

PodChecker: An Interpretable Fact-Checking Companion for Podcasts

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Abstract

We present PodChecker, a user-facing system for automated, claim-level fact-checking of podcast content. PodChecker processes podcast audio or RSS feeds by transcribing episodes, extracting atomic factual claims, and assigning each claim one of four fine-grained labels – *true*, *false*, *misleading/partially true*, or *unverifiable* – using retrieval-augmented verification. The system presents fact-checking results at the level of individual claims, accompanied by simple visual indicators and links to supporting/conflicting sources. This design, implemented via an interactive web-based interface, enables users to inspect fact-checking outputs and underlying evidence directly, supporting interpretable and critical engagement with long-form audio content. By presenting claim-level evidence and labels, PodChecker assists both general listeners and professional fact-checkers in assessing podcast factuality.

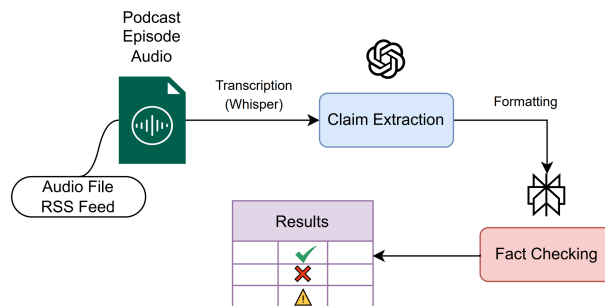


Figure 1: **PodChecker transforms podcast audio into interpretable, claim-level fact-checks** by performing (i) transcription via `whisper-small-en`, (ii) atomic factual claim extraction via `gpt-5-mini`, and (iii) retrieval-augmented verification of the extracted claims via `Sonar`.

Code — <https://github.com/annastatic/PodChecker>

Introduction

Podcasts have become an important part of online information ecosystems, serving as a venue for news consumption, political discussion, and public commentary (Shearer et al. 2023; Litterer, Jurgens, and Card 2024). While audience shares for traditional information media such as radio are in decline, audience shares for podcasts are on the rise (Aubin 2023), increasing their role in shaping public understanding of current events. The rise of podcasts as a dominant information medium brings with it the challenge of maintaining trustworthiness and credibility.

Compared to text-based media, podcasts pose distinct challenges for assessing information quality. Episodes are often long and conversational, with factual claims embedded alongside opinions and anecdotes (Setty and Becker 2025). Podcasts also tend to elicit relatively high levels of listener trust, often attributed to parasocial relationships between hosts and audiences (Johnson and McCall 2025; Schlütz and Hedder 2022). However, podcast production and distribution generally involve limited editorial oversight. Together,

these characteristics amplify the potential impact of unverified or misleading information in podcasts and underscore the need for effective fact-checking mechanisms tailored to this medium.

Fact-checking initiatives have traditionally relied on crowdsourced efforts or specialized organizations such as *Snopes* and *PolitiFact* (Pilarski, Solovev, and Pröllochs 2024; Lee et al. 2025). Rather than replacing these important actors, recent work has explored how automated systems can scale and support fact-checking efforts. In particular, advances in large language models (LLMs) have enabled automated fact-checking and claim verification at scale (Kim et al. 2024; Vykopal et al. 2024). LLM-based approaches typically decompose content into atomic factual claims (Min et al. 2023; Tang, Laban, and Durrett 2024) and verify each claim using retrieved external evidence (Lewis et al. 2020; Li et al. 2024). However, these methods have largely been developed and evaluated on written text, and have not been fully adapted to long-form spoken content such as podcasts. Meanwhile, existing computational work on podcast fact-checking has primarily focused on benchmark creation and annotation (Chun et al. 2025; Setty and Becker 2025) rather than developing end-to-end verification tools.

To bridge this gap, we present *PodChecker*, an LLM-powered fact-checking tool for podcasts and similar audio content. This end-to-end system leverages the strengths of

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Paper Checklist

1. For most authors...
 - (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? **Yes**
 - (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? **Yes**
 - (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? **Yes; we discuss the methodology of the system to back up claims about its usage.**
 - (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? **Yes; we acknowledge that podcast inputs reflect only English language audio on politics and current events topics.**
 - (e) Did you describe the limitations of your work? **Yes, the limitations are described in the section "Limitations and Future Work."**
 - (f) Did you discuss any potential negative societal impacts of your work? **No, because this is a demo paper with limited space.**
 - (g) Did you discuss any potential misuse of your work? **No, because this is a demo paper with limited space. However, we mention that PodChecker is a companion in the fact-checking process that produces probabilistic signals to discourage user overreliance on its automated assessments.**
 - (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? **Yes, we mention that the system does not store users' personal information (API keys) or third-party datasets**
 - (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? **Yes**
2. Additionally, if your study involves hypotheses testing...
 - (a) Did you clearly state the assumptions underlying all theoretical results? **NA**
 - (b) Have you provided justifications for all theoretical results? **NA**
 - (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? **NA**
 - (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? **NA**
 - (e) Did you address potential biases or limitations in your theoretical framework? **NA**
 - (f) Have you related your theoretical results to the existing literature in social science? **NA**

- (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? *NA*
3. Additionally, if you are including theoretical proofs...
- (a) Did you state the full set of assumptions of all theoretical results? *NA*
- (b) Did you include complete proofs of all theoretical results? *NA*
4. Additionally, if you ran machine learning experiments...
- (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? *NA*
- (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? *NA*
- (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? *NA*
- (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? *NA*
- (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? *NA*
- (f) Do you discuss what is “the cost“ of misclassification and fault (in)tolerance? *NA*
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
- (a) If your work uses existing assets, did you cite the creators? *Yes. Creators of datasets and podcasts are cited as references; AI/ML tools used in the system are cited via URLs in Table 1*
- (b) Did you mention the license of the assets? *Yes, where applicable. The license for the Spotify Podcast Dataset is discussed in Footnote 2 and Table 1*
- (c) Did you include any new assets in the supplemental material or as a URL? *Yes, they are included as a GitHub repository link.*
- (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? *Yes, where applicable. The Spotify Podcast Dataset is used in accordance with its publicly documented license. The remaining podcast content consists of accessible episodes produced for public dissemination, and was limited to short excerpts and cited.*
- (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? *No; the assets used do not contain personal or private information or offensive content*
- (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see ?)? *NA*
- (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see ?)? *NA*
6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...
- (a) Did you include the full text of instructions given to participants and screenshots? *NA*
- (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? *NA*
- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? *NA*
- (d) Did you discuss how data is stored, shared, and de-identified? *NA*

PodChecker System Details

PodChecker is made up of several external components, including models and a dataset. These tools and their purposes are cited in Table 1. Figures 3 and 4 show the LLM prompts used in the system pipeline.

```
Please breakdown the following transcript
into independent atomic facts. Ignore
basic information about the podcast,
such as the name and host. Ignore
promotional/ad content. Ignore personal
anecdotes. Here is one example:
Input: "She currently stars in the
romantic comedy series, Love and Destiny,
which premiered in 2019."
Output: [ {1: "She currently stars in Love
and Destiny."}, {2: "Love and and Destiny
is a romantic comedy series."}, {3 : "Love
and Destiny premiered in 2019."} ]
```

Figure 3: **1-Shot Prompt for Claim Extraction:** We instruct the LLM to decompose the transcript segment into a list of factual atomic claims. Podcast metadata, ad content, and personal anecdotes are explicitly excluded.

```
You are a fact-checker. Please check the
accuracy of the provided claim, taking
into account any previous claims provided
as context. Return one of these ratings:
true, false, misleading/partially true,
unverifiable.
Do not add any explanations or extraneous
formatting.
Here are 4 examples:
Input: "Antonio Guterres is the UN
Secretary General"
Output: "true"
...
```

Figure 4: ***k*-Shot Prompt for Fact Verification:** To verify claims generated in the claim extraction step, we instruct the LLM to act as a fact checker and assign a label to each one. Examples written by the authors are provided for guidance.

Table 1: **External Components Used in PodChecker**

Tool	Purpose	Link
Whisper small.en	A speech recognition model used to transcribe audio inputs.	https://huggingface.co/openai/whisper-small.en
gpt-5 mini	A LLM from OpenAI used to extract atomic claims from transcripts.	https://platform.openai.com/docs/models/gpt-5-mini
Sonar	A search LLM from Perplexity with real time web search capabilities used to fact-check each claim.	https://docs.perplexity.ai/getting-started/models/models/sonar
Spotify Podcast Dataset	A corpus of 100,000 podcasts, one of which was sampled for demonstration of PodChecker, licensed under a Creative Commons Attribution license.	https://research.atspotify.com/publications/100000-podcasts-a-spoken-english-document-corpus https://creativecommons.org/licenses/by/4.0/