Wikipedia and Trust

CPSC-298 Wikipedia Governance Research Project

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Abstract

Wikipedia is one of the world's most widely used open-source knowledge platforms, but its reliability is often questioned due to the fact that anyone can edit its content. One potential indicator of an article's trustworthiness is the number of revisions it has undergone. Frequent updates and changes on articles may reflect active community oversight and continuous quality improvement. This study investigates whether a higher number of revisions correlates with increased article reliability. Using the Wikipedia API, we collect data on random Wikipedia articles, including their revision histories, citation counts, article lengths, and contributor information. We then perform a basic sentiment analysis on article text to explore whether tone or neutrality relates to revision frequency. By analyzing how revision activity connects to article characteristics associated with trust, we aim to understand whether collaborative editing improves information quality. Our results will contribute to ongoing discussions about open-source knowledge governance and may help identify measurable indicators of reliability within large, user-generated platforms like Wikipedia.

Keywords

Wikipedia, governance, trust

1 Introduction

Wikipedia serves as a cornerstone of online information sharing, allowing users worldwide to collaboratively create and edit content. Despite its popularity, questions persist about how trustworthy its articles are, given that anyone can contribute edits. Traditional views associate trustworthiness with professional oversight, but Wikipedia's strength lies in its community-driven revision system. Frequent edits and transparent revision histories may provide a unique measure of accountability and reliability.

This study examines whether the number of revisions an article receives can serve as a proxy for its trustworthiness. If more revisions correlate with well-sourced, balanced, and accurate articles, then revision count could be used as a simple quantitative indicator of reliability. Conversely, if frequent revisions occur mostly on controversial or low-quality pages, it may indicate that editing activity alone is not a sufficient measure of trust

This paper investigates the following research questions:

(1) Does the number of revisions to a Wikipedia article correlate with its perceived or measured trustworthiness?
(2) Do highly revised articles contain more citations or show more balanced sentiment than less revised ones?
(3) How might revision patterns vary across article categories or topics?

The main contributions of this work are:

- First contribution - e.g., novel analysis of X
- Second contribution - e.g., findings about Y
- Third contribution - e.g., methodology for Z

The following sections describe our approach to analyzing Wikipedia's revision data using the Wikipedia API. We extracted metadata such as revision counts, article lengths, and the number of cited sources to explore how these factors relate to perceived trustworthiness. To investigate these relationships, we collected a randomized sample of Wikipedia articles and analyzed key metrics including revision frequency, contributor diversity, and sentiment balance. The next section outlines our data collection process and the tools used to conduct this analysis.

Section 2 reviews related work on Wikipedia governance. Section 3 describes our data and methods. Section 4 presents our findings. Section 5 discusses implications and limitations. Section 6 concludes and suggests future work.

2 Related Work

[Brief paragraph introducing the landscape of related research]

2.1 Sentiment Analysis

- Language expresses opinions and emotions through sentence structure and context
- Sentimental analysis looks for signs of positive or negative attitudes in a text The paper mainly focuses on linguistic features (tone, negation("not great") and intensifiers("very happy")) these change the meaning of a sentence completely
- Sarcasm, irony, and formality make it hard for computers to tell what emotion a writer feels/means
  - Most sentiment systems are built using machine learning or word lists (lexicons), but it can easily misread neutral writing

Using more linguistic knowledge like grammar, syntax, and context can help make sentimental analysis more accurate and less biased. https://www.annualreviews.org/content/journals/10.1146/annurev-linguistics-011415-040518 [?]

2.2 Bias in Language Models

- Bias in large language models (LLMs): how models are trained and how the output is generated
  - Data-selection bias: if a model is trained on texts that over represent certain groups, topics, or viewpoints, it's outputs will reflect imbalances
  - Mis-representation, omission of certain viewpoints, or skewed sentiment towards certain groups

Language models trained on biased internet data might misjudge the tone of neutral, factual writing or show unfair polarity towards controversial subjects. Reseraches must carefully test and interpret model behavior when they're using sentiment tools because it can lead to more damage. https://dl.acm.org/doi/full/10.1145/3597307

2.3 Measuring "trust", Reliability, and Interaction of Views + Revisions

- Pages with high revision activity might indicatie contentiousness (less stable content) compared to pages with many views but fewer edits which might indicate that the content is stable and trustworthy
- Ratio of views to revisions
  - There are degrees to stability and contention that should be measured empirically
  - Not all edits are equal (some are minor dixes) and high view counts might reflect controversy rather than trust so context matters

https://ieeexplore.ieee.org/abstract/document/5365214

2.4 Our Work in Context

[Explain how your work differs from or builds upon existing research. What gap are you filling?]

3 Methodology

Data was collected using MediaWiki API, which provides access to articles and metadata from Wikipedia. Wikipedia data is publicly accessible and no private user data is collected.To ensure a diverse and unbiased sample of articles are selected, the random generator parameter is used. The following data is retrieved:

- Extracted text content (plain text summary)
- Article Title
- Date of last revision
- Number of revision
- Number of contributors
- Article text length
- Number of external links

3.1 Data Collection

- Tools including MediaWiki API and Python's requests library were used.
- API Parameters used:
  - "action" : "query"
    - To retrieve article metadata
  - "format" : "json"
    - Ensures data parsing
  - "generator" : "random"
    - Select random articles
  - "prop" : "revisions|extracts|contributors|extlinks"
    - Obtains information about revisions, summaries, contributors, and sources
  - "ellimit" : "max"
    - Retrieves all external links
  - "rvlimit" : 1
    - Limits revision data to 1 to ensure efficiency

The study examines how the number of views and revisions correlate by:

- Calculating ratios between different pages.
- Taking these ratios to determine levels of trust.
- Analyzing pages to identify emerging patterns.

The research project repository can be found at GitHub Repository. The main code file is available at Source Code File.

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 . . . .

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.