Use of AI to Detect Wikipedia Articles Suitable for Learning

CPSC-298 Wikipedia Governance Research Project

Arya Kumar, Krish Garg
Chapman University
Orange, USA
arkumar@chapman.edu,kgarg@chapman.edu

Abstract

As generative AI continues to integrate into digital learning environments, questions have emerged about how effectively online information sources—particularly Wikipedia—support meaningful learning. While Wikipedia is widely used by students, the educational quality of its articles varies significantly.

This project investigates how large language models (LLMs) can be trained to evaluate and classify Wikipedia articles based on their pedagogical value. Drawing from research on instructional design, text coherence, and cognitive load theory, the first phase examines which linguistic and structural features make educational materials effective for learning. The second phase applies these insights to train an LLM that diagnoses whether a given Wikipedia article facilitates understanding or promotes misconceptions.

Using the Wikipedia API and OpenAI's Apps SDK, the system enables real-time interaction between Wikipedia content and ChatGPT, allowing dynamic analysis and feedback on article quality. By combining educational theory with AI-driven analysis, this project aims to create a tool that not only identifies high-quality learning resources but also informs how AI can enhance open-access educational ecosystems.

Keywords

Wikipedia, governance, [add your keywords here]

1 Introduction

Motivation. Wikipedia is among the most frequently consulted learning resources, yet the instructional quality of its articles is uneven. As generative AI becomes embedded in study workflows, there is an opportunity to use large language models (LLMs) not only to summarize content but to *diagnose* whether an article supports effective learning.

Background. Prior work in educational psychology and instructional design highlights the importance of coherence, scaffolding, conceptual density, and self-explanation for learning effectiveness [1, 3, 8]. Recent studies further show that AI tutors designed with research-based reasoning strategies can meet or even exceed active learning classrooms [6], and that Socratic, step-by-step guidance (including Chain-of-Thought prompting) can preserve critical thinking while improving problem-solving [2, 5]. In parallel, Wikipedia's governance and quality dynamics have been extensively studied [9, 11].

Research questions. This paper investigates:

(1) Which textual and structural characteristics make Wikipedia articles effective for learning according to established educational psychology research?
(2) Can an LLM be trained to diagnose the quality of a Wikipedia article using these characteristics?
(3) How does the model's assessment compare to human expert judgments of article quality?
(4) What are the implications for AI-assisted learning and the reliability of open educational resources?

Contributions. The main contributions are:

- A synthesis of linguistic/structural features linked to educational effectiveness (e.g., coherence, hierarchy depth, example density, readability).
- A Chain-of-Thought (CoT) LLM "Wiki Diagnostic Tutor" that retrieves Wikipedia content via API and classifies articles as *effective/neutral/ineffective* with interpretable rationales.
- An evaluation comparing automated metrics to expert educator ratings, plus ablations quantifying which features matter most.
- A reproducible pipeline and dataset of article summaries and human rubric scores for future research.

Paper outline. Section **??** reviews related work. Section 6 details data and methods. Section 7 reports findings. Section 8 discusses implications and limitations. Section 9 concludes.

2 Related Work

Overview. Our study spans three literatures: (i) instructional quality and writing/learning research, (ii) AI tutoring and reasoning methods (Socratic, CoT), and (iii) Wikipedia governance and quality dynamics.

2.1 Instructional Quality, Writing Attitudes, and Critical Thinking

Clear definitions, consistent constructs, and coherence are central to educational quality. Reviews of writing attitudes stress definitional clarity and theoretically grounded measures [3]. Classic reviews of critical thinking in education emphasize how pedagogical design affects higher-order thinking [8]. Practitioner scholarship highlights self-explanation as an effective learning strategy [1]. In EFL contexts, meta-synthesis work catalogs strategies (e.g., scaffolding, feedback) that improve academic writing and learner motivation [4].

2.2 AI Tutors, Socratic Guidance, and Chain-of-Thought

Randomized studies show well-designed AI tutors can outperform in-class active learning on engagement and learning gains [6]. For safer pedagogy, LLMs that guide via questions rather than reveal answers can preserve critical thinking [2]. Chain-of-Thought (CoT)

prompting operationalizes stepwise reasoning to increase accuracy and interpretability in complex tasks [5].

2.3 Wikipedia Governance, Bias, and Quality

Wikipedia's collaborative norms and governance shape content quality and reliability [9]. Behavioral analyses of deletion practices investigate potential systemic biases and their implications for coverage and quality [11]. These threads motivate automated, theory-informed evaluations of article *educational* quality.

2.4 Our Work in Context

We bridge these strands by (1) turning instructional design findings into measurable text features and (2) embedding those features into a CoT-enabled tutor that retrieves content via the Wikimedia REST API and classifies pedagogical quality with human-interpretable rationales.

3 Methodology

3.1 Overview

This project is divided into two main tracks that work together to explore how AI can evaluate the educational quality of Wikipedia articles. **Track A** investigates how linguistic and structural features relate to effective learning. **Track B** develops and tests a large language model (LLM) that can automatically classify articles based on their educational usefulness. Insights from both tracks are combined to build an AI system that can explain why an article may or may not be effective for learning.

3.2 Data Collection

For **Track A**, we conducted a literature review focused on instructional text design—specifically looking at coherence, scaffolding, conceptual density, and explanatory depth. Based on this review, we compiled a labeled dataset of Wikipedia articles that have been evaluated for educational quality by experts or previous research. Each article's revision ID and access date were recorded to ensure reproducibility.

For **Track B**, we used the Wikipedia API in combination with the OpenAI Apps SDK to retrieve article content in real time. The program fetches summaries of user-selected Wikipedia articles and prepares them for model input. This allows the system to dynamically analyze any article the user is interested in.

3.3 Data Processing

After collection, the articles were cleaned and formatted for consistency. We removed unnecessary markup, standardized section headings, and organized the data into labeled examples for model training. This process ensured that both the linguistic and structural features of each article could be accurately analyzed by the LLM.

3.4 Analysis Methods

In **Track A**, we examined which linguistic and structural features—such as readability, sentence complexity, and organization—were most closely associated with higher educational quality. These features were identified through existing research and the labeled Wikipedia dataset.

In **Track B**, we trained and refined a chain-of-thought (CoT) LLM to classify articles as educationally effective, neutral, or ineffective. The model was fine-tuned using annotated examples and prompt engineering to improve its ability to explain reasoning behind each classification.

To evaluate the model, we compared its predictions to expert labels using standard metrics such as accuracy, precision, and F1 score. A subset of model outputs was also reviewed by educators to qualitatively assess reasoning clarity and alignment with human judgment.

3.5 Integration

After both tracks were completed, we integrated the findings. The linguistic and structural insights from Track A informed the model's reasoning process in Track B, allowing the final system to not only score article quality but also provide an interpretable explanation for its decision.

3.6 Deliverables

The project results include:

- A written report summarizing the linguistic and educational factors that make instructional writing more effective.
- A functional prototype, the *Wiki Diagnostic LLM*, which connects to the Wikipedia API via the OpenAI Apps SDK and evaluates the educational suitability of articles in real time.

4 Results

[Brief paragraph introducing your main findings]

4.1 [Finding 1 - descriptive title]

[Present your first main finding]

4.2 [etc]

[Present your second main finding]

5 Discussion

5.1 Interpretation of Results

[What do your findings mean? How do they answer your research questions?]

5.2 Implications

[What are the broader implications of your work? For Wikipedia? For research? For practice?]

5.3 Limitations

[Be honest about limitations: data constraints, methodological issues, scope boundaries, etc.]

5.4 Future Work

[What questions remain? What should future research investigate?]

6 Conclusion

[Restate the problem you investigated]

[Summarize your approach and key findings]

[Emphasize your main contributions]

[End with a forward-looking statement about the importance of your work or future directions]

Acknowledgments

We thank . . . for . . . .

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A AI Usage Documentation

A.1 Literature Review

[Describe how you used AI agents for literature review. Reference your .prompt.md file.]

Example: We used an AI agent workflow (see the file literature-review.prompt.md) to systematically process research papers. The agent extracted summaries, methodology descriptions, and key findings from papers in our bibliography.

A.2 Data Analysis

[If you used AI for data analysis, code generation, or statistical work, document it here]

A.3 Writing Assistance

[Document any AI assistance in writing: brainstorming, editing, restructuring, etc.]

Example: We used Claude/ChatGPT to help with [specific task, e.g., "improving clarity of the abstract" or "suggesting visualizations for our data"].

A.4 Code Development

[If AI helped you write code for data collection or analysis, document it]

A.5 Verification

[How did you verify AI-generated content? What human oversight did you apply?]

All AI-generated content was reviewed, verified against primary sources, and edited by the human author(s). Factual claims were cross-checked with original papers and data.