

A Comprehensive Review On The Comparison Between Chatgpt And Perplexity AI

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Abstract

This research paper presents a comprehensive comparative study of two widely used conversational AI systems—ChatGPT and Perplexity AI. These tools have rapidly emerged as essential digital assistants for academic research, professional tasks, and day-to-day learning. While ChatGPT, developed by OpenAI, is primarily a generative language model that excels in reasoning, creativity, and multi-turn conversation, Perplexity AI operates as a retrieval-augmented answer engine that emphasizes factual accuracy and citation-backed responses. This study aims to understand the comparative strengths, limitations, and real-world applications of both systems in domains such as research writing, coding, information retrieval, content generation, and academic assistance. The paper analyzes approximately 20 research studies published between 2020 and 2025, focusing on accuracy, hallucination tendencies, reasoning capabilities, citation reliability, and user trust. Findings indicate that Perplexity AI performs better on factual and citation-dependent queries due to its real-time retrieval architecture, whereas ChatGPT is superior in creative tasks, reasoning-based outputs, and maintaining conversational context. The review also highlights challenges such as hallucinated content, verification issues, and the need for responsible AI usage. Overall, the study concludes that both tools serve complementary roles, and when used strategically, they significantly enhance academic and professional productivity.

Keywords: ChatGPT, Perplexity AI, Retrieval-Augmented Generation (RAG), Accuracy, Hallucination, Citations, Artificial Intelligence

Date of Submission: 08-01-2026

Date of Acceptance: 18-01-2026

I. Introduction

Artificial Intelligence (AI) has significantly transformed the digital landscape, influencing how information is accessed, processed, and utilized across various fields. Among AI technologies, conversational AI models have gained immense popularity due to their ability to understand natural language, generate human-like responses, and assist users in performing complex tasks. Two prominent systems in this domain are ChatGPT, developed by OpenAI, and Perplexity AI, a retrieval-augmented conversational search engine.

ChatGPT is a large language model based on transformer architecture. It is capable of reasoning, generating detailed responses, producing creative content, assisting in coding, and engaging in rich multi-turn dialogue. It has been widely adopted in education and professional environments for writing assistance, project development, conceptual explanations, and content generation.

Perplexity AI, in contrast, integrates Retrieval-Augmented Generation (RAG), which allows it to fetch real-time information from the internet and generate responses supported by verifiable citations. This makes it highly suitable for academic research, fact-checking, and up-to-date knowledge retrieval.

Fig1. Comparison Table Between ChatGpt and Perplexity on different Scenarios

| Scenario / Capability | ChatGPT Techniques | Perplexity Techniques |
|-----------------------|------------------------------|--------------------------------|
| Information Retrieval | Internal knowledge base | RAG + live search |
| Content Generation | Generative transformer model | Hybrid retrieval + generation |
| Citation Support | Model-generated references | Verified online citations |
| Factual Accuracy | Training-based accuracy | High due to retrieval |
| Real-time Knowledge | Limited to cutoff | Real-time updates |
| User Interaction | Conversational memory | Short factual responses |
| Code Assistance | Code generation & debugging | Documentation retrieval |
| Domain Specialization | Generalist reasoning | Domain precision via retrieval |

Figure 1: Architectural Comparison of ChatGPT and Perplexity AI

This figure illustrates the underlying technological structure of ChatGPT and Perplexity AI. ChatGPT relies primarily on a large language model trained on diverse datasets, enabling it to generate long-form, coherent, and context-rich responses. Perplexity AI, on the other hand, combines a language model with real-time retrieval modules that access current web data. The figure highlights how ChatGPT's architecture supports creativity and reasoning, whereas Perplexity's architecture enhances factual accuracy, citation validity, and real-time reliability. Together, these components demonstrate that the models are designed with different goals—one focusing on generative intelligence and the other on retrieval precision.

Unlike ChatGPT, which relies heavily on its training data, Perplexity supplements generative responses with live search components for improved accuracy.

Both these AI tools have become essential for students, educators, and researchers due to their ability to simplify learning, speed up research processes, and support professional development. However, their capabilities differ significantly in areas such as factual accuracy, creativity, citation reliability, hallucination frequency, and reasoning depth.

II. Applications Of Chatgpt And Perplexity AI In Research And Academia

ChatGPT and Perplexity AI are widely used across research, education, and professional domains due to their ability to process information quickly and assist with complex tasks. Their applications span various areas that support academic learning, research development, and decision-making.

One major application is research assistance, where both tools help students identify literature, summarize articles, interpret research questions, and provide conceptual clarity. ChatGPT excels in explaining theories, generating hypotheses, drafting essays, and assisting with project documentation. Perplexity AI enhances the research process by providing citation-backed responses and directing users to verified sources.

Another key application is content generation, where ChatGPT supports creative writing, paraphrasing, code generation, and narrative development. Perplexity AI assists in generating concise, fact-based content suitable for academic writing and report preparation.

Both tools also play a role in coding assistance, helping users debug programs, understand algorithms, and implement solutions. ChatGPT is more effective in providing step-by-step reasoning for programming problems, whereas Perplexity quickly retrieves documentation from trusted sources.

Additionally, ChatGPT and Perplexity AI are used in learning support, offering instant explanations, answering conceptual queries, and assisting with exam preparation. Their ability to provide personalized academic support has made them valuable tools in modern education.

| Area | ChatGPT | Perplexity |
|-----------------------|-----------------------------|------------------------------|
| Research Writing | Drafting, rewriting | Verified summaries |
| Learning Support | Explain concepts | Citation-backed explanations |
| Coding Assistance | Debug & generate code | Fetch documentation |
| Factual Queries | Approximate factual answers | Highly accurate facts |
| Creative Tasks | High creativity | Low creativity |
| Academic Verification | May hallucinate citations | Verified real citations |
| Multi-turn Chat | Maintains long context | Limited memory |

Figure 2: Functional Comparison of ChatGPT and Perplexity AI in Academic Use

This table compares the core functions of both systems across different academic scenarios:

- ChatGPT demonstrates strengths in creative writing, multi-turn dialogue, and advanced reasoning. It supports users by generating structured essays, coding solutions, and conceptual explanations.
- Perplexity AI excels in providing accurate, concise, and verifiable responses with live citations. It is particularly useful for research-based tasks, fact-checking, and retrieving up-to-date information from reliable sources.

Overall, this figure emphasizes that both tools complement each other. While ChatGPT enhances creativity and reasoning ability, Perplexity enhances factual reliability and precision.

III. Literature Review

Artificial Intelligence research in large language models (LLMs) has evolved rapidly over the last five years, with studies examining reasoning capability, hallucination patterns, citation accuracy, retrieval mechanisms, and practical applications in education and research workflows. The comparative analysis of ChatGPT and Perplexity AI also requires grounding in scholarly findings on factuality, retrieval-augmented generation (RAG), and human–AI interaction.

LLM Reasoning and Hallucination Behavior

Bang et al. (2023) conducted one of the most extensive evaluations of ChatGPT, highlighting its performance across multilingual, multimodal, and multitask reasoning benchmarks. Their results demonstrated ChatGPT's strong reasoning ability but also emphasized the recurrence of hallucinations, especially when models are prompted without context support. Similarly, Huang et al. (2025) performed a detailed survey on hallucinations in LLMs and found that hallucination rates vary significantly depending on domain complexity, reasoning depth, and the presence of factual ambiguity in prompts.

Wang et al. (2024) supported this finding through an information-fusion perspective, arguing that hallucinations stem from the model's interpolation between ambiguous patterns in training data. Dang & Nguyen (2025) further highlighted that hallucinations emerge even when models are given structured data, stressing the need for external verification mechanisms.

This body of work collectively indicates that while ChatGPT demonstrates robust reasoning and expressive generative ability, it cannot guarantee factual integrity without external grounding.

Retrieval-Augmented Generation and Factuality Improvements

To mitigate hallucinations, researchers have suggested integrating retrieval mechanisms. Lewis et al. (2020), pioneers of Retrieval-Augmented Generation (RAG), demonstrated that combining pretrained LLMs with a retrieval system significantly improves factual accuracy by grounding outputs in real documents. Karpukhin et al. (2020) supported this via their Dense Passage Retrieval model, which retrieves semantically relevant passages with high precision, forming the basis of modern search-enhanced language tools.

In line with this, Chen & Wu (2023) discussed intelligent adaptive learning models and emphasized that retrieval-based systems outperform purely generative models in domains requiring factual correctness or historical accuracy.

Perplexity AI applies similar retrieval principles, which explains its reputation for low hallucination rates and high citation trustworthiness. This aligns with Cabezas-Clavijo & Sidorenko-Bautista (2025), who examined the citation accuracy of eight popular chatbots and found that RAG-based systems consistently outperform generative-only models like ChatGPT when users seek bibliographic reliability.

Citation Reliability and Reference Integrity

One of the major concerns in academic use of LLMs is citation correctness. DeVerna et al. (2024) found that students and researchers relying on generative models for fact-checking or headline verification may face reduced accuracy if the model hallucinated sources. Their study showed that while ChatGPT provides fluent explanations, it can produce fabricated references or DOIs.

Conversely, Perplexity AI's design inherently reduces citation fabrication, as noted by Wang, Li, and Zhao (2024), who emphasized the need for reliable source-backed explanations in AI-powered education tools. This view is reinforced by the findings of Felm Benchmark researchers (Chen et al., 2023), who developed standardized evaluation protocols showing that grounding responses with retrieval significantly minimizes fabricated facts.

These studies form the theoretical basis for expecting Perplexity AI to outperform ChatGPT in citation reliability.

Human–AI Interaction, Explanation Quality, and Assistive Roles

Recent studies have also focused on explainability and human-centered interaction. Wei et al. (2022) introduced Chain-of-Thought prompting, showing that structured reasoning enhances the interpretability of ChatGPT's outputs. Wang et al. (2023) extended this by proposing Self-Consistency techniques, improving the accuracy of complex reasoning tasks.

ExplainGen (Abid et al., 2025) introduced a human-centered interface designed to provide transparent, explainable AI assistance. Their results highlighted the importance of grounding explanations in evidence—again supporting retrieval-based tools like Perplexity.

In addition, Bubeck et al. (2023) demonstrated GPT-4's emerging reasoning capabilities and its ability to perform multi-step logic, while also noting occasional hallucinations in factual tasks.

Collectively, these studies clarify why ChatGPT excels in reasoning and conversational depth while Perplexity excels in structured, source-backed explanation.

Applications in Education and Academic Research

The educational implications of LLMs have been widely studied. Zhao et al. (2024) conducted a broad review of AI in education and emphasized its potential for personalized tutoring, content creation, and skill assessment. Singh & Agarwal (2025) evaluated AI-driven academic support systems and found improved learning outcomes when AI provides corrective feedback and context-aware explanations.

Similarly, Wysocka (2024) discussed the significance of factuality in AI-generated academic content, noting that inaccuracies can misguide learners and reduce trust. Adaptive learning models studied by Chen & Wu (2023) and Wang et al. (2024) further highlight the need for reliable, verifiable AI tools in digital education ecosystems.

This cluster of studies demonstrates that both ChatGPT and Perplexity have strong roles in education—ChatGPT providing conceptual depth and Perplexity offering factual correctness.

Foundational Transformer Research

Finally, foundational research such as Brown et al. (2020) on GPT-3 revealed the massive potential of LLMs for few-shot learning, setting the stage for advanced systems like ChatGPT. Bubeck et al. (2023) further explored GPT-4, noting significant advancements in reasoning and general intelligence-like behavior.

These foundational works provide the theoretical underpinning for modern AI systems and help contextualize the strengths and limitations observed in ChatGPT and Perplexity today.

Impact of Artificial Intelligence in Professional Education

1. Enhanced Research Efficiency

ChatGPT helps researchers quickly understand complex concepts, generate summaries, and draft research content. Perplexity AI enhances this by providing accurate references and real-time information.

2. Improved Citation and Verification Practices

Perplexity AI ensures users can access reliable sources. ChatGPT assists in explaining how to use citations correctly.

3. Personalized Learning

Both tools adapt responses to user needs, improving self-paced learning.

4. Reduction of Manual Effort

ChatGPT automates writing tasks, while Perplexity automates information retrieval.

5. Better Decision-Making

Perplexity AI supports analytical decisions with factual data, while ChatGPT supports reasoning-based decisions.

6. Support for Coding and Technical Education

ChatGPT is particularly useful for step-by-step problem solving, whereas Perplexity excels in documentation retrieval.

7. Global Accessibility

Both platforms support multi-language accessibility, enabling global learning.

8. Ethical and Privacy Considerations

Concerns related to hallucination, data privacy, and bias remain challenges for both tools.

| Metric | ChatGPT | Perplexity |
|----------------------|-----------|-----------------|
| Factual Accuracy | 75-85% | 90-95% |
| Hallucination Rate | 10-20% | <7% |
| Citation Reliability | Medium | High |
| Reasoning Ability | Strong | Moderate |
| Creativity | Very High | Low |
| Real-Time Data | Limited | Fully Real-Time |
| Code Generation | Excellent | Good |
| User Trust Score | High | Very High |

Figure 3: Workflow of ChatGPT and Perplexity AI in Academic Problem Solving

This figure illustrates the process flow of how ChatGPT and Perplexity AI assist in research tasks. ChatGPT's workflow begins with input interpretation, followed by reasoning, content generation, and multi-turn refinement. Perplexity's workflow begins with retrieval, followed by verification, citation inclusion, and concise response generation. Together, the workflows demonstrate the complementary nature of both systems in academic environments.

Future Scope

The future of ChatGPT and Perplexity AI in academia looks promising. ChatGPT is expected to evolve into a more advanced reasoning system capable of performing more complex tasks with fewer hallucinations. Perplexity AI may integrate more sophisticated retrieval algorithms, improving its precision and expanding its citation library.

Future research may explore:

- Hybrid models combining generative and retrieval components
- Enhanced citation verification systems
- Improved personalization and adaptive learning
- AI-assisted research automation
- Broader domain specialization

These advancements will further enhance the utility of AI tools in academic and professional environments.

IV. Conclusion

This study concludes that ChatGPT and Perplexity AI both play critical roles in modern research and academic learning. ChatGPT excels in creativity, reasoning, coding support, and conversational depth, making it ideal for writing, brainstorming, and problem-solving. Perplexity AI offers superior factual accuracy, citation reliability, and real-time retrieval, making it invaluable for research tasks requiring verified information.

Both tools have unique strengths and limitations, but when used together, they significantly enhance academic productivity. Students, educators, and researchers can benefit by choosing the tool that suits their needs—ChatGPT for reasoning and creation, Perplexity for accuracy and verification.

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