papers)</i> , pages 809–819. Association for	1869
1821	Lu Sun, Stone Tao, Junjie Hu, and Steven P. Dow. 2024.	Computational Linguistics.	1870
1822	Metawriter: Exploring the potential and perils of AI		
1823	writing support in scientific peer review . <i>Proc. ACM</i>	Yangjie Tian, Xungang Gu, Aijia Li, He Zhang, Ruohua	1871
1824	<i>Hum. Comput. Interact.</i> , 8(CSCW1):1–32.	Xu, Yunfeng Li, and Ming Liu. 2024. Overview of	1872
1825		the NLPCC2024 shared task 6: Scientific literature	1873
1826	Teo Susnjak, Peter Hwang, Napoleon H. Reyes, Andre	survey generation . In <i>Natural Language Processing</i>	1874
1827	L. C. Barczak, Timothy R. McIntosh, and Surangika	<i>and Chinese Computing - 13th National CCF Con-</i>	1875
1828	Ranathunga. 2024. Automating research synthe-	<i>ference, NLPCC 2024, Hangzhou, China, November</i>	1876
1829	sis with domain-specific large language model fine-	<i>1-3, 2024, Proceedings, Part V</i> , volume 15363 of	1877
1830	tuning . <i>CoRR</i> , abs/2404.08680.	<i>Lecture Notes in Computer Science</i> , pages 400–408.	1878
1831		Springer.	1879
1832	Don R. Swanson. 1986. Undiscovered public knowl-		
1833	edge . <i>The Library Quarterly: Information, Commu-</i>	Venktesh V, Abhijit Anand, Avishek Anand, and Vinay	1880
1834	<i>nity, Policy</i> , 56(2):103–118.	Setty. 2024. Quantemp: A real-world open-domain	1881
1835		benchmark for fact-checking numerical claims . In	1882
1836		<i>Proceedings of the 47th International ACM SIGIR</i>	1883
1837		<i>Conference on Research and Development in Infor-</i>	1884
1838		<i>mation Retrieval, SIGIR 2024, Washington DC, USA,</i>	1885
1839		<i>July 14-18, 2024</i> , pages 650–660. ACM.	1886
1840			
1841		Juraj Vladika and Florian Matthes. 2023. Scientific	1887
1842		fact-checking: A survey of resources and approaches .	1888
1843		In <i>Findings of the Association for Computational</i>	1889

1890	Linguistics: <i>ACL 2023, Toronto, Canada, July 9-14, 2023</i> , pages 6215–6230. Association for Computational Linguistics.	1947	
1891		1948	
1892		1949	
1893	Juraj Vladika and Florian Matthes. 2024a. Comparing knowledge sources for open-domain scientific claim verification . In <i>Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2024 - Volume 1: Long Papers, St. Julian's, Malta, March 17-22, 2024</i> , pages 2103–2114. Association for Computational Linguistics.	1950	
1894		1951	
1895		1952	
1896			
1897		Haiming Wang, Huajian Xin, Zhengying Liu, Wenda Li, Yinya Huang, Jianqiao Lu, Zhicheng Yang, Jing Tang, Jian Yin, Zhenguo Li, and Xiaodan Liang. 2024a. Proving theorems recursively . <i>CoRR</i> , abs/2405.14414.	1953
1898		1954	
1899		1955	
1900		1956	
1901	Juraj Vladika and Florian Matthes. 2024b. Improving health question answering with reliable and time-aware evidence retrieval . In <i>Findings of the Association for Computational Linguistics: NAACL 2024, Mexico City, Mexico, June 16-21, 2024</i> , pages 4752–4763. Association for Computational Linguistics.	1957	
1902		1958	
1903		1959	
1904		1960	
1905		1961	
1906		1962	
1907	Juraj Vladika, Phillip Schneider, and Florian Matthes. 2024. Healthfc: Verifying health claims with evidence-based medical fact-checking . In <i>Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation, LREC/COLING 2024, 20-25 May, 2024, Torino, Italy</i> , pages 8095–8107. ELRA and ICCL.	1963	
1908		1964	
1909		1965	
1910			
1911		Haiming Wang, Ye Yuan, Zhengying Liu, Jianhao Shen, Yichun Yin, Jing Xiong, Enze Xie, Han Shi, Yujun Li, Lin Li, Jian Yin, Zhenguo Li, and Xiaodan Liang. 2023b. Dt-solver: Automated theorem proving with dynamic-tree sampling guided by proof-level value function . In <i>Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023</i> , pages 12632–12646. Association for Computational Linguistics.	1966
1912		1967	
1913		1968	
1914	David Wadden, Shanchuan Lin, Kyle Lo, Lucy Lu Wang, Madeleine van Zuylen, Arman Cohan, and Hannaneh Hajishirzi. 2020. Fact or fiction: Verifying scientific claims . In <i>Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020</i> , pages 7534–7550. Association for Computational Linguistics.	1969	
1915		1970	
1916		1971	
1917		1972	
1918		1973	
1919		1974	
1920		1975	
1921			
1922	David Wadden, Kyle Lo, Bailey Kuehl, Arman Cohan, Iz Beltagy, Lucy Lu Wang, and Hannaneh Hajishirzi. 2022a. Scifact-open: Towards open-domain scientific claim verification . In <i>Findings of the Association for Computational Linguistics: EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022</i> , pages 4719–4734. Association for Computational Linguistics.	1976	
1923		1977	
1924		1978	
1925		1979	
1926		1980	
1927		1981	
1928		1982	
1929		1983	
1930	David Wadden, Kyle Lo, Lucy Lu Wang, Arman Cohan, Iz Beltagy, and Hannaneh Hajishirzi. 2022b. Multivers: Improving scientific claim verification with weak supervision and full-document context . In <i>Findings of the Association for Computational Linguistics: NAACL 2022, Seattle, WA, United States, July 10-15, 2022</i> , pages 61–76. Association for Computational Linguistics.	1984	
1931		1985	
1932		1986	
1933		1987	
1934		1988	
1935		1989	
1936		1990	
1937			
1938	David Wadden, Kejian Shi, Jacob Morrison, Aakanksha Naik, Shruti Singh, Nitzan Barzilay, Kyle Lo, Tom Hope, Luca Soldaini, Shannon Zejiang Shen, Doug Downey, Hannaneh Hajishirzi, and Arman Cohan. 2024. Sciriff: A resource to enhance language model instruction-following over scientific literature . <i>CoRR</i> , abs/2406.07835.	1991	
1939		1992	
1940		1993	
1941		1994	
1942			
1943		Yidong Wang, Qi Guo, Wenjin Yao, Hongbo Zhang, Xin Zhang, Zhen Wu, Meishan Zhang, Xinyu Dai, Min Zhang, Qingsong Wen, Wei Ye, Shikun Zhang, and Yue Zhang. 2024e. Autosurvey: Large language models can automatically write surveys . <i>CoRR</i> , abs/2406.10252.	1995
1944		1996	
1945	Gengyu Wang, Kate Harwood, Lawrence Chillrud, Amith Ananthram, Melanie Subbiah, and Kathleen R.	1997	
1946		1998	
		1999	
		2000	
		2001	
		2002	
		2003	

2004	learning for context-specific citation generation. In	TRIGO: benchmarking formal mathematical proof re-	2060
2005	<i>Thirty-Sixth AAAI Conference on Artificial Intelli-</i>	duction for generative language models. In <i>Proceed-</i>	2061
2006	<i>gence, AAAI 2022, Thirty-Fourth Conference on In-</i>	<i>ings of the 2023 Conference on Empirical Methods</i>	2062
2007	<i>novative Applications of Artificial Intelligence, IAAI</i>	<i>in Natural Language Processing, EMNLP 2023, Sin-</i>	2063
2008	<i>2022, The Twelfth Symposium on Educational Ad-</i>	<i>gapore, December 6-10, 2023, pages 11594–11632.</i>	2064
2009	<i>vances in Artificial Intelligence, EAAI 2022 Virtual</i>	Association for Computational Linguistics.	2065
2010	<i>Event, February 22 - March 1, 2022, pages 11449–</i>		
2011	<i>11458. AAAI Press.</i>		
2012	Jane Webster and Richard T. Watson. 2002. Analyzing	Ziyang Xu. 2025. <i>Patterns and purposes: A cross-</i>	2066
2013	the past to prepare for the future: Writing a literature	<i>journal analysis of ai tool usage in academic writing.</i>	2067
2014	review. <i>MIS Q.</i> , 26(2).	<i>Preprint, arXiv:2502.00632.</i>	2068
2015	Yixuan Weng, Minjun Zhu, Guangsheng Bao, Hongbo	An Yang, Baosong Yang, Beichen Zhang, Binyuan	2069
2016	Zhang, Jindong Wang, Yue Zhang, and Linyi	Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayi-	2070
2017	Yang. 2024. <i>Cyclere searcher: Improving auto-</i>	heng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian	2071
2018	<i>mated research via automated review. CoRR,</i>	Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang,	2072
2019	<i>abs/2411.00816.</i>	Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang,	2073
2020	Nigel L. Williams, Stanislav Ivanov, and Dimitrios	Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei	2074
2021	Buhalis. 2023. <i>Algorithmic ghost in the research</i>	Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men,	2075
2022	<i>shell: Large language models and academic knowl-</i>	Runji Lin, Tianhao Li, Tingyu Xia, Xingzhang Ren,	2076
2023	<i>edge creation in management research. CoRR,</i>	Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang,	2077
2024	<i>abs/2303.07304.</i>	Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and	2078
2025	Jinxuan Wu, Wenhan Chao, Xian Zhou, and Zhunchen	Zihan Qiu. 2024a. <i>Qwen2.5 technical report. CoRR,</i>	2079
2026	Luo. 2023. <i>Characterizing and verifying scientific</i>	<i>abs/2412.15115.</i>	2080
2027	<i>claims: Qualitative causal structure is all you need.</i>	Kaiyu Yang and Jia Deng. 2019. <i>Learning to prove the-</i>	2081
2028	In <i>Proceedings of the 2023 Conference on Empirical</i>	<i>orems via interacting with proof assistants. In Pro-</i>	2082
2029	<i>Methods in Natural Language Processing, EMNLP</i>	<i>ceedings of the 36th International Conference on Ma-</i>	2083
2030	<i>2023, Singapore, December 6-10, 2023, pages 13428–</i>	<i>chine Learning, ICML 2019, 9-15 June 2019, Long</i>	2084
2031	<i>13439. Association for Computational Linguistics.</i>	<i>Beach, California, USA, volume 97 of Proceedings</i>	2085
2032	Zijian Wu, Jiayu Wang, Dahua Lin, and Kai Chen. 2024.	<i>of Machine Learning Research, pages 6984–6994.</i>	2086
2033	<i>Lean-github: Compiling github LEAN repositories</i>	PMLR.	2087
2034	<i>for a versatile LEAN prover. CoRR, abs/2407.17227.</i>	Kaiyu Yang, Aidan M. Swope, Alex Gu, Rahul Chala-	2088
2035	Amelie Wüthrl, Yarik Menchaca Resendiz, Lara Grim-	mala, Peiyang Song, Shixing Yu, Saad Godil, Ryan J.	2089
2036	minger, and Roman Klinger. 2024a. <i>What makes</i>	Prenger, and Animashree Anandkumar. 2023a. <i>Le-</i>	2090
2037	<i>medical claims (un)verifiable? analyzing entity and</i>	<i>andojo: Theorem proving with retrieval-augmented</i>	2091
2038	<i>relation properties for fact verification. In Proceed-</i>	<i>language models. In Advances in Neural Information</i>	2092
2039	<i>ings of the 18th Conference of the European Chap-</i>	<i>Processing Systems 36: Annual Conference on Neu-</i>	2093
2040	<i>ter of the Association for Computational Linguistics,</i>	<i>ral Information Processing Systems 2023, NeurIPS</i>	2094
2041	<i>EACL 2024 - Volume 1: Long Papers, St. Julian’s,</i>	<i>2023, New Orleans, LA, USA, December 10 - 16,</i>	2095
2042	<i>Malta, March 17-22, 2024, pages 2046–2058. Asso-</i>	<i>2023.</i>	2096
2043	<i>ciation for Computational Linguistics.</i>	Zhishen Yang, Raj Dabre, Hideki Tanaka, and Naoaki	2097
2044	Amelie Wüthrl, Dustin Wright, Roman Klinger, and	Okazaki. 2023b. <i>Scicap+: A knowledge augmented</i>	2098
2045	Isabelle Augenstein. 2024b. <i>Understanding fine-</i>	<i>dataset to study the challenges of scientific figure</i>	2099
2046	<i>grained distortions in reports of scientific findings.</i>	<i>captioning. In Proceedings of the Workshop on Scientific</i>	2100
2047	In <i>Findings of the Association for Computational</i>	<i>Document Understanding co-located with 37th AAAI</i>	2101
2048	<i>Linguistics, ACL 2024, Bangkok, Thailand and vir-</i>	<i>Conference on Artificial Intelligence (AAAI 2023), Re-</i>	2102
2049	<i>tual meeting, August 11-16, 2024, pages 6175–6191.</i>	<i>mote, February 14, 2023, volume 3656 of CEUR</i>	2103
2050	Association for Computational Linguistics.	<i>Workshop Proceedings. CEUR-WS.org.</i>	2104
2051	Huajian Xin, Daya Guo, Zhihong Shao, Zhizhou Ren,	Zonglin Yang, Xinya Du, Junxian Li, Jie Zheng, Sou-	2105
2052	Qihao Zhu, Bo Liu, Chong Ruan, Wenda Li, and	janya Poria, and Erik Cambria. 2024b. <i>Large lan-</i>	2106
2053	Xiaodan Liang. 2024. <i>Deepseek-prover: Advancing</i>	<i>guage models for automated open-domain scientific</i>	2107
2054	<i>theorem proving in llms through large-scale synthetic</i>	<i>hypotheses discovery. In Findings of the Association</i>	2108
2055	<i>data. CoRR, abs/2405.14333.</i>	<i>for Computational Linguistics, ACL 2024, Bangkok,</i>	2109
2056	Jing Xiong, Jianhao Shen, Ye Yuan, Haiming Wang,	<i>Thailand and virtual meeting, August 11-16, 2024,</i>	2110
2057	Yichun Yin, Zhengying Liu, Lin Li, Zhijiang Guo,	<i>pages 13545–13565. Association for Computational</i>	2111
2058	Qingxing Cao, Yinya Huang, Chuanyang Zheng,	<i>Linguistics.</i>	2112
2059	Xiaodan Liang, Ming Zhang, and Qun Liu. 2023.	Zonglin Yang, Xinya Du, Rui Mao, Jinjie Ni, and Erik	2113
		Cambria. 2023c. <i>Logical reasoning over natural lan-</i>	2114
		<i>guage as knowledge representation: A survey. CoRR,</i>	2115
		<i>abs/2303.12023.</i>	2116

Miami, FL, USA, November 12-16, 2024, pages 8783–8817. Association for Computational Linguistics.

Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. 2023a. A survey of large language models. *arXiv preprint arXiv:2303.18223*.

Xueliang Zhao, Wenda Li, and Lingpeng Kong. 2023b. *Decomposing the enigma: Subgoal-based demonstration learning for formal theorem proving*. *CoRR*, abs/2305.16366.

Kunhao Zheng, Jesse Michael Han, and Stanislas Polu. 2022. *minif2f: a cross-system benchmark for formal olympiad-level mathematics*. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net.

Yizhen Zheng, Huan Yee Koh, Jiaxin Ju, Anh T. N. Nguyen, Lauren T. May, Geoffrey I. Webb, and Shirui Pan. 2023. *Large language models for scientific synthesis, inference and explanation*. *CoRR*, abs/2310.07984.

Yangqiaoyu Zhou, Haokun Liu, Tejes Srivastava, Hongyuan Mei, and Chenhao Tan. 2024. *Hypothesis generation with large language models*. *CoRR*, abs/2404.04326.

Kun Zhu, Xiaocheng Feng, Xiachong Feng, Yingsheng Wu, and Bing Qin. 2023. *Hierarchical catalogue generation for literature review: A benchmark*. In *Findings of the Association for Computational Linguistics: EMNLP 2023, Singapore, December 6-10, 2023*, pages 6790–6804. Association for Computational Linguistics.

A Further Discussion

Open Question: What is the difference between AI for science and AI for research? We posit that AI for research constitutes a subset of AI for science. While AI for research primarily focuses on supporting or automating the research process, it is not domain-specific and places greater emphasis on methodological advancements. In contrast, AI for science extends beyond the research process to include result-oriented discovery processes within specific domains, such as materials design, drug discovery, biology, and the solution of partial differential equations (Zheng et al., 2023; AI4Science and Quantum, 2023; Zhang et al., 2024d).

Open Question: What is the difference between hypothesis generation and scientific discovery? Hypothesis generation, which is primarily based on literature-based review (LBD) (Swanson, 1986; Sebastian et al., 2017), emphasizing the process by

which researchers generate new concepts, solutions, or approaches through existing research and their own reasoning. Scientific discovery encompasses not only hypothesis generation, but also innovation in fields like molecular optimization and drug development (Ye et al., 2024; Liu et al., 2024b), driven by outcome-oriented results.

Open Question: What is the difference between systematic literature review and related work generation? Existing research frequently addresses the systematic literature survey, which constitutes a component of the knowledge synthesis process during hypothesis formulation, alongside the related work generation phase in manuscript writing (Luo et al., 2025). However, we argue that these two tasks are distinct in nature. The systematic literature survey primarily focuses on summarizing knowledge extracted from diverse scientific documents, thereby assisting researchers in acquiring an initial understanding of a specific field (Altamami and Menai, 2022). In contrast, related work generation focuses on the writing process, emphasizing selection of pertinent literature and effective content structuring (Nishimura et al., 2024).

Discussion: The involvement of AI in manuscript writing The application of AI in manuscript writing has been accompanied by significant controversy. As LLMs demonstrated advanced capabilities, an increasing number of researchers began adopting these systems for scholarly composition (Liang et al., 2024b; Gao et al., 2023a). This trend raised concerns within the academic community (Salvagno et al., 2023), with scholars explicitly opposing the attribution of authorship to AI systems (Lee, 2023). Despite these reservations, the substantial time efficiencies offered by this technology led researchers to gradually accept AI-assisted writing practices (Gruda, 2024; Huang and Tan, 2023; Chen, 2023). This shift ultimately led to formal guidelines issued by leading academic journals (Ganjavi et al., 2024; Xu, 2025).

B Challenges

B.1 Hypothesis Formulation

Knowledge Synthesize Existing paper recommendation systems predominantly rely on the metadata of existing papers to recommend related articles, often lacking specificity. By LLMs, dynamic user profiles can be constructed to provide

personalized literature recommendations and enhance the richness of associated information for recommended articles, ultimately improving the user experience. In the Systematic Literature Review phase, outline generation frequently produces repetitive results with insufficient hierarchical structure. Furthermore, the full-text generation process is susceptible to hallucinations, a common issue observed in LLMs (Huang et al., 2023; Bolaños et al., 2024; Susnjak et al., 2024).

Hypothesis Generation Pre-trained models that rely on prompts encounter challenges in balancing novelty and feasibility during hypothesis generation. Further optimization is necessary to dynamically adjust the relative emphasis on novelty, feasibility, and validity in this process (Li et al., 2024c). Moreover, existing research on hypothesis generation frequently employs novelty and feasibility as evaluation metrics; however, these metrics are characterized by significant uncertainty.

B.2 Hypothesis Validation

Existing approaches to scientific claim verification are largely restricted to specific domains, thereby limiting their practical applicability (Vladika and Matthes, 2023). In the field of theorem proving, challenges arise due to data scarcity and the absence of standardized evaluation benchmarks (Li et al., 2024e). Meanwhile, experiment verification faces significant limitations, as automatically generated experiments often lack methodological rigor, practical feasibility, and alignment with the original research objectives (Lou et al., 2024).

B.3 Manuscript Publication

Similar to systematic literature surveys, manuscript writing is also adversely affected by hallucination issues (Athaluri et al., 2023; Huang et al., 2023). Even when forced citation generation is employed, incorrect references may still be introduced (Aljamaan et al., 2024). Furthermore, the text generated by models requires meticulous examination by researchers to avoid ethical concerns, such as plagiarism risks (Salvagno et al., 2023). AI-generated manuscript reviews frequently provide vague suggestions and are susceptible to biases (Chamoun et al., 2024; Drori and Te’eni, 2024). Additionally, during meta-review generation, models are prone to being misled by erroneous information originating from the manuscript review process.

Task	Benchmark	Domain	Size	Input	Output	Metric
Hypothesis Formulation	SCHOLAT (Li et al., 2020)	Research Paper Recommendation	34,518	-	-	Recall+Precision+F1-score
	ACL selection network (Tao et al., 2020)	Research Paper Recommendation	18,718	Topics	Related Papers	Accuracy
	CiteSeer (Kang et al., 2021)	Research Paper Recommendation	1,100	Paper	Related Papers	Correlation Coefficient
	SciReviewGen (Kasanishi et al., 2023)	Systematic Literature Review	10,000+	Abstracts	Literature review	ROUGE
	FacetSum (Meng et al., 2021)	Systematic Literature Review	60,024	Source Text+Facet	Summary of Facet	ROUGE
	BigSurvey (Liu et al., 2022)	Systematic Literature Review	7,000+	Abstracts	Survey Paragraph	ROUGE, F1-score
	SCHOLARQABENCH (Asai et al., 2024)	Systematic Literature Review	2,200	Question	Answer with Citations	Accuracy, Coverage, Citations + Relevance, Usefulness
	HiCad (Zhu et al., 2023)	Systematic Literature Review	7,600	Reference Papers	Catalogues	Catalogue Edit Distance Similarity (CEDS) + Catalogue Quality Estimate (CQE)
	CLUSTREC-COVID (Katz et al., 2024)	Systematic Literature Review	2,284	Titles, Abstracts	Topic	Clusters per Topic
	CHIME (Hsu et al., 2024)	Systematic Literature Review	2,174	Topic	Hierarchies	F1-score
	Tian et al. (2024)	Systematic Literature Review	700	Subject, Reference	Title, Content	-
	MASSW (Zhang et al., 2024c)	Hypothesis Generation	152,000	Context of Literature	Hypothesis	BLEU, ROUGE, BERTScore, + Cosine Similarity, BLEURT
	IdeaBench (Guo et al., 2024)	Hypothesis Generation	2,374	Instruction, Background Information	Hypothesis	Insight Score, BERTScore, Novelty, + LLM Similarity Rating, Feasibility
	SCIMON (Wang et al., 2024c)	Hypothesis Generation	-	Background Context	Idea	ROUGE, BERTScore + BARTScore, Novelty
	Kumar et al. (2024)	Hypothesis Generation	100	Paper without Future Work	Idea	Idea Alignment Score, Idea Distinctness Index
Hypothesis Validation	DISCOVERYBENCH (Majumder et al., 2024b)	Hypothesis Generation	1,167	Data	Discovery	Hypothesis Match Score
	LivIdeasBench (Ruan et al., 2024a)	Hypothesis Generation	-	Scientific Keywords	Idea	Originality, Feasibility + Fluency, Flexibility
	MOOSEYang et al. (2024b)	Hypothesis Generation	50	Background, Inspiration	Hypothesis	Validity, Novelty + Helpfulness
	SciRIFF (Wadden et al., 2024)	Scientific Claim Verification	137,000	Evidence, Task prompt	Structured Paragraph	F1, BLEU
	SCIFACT (Wadden et al., 2020)	Scientific Claim Verification	1,409	Claim, Evidence	Rationale Sentences, Label	Precision, Recall, Micro-F1
	SCIFACT-OPEN (Wadden et al., 2022a)	Scientific Claim Verification	279	Claim, Evidence	Rationale Sentences, Label	Precision, Recall, Micro-F1
	MISSCI (Glockner et al., 2024b)	Scientific Claim Verification	435	Claim, Premise, Context	Verification	Micro F1-score, P@1, Arg@1 + METEOR Score, BERTScore + NLI-A, NLI-S, Matches@1
	FEVER (Thorne et al., 2018)	Scientific Claim Verification	185,445	Claim, Evidence	Label, Necessary Evidence	F1-Score, Oracle Accuracy + Accuracy, Recall
	XClaimCheck (Kao and Yen, 2024)	Scientific Claim Verification	16,177	Claim, Evidence	Label, Argument	Macro-F1, Accuracy
	HEALTHVER (Sarrouiti et al., 2021)	Scientific Claim Verification	14,330	Claim, Evidence	Label	Macro Precision, Macro Recall + Macro F1-score, Accuracy
	QuanTemp (V et al., 2024)	Scientific Claim Verification	15,514	Claim, Evidence	Label	Weighted-F1 Score, Macro-F1, BLEU, + BERTScore, Cohen's Kappa Score + Human Evaluation
	SCITAB (Lu et al., 2023)	Scientific Claim Verification	1,225	Claim, Evidence	Label	Macro-F1
	Check-COVID (Wang et al., 2023a)	Scientific Claim Verification	1,504	Claim	Evidence	Accuracy, Precision, Recall, Macro-F1
	HealthFC (Vladika et al., 2024)	Scientific Claim Verification	750	Claim, Evidence	Label	Precision, Recall, F1-Macro
	FACTKG (Kim et al., 2023)	Scientific Claim Verification	108,000	Claim, Evidence	Label	Accuracy
Manuscript Publication	BEAR-FACT (Wühl et al., 2024a)	Scientific Claim Verification	1,448	+Entity/Relation Information	Label	F1-Score
	MINIF2F (Zheng et al., 2022)	Theorem Proving	488	Problem, Theorem	Proof	Pass Rate
	FIMO (Liu et al., 2023a)	Theorem Proving	149	Problem, Theorem, statements	Proof	Pass Rate
	LeanDojo (Yang et al., 2023a)	Theorem Proving	98,734	Problem, Theorem	Proof	R@k, MRR, Pass Rate
	Lean-github (Wu et al., 2024)	Theorem Proving	28,597	Problem, Theorem	Proof	Accuracy, Pass Rate
	TRIGO-real (Xiong et al., 2023)	Theorem Proving	427	Problem, Theorem	Proof	Pass Rate, Accuracy, EM@n
	TRIGO-web (Xiong et al., 2023)	Theorem Proving	453	Problem, Theorem	Proof	Pass Rate, Accuracy, EM@n
	TRIGO-gen (Xiong et al., 2023)	Theorem Proving	453	Problem, Theorem	Proof	Pass Rate, Accuracy, EM@n
	CoqGym (Yang and Deng, 2019)	Theorem Proving	71,000	Problem, Theorem	Proof	Success Rate
	MLAgentBench (Huang et al., 2024b)	Experiment Validation	13	-	-	Competence, Efficiency
	AAAR-1.0 (Lou et al., 2024)	Experiment Validation	-	Instance, Papers	Design, Explanation	S-F1, S-Precision, S-Recall + S-Match, ROUGE
	TASKBENCH (Shen et al., 2024)	Experiment Validation	17,331	-	-	ROUGE, t-F1, v-F1 + Normalized Edit Distance
	Spider2-V (Cao et al., 2024a)	Experiment Validation	494	Task	Experiment Execution	Success Rate
	CORE-Bench (Siegel et al., 2024)	Experiment Validation	270	Task Requirements	Experiment Result	Accuracy
	SUPER (Bogin et al., 2024)	Experiment Validation	801	Task Requirements	-	Accuracy, Landmark-Based Evaluation
	LAB-Bench (Laurent et al., 2024)	Experiment Validation	2400	Multiple-choice Question	Answer	Accuracy, Precision, Coverage
Manuscript Publication	SciCap+ (Yang et al., 2023b)	Manuscript Writing	414,000	Figure, OCR tokens + Mention Paragraph	Caption	BLEU, ROUGE, METEOR + CIDEr, SPICE
	AAN Corpus (Radev et al., 2013)	Manuscript Writing	-	-	-	-
	SciSummNet (Yasunaga et al., 2019)	Manuscript Writing	1,000	Paper, Citation Sentence	Summary	ROUGE
	CiteBench (Funkquist et al., 2023)	Manuscript Writing	358,765	Cited Papers, Context	Citation Text	ROUGE, BERTScore
	ALCE (Gao et al., 2023b)	Manuscript Writing	3,000	Question	Answer with Citations	Recall, Precision
	GCite (Wang et al., 2022b)	Manuscript Writing	2,500	Citing/Cited Paper	Citation Text	BLEU, ROUGE
	ARXIVEDITS (Jiang et al., 2022b)	Manuscript Writing	1,000	Sentence Pairs	Sentence, Intent	Precision, Recall, F1-score
	CASIMIR (Jourdan et al., 2024)	Manuscript Writing	15,646	Original Sentence	Revised Sentence	Exact-match (EM), SARI, BLEU, + ROUGE-L, BertScore
	ParaRev (Jourdan et al., 2025)	Manuscript Writing	48,203	Original Paragraph	Revised Paragraph	ROUGE-L, SARI + BertScore
	MRd (Shen et al., 2022)	Peer Review	7,089	Reviews	Meta-Review	ROUGE
	ORSUM (Zeng et al., 2024)	Peer Review	15,062	Reviews	Meta-Review	ROUGE-L, BERTScore, FACTCC + SummaC, DiscoScore
	PeerRead v1 (Kang et al., 2018)	Peer Review	107,000	Reviews	Accept/Reject	Accuracy
	NLPeer (Dyck et al., 2023)	Peer Review	5,000	Reviews, Paper	Review Score, Connection, + Review Category	MRSE, F1-macro + Precision, Recall
	AMPERE (Hua et al., 2019)	Peer Review	400	Review	Review with Type	Precision, Recall, F1-score
	MOPRD (Lin et al., 2023b)	Peer Review	6,578	Reviews, Paper	Editorial Decision, Review, + Meta-Review, Author Rebuttal	ROUGE, BARTScore
	ARIES (D'Arcy et al., 2024b)	Peer Review	1,720	Review Comment, Edits	Comment-Edit Pairs	Precision, Recall, F1-score Aspect Coverage, Aspect Recall, + Semantic Equivalence
Manuscript Publication	ASAP-Review (Yuan et al., 2022)	Peer Review	-	Paper	Review	+ Human: Recommendation Accuracy (RAcc), + Informativeness (Info), Aspect-level, + Constructiveness (ACon), and Summary accuracy
	ReviewMT (Tan et al., 2024)	Peer Review	26,841	Paper	Review Dialogue	ROUGE, BLEU, METEOR
	ReAct (Choudhary et al., 2021)	Peer Review	6,250	Review	Classification of Review	Accuracy
	PEERSUM (Li et al., 2023)	Peer Review	-	Reviews	Meta-Review	ROUGE, BERTScore, UniEval, ACC

Table 1: An overview of benchmarks on AI for research.

Tool	Research Recommendation	Paper	Systematic Literature Review	Hypothesis Generation	Scientific Claim Verification	Theorem Proving	Experiment Verification	Manuscript Writing	Peer Review	Reading Assistance
GPT Researcher			✓							
Concensus	✓		✓		✓					
Elicit	✓		✓							
Undermind	✓		✓							
Byte-science										✓
OpenScholar	✓		✓							
Explainpaper										✓
Uni-finder										✓
You.com	✓		✓	✓	✓	✓	✓	✓	✓	✓
OpenResearcher	✓		✓	✓		✓	✓	✓	✓	✓
Sider	✓		✓					✓		✓
SciSpace	✓		✓					✓	✓	✓
Scholar AI	✓		✓	✓	✓	✓	✓	✓	✓	✓
Data Analysis & Report AI	✓		✓					✓	✓	✓
AskYourPDF	✓		✓	✓	✓	✓	✓	✓	✓	✓
Writefull								✓	✓	
AI Scientist	✓			✓			✓	✓	✓	
ResearchFlow	✓		✓		✓	✓	✓	✓	✓	✓
Connected Paper	✓							✓		
PICO Portal	✓									
STORM	✓		✓					✓		
Enago Read	✓		✓	✓	✓	✓				✓
SciSpace	✓		✓		✓	✓		✓	✓	✓
Iris.ai	✓		✓		✓					✓
Litmaps	✓									
Scite			✓							✓
Inciteful	✓									
Research Rabbit	✓									
MirrorThink	✓		✓		✓		✓			✓
Jenni AI	✓							✓		✓
ResearchBuddies	✓		✓							
Silatus										
Textero.ai	✓		✓							
Pasa	✓									
gpt_academic			✓					✓	✓	✓
Isabelle						✓		✓		
Proverbot9001						✓				
LeanCopilot						✓				
llmstep						✓				
GenGO			✓							
Cool Papers	✓									✓
Penelope.ai									✓	
Semantic Scholar	✓								✓	
HeadlineAnalyzer								✓		
Quillbot			✓					✓	✓	✓
Langsmith Editor								✓		
Agent Laboratory	✓		✓				✓	✓		
Covidence										
Aminer	✓		✓	✓	✓	✓	✓	✓		✓
Iflytek	✓		✓		✓	✓	✓	✓		✓
Scinence42:Dora			✓					✓		
ChatDOC			✓							✓
Hyperwrite	✓		✓					✓		
chatgpt_academic							✓			
Wordvice.AI								✓		
Writesonic								✓		

Table 2: Tools for Research Paper Assistance

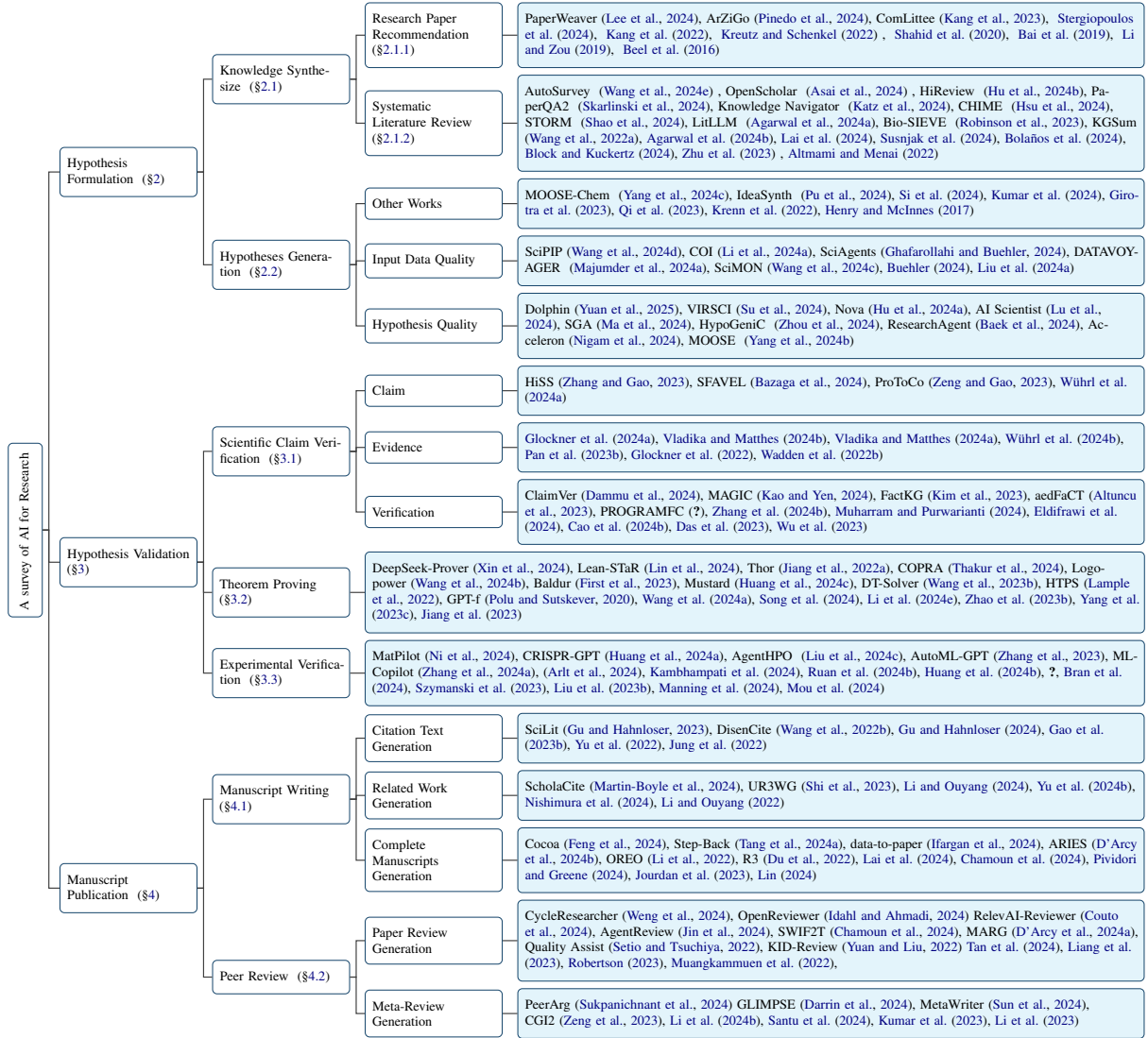


Figure 6: Taxonomy of Hypothesis Formulation, Hypothesis Validation and Manuscript Publication (Full Edition).