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How do AI-generated Podcasts Influence the Opinions of Users on Debated Topics? A User-Centered Exploration

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TUDelft

How do AI-generated Podcasts Influence the Opinions of Users on Debated Topics? A User-Centered Exploration

by

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TUDelft

Preface

Over the past seven months, I have dedicated significant effort to my thesis project, gaining invaluable lessons throughout the process. This project has equipped me with the essential skills for conducting rigorous and methodical scientific research. Additionally, it allowed me to enhance my technical and practical abilities, particularly in working with generative AI tools like NotebookLM, as well as in designing, developing, and executing large-scale empirical experiments.

The successful completion of my thesis would not have been possible without the support of many individuals. First and foremost, I extend my deepest gratitude to my supervisor, Ujwal Gadiraju, for his conscientious guidance and professional expertise. I am also immensely grateful to my daily co-supervisor, Gaole He, for his practical advice and insightful feedback. Lastly, I would like to thank Thomas Höllt, the committee member, for taking the time to engage in discussions about my work and participate in my thesis defense.

Junjie Wang
Delft, May 2025

Contents

Abstract

As technology advances, people are increasingly exposed to vast amounts of information. When they browse through the information, their perspectives on certain topics—particularly controversial ones—can gradually shift, ultimately influencing their life decisions. These shifts can have profound societal implications, making it essential to examine the factors that shape people's opinions. In recent years, some research has explored how users form opinions on debated topics through web searches. However, these studies have been limited by their focus on traditional information presentation formats (such as Search Engine Results Pages) and the ignorance of other presentation modes (like podcasts). This paper aims to investigate an innovative presentation format: AI-generated podcasts. Using the *Audio Overview* feature of NotebookLM, we created podcasts based on SERP sources and generated summaries using the same AI model as a control. To comprehensively analyze how different presentation formats affect opinion changes on controversial topics, we recruited participants from Prolific and conducted a 3×3 between-subjects study. In this study, participants were exposed to content under varying conditions (different presentation medium and viewpoint bias). The results show that presentation modes have no significant differences in influencing attitude change, with all modes aligning in direction with the viewpoint bias. While attitude change varies significantly between different kinds of debated topics, the degree of controversiality does not affect how presentation modes influence these changes.

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Introduction

1.1. Background

There are many debated topics in our daily lives - such as whether obesity should be classified as a disease and whether zoos are ethical - where people often hold differing views. The opinion formation on these debated topics is very important because it can influence people's decision-making (like eating habits and voting choice) in their life. Collectively, these influences can have a broader impact on the whole society [21]. Therefore, it is necessary to investigate the factors that can affect people's opinions.

With the rapid development of Internet technologies in recent decades, online platforms have become increasingly accessible, leading to a dramatic growth in Internet users worldwide. This digital expansion has elevated online information as a critical factor in shaping public opinion. When people encounter various information sources through digital media, their perspectives on debated issues can undergo significant transformation over time (see Figure 1.1).

The contemporary digital landscape offers diverse online information sources across multiple modalities. First of all, modern users consume content not just through traditional text-based reading, but also through auditory and visual formats. Podcasts exemplify this multimodal shift, providing an interactive listening experience that has seen remarkable growth - recent estimates project over 254 million regular podcast listeners by early 2024 [13]. Besides, the information ecosystem has been transformed by the emergence of artificial intelligence. The proliferation of generative AI technologies has led to an exponential increase in AI-generated content (AIGC), ranging from automated news articles to algorithmically personalized advertisements [28]. This development fundamentally alters the nature of online information production and consumption.

The widespread adoption of podcasts and AIGC has many risks. Specifically, researchers found that multimedia presentation and podcasts have more positive effects on knowledge acquisition compared to the traditional presentation way [18, 15]. It is possible that similar phenomena can occur in a web search setting, in which the user's opinion is largely influenced by the podcasts. For AIGC, the AI models can perpetuate

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or amplify existing societal biases, as well as spread false information, incite violence, or harm individuals or organizations [5]. This can lead to the formation of inaccurate public opinions regarding critical issues.

Many researchers have investigated how Internet users form opinions on debated topics [10, 20, 3, 27], most of them focus on Search Engine Results Page (SERP, see Figure 1.2) and the influence of different biases in it (including ranking bias [12], position bias [17], and cognitive bias [1]). However, these works didn't consider other presentation media (like podcasts) and content types (like AIGC). We aim to address this gap by examining how AI-generated podcasts influence users' opinions on debated topics. Additionally, AI-generated summaries have emerged as a prominent information medium in recent years. Therefore, we will also investigate their effects on attitude change and compare them with those of AI-generated podcasts.
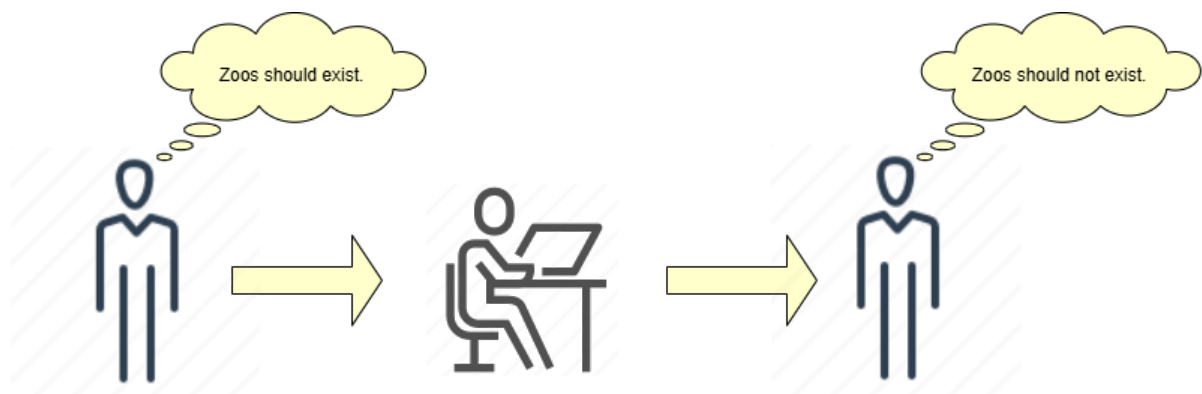

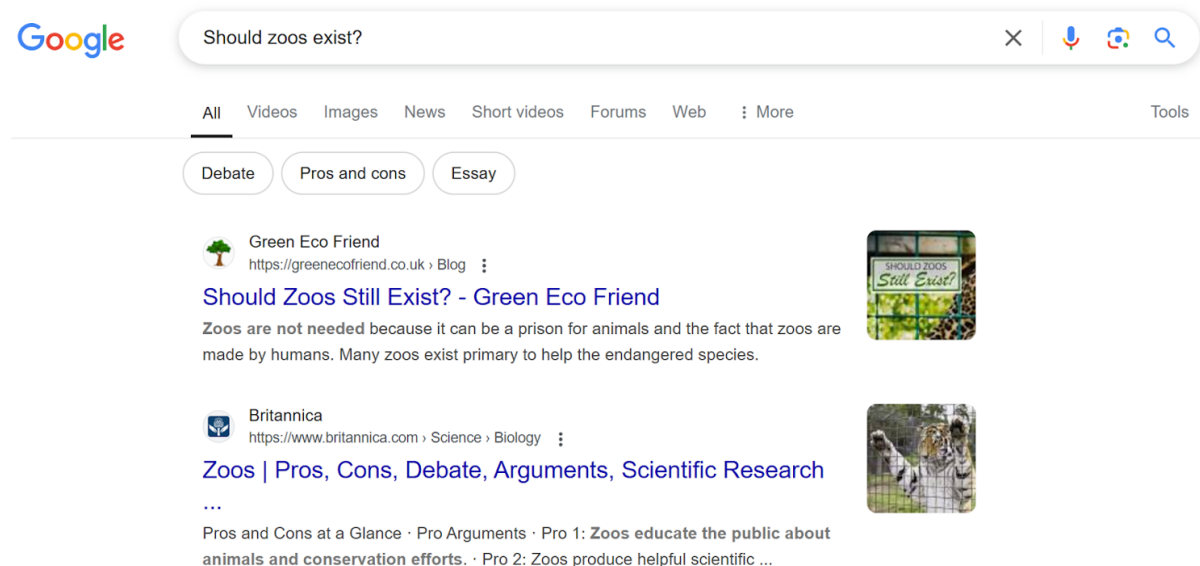Figure 1.1: People's Attitude Change After Being Exposed to Information Sources

Figure 1.2: Snapshot of a Search Engine Results Page

1.2. Research Questions

In this thesis, we aim to understand the effect of AI-generated podcasts on users' attitude change and compare it with other presentation modes[1] (SERPs and AI generated summaries), so we proposed the following research question:

RQ1. *How do different information presentation modes influence searchers' opinion change on controversial topics?*

Previous research has demonstrated that when search engine rankings are biased toward a particular viewpoint, users tend to adopt the favored perspective—a phenomenon known as the search engine manipulation effect (SEME) [11]. We aim to investigate whether this effect persists with AI-generated summaries and podcasts derived from SERPs. Specifically, we want to examine whether users' attitudes shift in alignment with the viewpoint bias (supporting, neutral, or opposing) embedded in the content. To explore this, we proposed another research question:

RQ2. *How do different viewpoint biases in presentation modes influence searchers' opinion change on controversial topics?*

Information on the Internet is diverse, including sources with different topics (moderately controversial topics and highly controversial topics). It is necessary to consider this factor when investigating the effects of presentation modes, so we proposed the third research question:

RQ3. *To what extent does the degree of controversiality moderate the influence of presentation modes on searchers' opinion change?*

To answer these questions, we conducted a rigorous study, using topics with different degrees of controversiality and content with different presentation modes and viewpoint biases.

1.3. Contributions

This project is the first attempt to investigate the role of AI-generated podcasts in shaping user opinions and evaluate their effectiveness relative to alternative presentation modes. Specifically, the main contributions of this thesis are as follows:

- We developed an experimental platform using Flask and used the Prolific platform to recruit the required number of participants.

- We ran a 3×3 between-subjects study[2] (N = 324) for 6 topics (3 moderately controversial and 3 highly controversial) to understand how the combination of different presentation modes and viewpoint biases in the content can influence users' attitude change.

- We found that while there is some difference in the impact of presentation modes on attitude change (AI-generated podcast demonstrates stronger influence compared to other presentation modes), the difference is not statistically significant.

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[1]In this thesis, "presentation mode" and "presentation medium" are used interchangeably.
[2]Our preregistration is available at https://osf.io/msb4e.

- We found that across all presentation modes, the direction of influence generally aligns with the viewpoint bias.

- We found that the attitude change observed in the two types of debated topics differs significantly; however, the level of controversiality does not moderate the effect of the presentation modes.

1.4. Thesis Outline

This thesis consists of the following chapters. In Chapter 2, we discuss the previous work related to user's opinion formation on debated topics in web search, multimodal presentation of information, and AI-generated podcasts. Next, we describe our hypotheses and the experiment materials in Chapter 3. After that, we introduce our experiment design and the details of the study in Chapter 4. Then, we present the experiment results in Chapter 5 and discuss the interpretation and limitations in Chapter 6. Finally, we conclude the thesis in Chapter 7.

2

Related Work

To help the readers better understand the background and context of the thesis, in this section, I will introduce some related works, focusing on three most relevant areas: User's Opinion Formation on Debated Topics in Web Search (§2.1), Multimodal Presentation of Information (§2.2), AI-generated Podcasts (§2.3).

2.1. User's Opinion Formation on Debated Topics in Web Search

Web search engines offer quick and easy access to the vast array of resources that may meet users' information needs. However, they are more than neutral tools for finding relevant content [4]. Web search plays a significant role in shaping opinions by offering access to information that can directly or indirectly influence users' perspectives and beliefs. Whether exploring a topic to satisfy personal curiosity or seeking advice on personal, business, or social matters, search engines help individuals form their viewpoints [6].

Opinion formation can involve minor decisions, like choosing an outfit, but it can also extend to more significant and often controversial topics that are under active debate. These debated issues, known as socio-scientific topics, are subjects of ongoing discussion that lack an obvious solution—at least according to some participants or observers [22]. They range from overwhelmingly one-sided matters with established scientific consensus, such as the Earth's shape, to more divisive issues that have valid arguments on both sides, like the ethical considerations surrounding zoos.

Searches on debated topics can influence individual users' opinions and subsequent choices—such as decisions about adopting veganism, choosing financial strategies, or selecting candidates to support. Collectively, these influences can have a broader impact on democratic societies as a whole. Considering the role search engines play in shaping opinions—a purpose they weren't originally designed to serve—it is essential to deepen our understanding of the challenges involved and to enhance system features that support responsible opinion formation [21].

Looking for information on the Internet inherently requires cognitive effort, particularly to overcome biases that can occur during the search process [21]. These biases can originate from the user (such as cognitive biases) [26], the search engine (including biases in data, relevance criteria, and ranking algorithms) [25], or from the interaction between them (such as biases related to presentation, over-reliance, and context) [2].

In the last several years, a growing body of literature strives to understand the impact of different biases on user opinion change for the debated topics. Draws et al. [10] investigated whether order effects (users assign more weight to information drawn from higher ranked results) contribute to SEME (search engine manipulation effect, which means attitude change due to viewing a biased ranked list of search results). They found that order effects may not be an underlying mechanism of SEME, but exposure effects (users adopting the majority viewpoint among the results they examine) may be a contributing factor to users' attitude change. Rieger et al. [20] did a research about the impact of exposure and interaction biases during web search on debated topics. They exposed participants to three SERP ranking bias conditions (balanced, biased supporting, and biased opposing), logged their interactions to then compute metrics (confirmation bias, position bias, and search effort). The results show that searchers' attitude strength and prior knowledge, but not exposure effects, impact attitude change and knowledge gain. Bink et al. [3] investigated whether biased featured snippets can affect user attitudes on commonly debated topics on multiple viewpoint dimensions. They found that users were not only significantly affected by the answers' stances but also adapted the featured snippets' logic into their own post-search argumentation. Wang et al. [27] studied users' opinion changes on debated topics and confirmation bias at the session level. They found that the majority of attitude changes occur in the first query, and the differences in click-based behaviors could be influenced both by SERP presentation and by confirmation bias.

All these works are limited because they only focus on the traditional information presentation mode (i.e. SERP) and the biases in it. We will go further by exploring a relatively novel presentation medium, which is podcast. We want to see if this new factor (i.e. presentation medium) can make a difference.

2.2. Multimodal Presentation of Information

Multimodal presentation utilizes multiple forms of digital communication, such as videos, interactive slides, audio clips, music, and more, to effectively convey a message. Compared to the traditional presentation way (i.e. text), it can create a more captivating and immersive experience.

There are many works which study the usage and benefits of multimedia presentation. In [8], The researchers conducted an experiment with university students to assess cognitive load while they viewed different combinations of text, images, and audio-narration. They found that using images with audio-narration was most effective in reducing cognitive load and enhancing information comprehension. Another study [18] compared the performance of students who were exposed to multimedia presentations with that of students who were exposed to traditional teaching materials, and the results show that the use of multimedia presentations led to improved

short-term learning outcomes and increased student motivation. Similarly, [23] found that the use of audiovisual learning media can improve student learning outcomes, especially in rhetoric and presentation skills.

Podcast is a form of multimodal presentation. It has become an increasingly popular medium for information dissemination and entertainment, offering a flexible and convenient way to consume content. Many studies found that podcasts have positive effects on knowledge acquistion. For example, [15] explored how podcasts can be used as a tool to improve listening comprehension skills for students learning English as a Foreign Language (EFL), the results show that students' listening comprehension skills improved after taking part in the learning cycles which integrated podcasts. Similarly, [7] found that the students who created and used podcasts demonstrated significant improvement in their linguistic competence, particularly in their speaking and listening skills.

Previous research has demonstrated that multimodal presentation and podcasts can enhance knowledge acquisition. Building on these findings, we aim to investigate whether a similar effect occurs in web search by comparing the impact of SERPs (Search Engine Results Pages) and podcasts derived from them.

2.3. AI-generated Podcasts

The emergence of AI, particularly large language models (LLMs), has significantly impacted the podcasting landscape, automating various aspects of podcast production and enabling the creation of engaging and personalized content [24].

Some works highlight the potential of AI-generated podcasts to enhance learning experiences in educational settings. For instance, a study using the PAIGE system, which personalizes educational podcasts based on student profiles, revealed significant improvements in knowledge retention for certain subjects when compared to generalized podcasts and textbook reading [9]. Another study explored the use of Google NotebookLM, a multi-featured AI tool that includes automatic podcast generation. Researchers found that NotebookLM effectively transformed static historical documents into dynamic learning materials, creating engaging podcasts that facilitated critical thinking and deeper student discussions [16]. Beyond education, AI-generated podcasts hold promise for making research papers more accessible and engaging for researchers. The PaperWave prototype, designed to convert academic paper PDFs into conversational podcasts, illustrates this potential [29]. A field study involving PaperWave demonstrated its effectiveness in enabling "mobile reading," allowing researchers to listen to papers in various contexts where visual reading was impractical. The conversational format of the generated podcasts also provided a different emphasis on information compared to text-based reading, potentially leading to new insights and understanding.

Although AI-generated podcasts have many benefits and application scenarios, they also have a lot of potential risks. For example, some podcasts can be misleading and affect user's opinion. That's why we choose to focus on the attitude change effects of AI-generated podcasts, which is underexplored in previous works.

3

Preliminaries

3.1. Goal and Hypotheses

As mentioned in Section 1.1, podcast may have greater influence on user's opinion change than traditional presentation modes, so we proposed the following hypothesis:

Hypothesis 1 (H1). *The presentation mode affects searcher's opinion change on controversial topics. Specifically, podcast has more influence on searcher's opinion change compared to other presentation modes.*

Also, exposure effects (being exposed to messages pertaining to a particular viewpoint increases an individuals' favorability towards that viewpoint) also affect people's opinion formation [1], so we proposed the following hypothesis:

Hypothesis 2 (H2). *For all the presentation modes, the viewpoint bias of content predicts searcher's opinion change. Specifically, the direction of influence will be consistent with the viewpoint bias.*

What's more, it was found that people are not likely to change their opinion towards highly controversial topics, especially when their opinion is strong, so we proposed the following hypothesis:

Hypothesis 3 (H3). *The degree of controversiality moderates the effect of presentation modes on attitude change. Specifically, compared to moderately controversial topics, the relative influence of podcasts will be smaller under highly controversial topics.*

The goal of our experiments is to test the above hypotheses by exploring the impact of presentation mode, viewpoint bias and degree of controversiality on user's attitude change.

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3.2. Materials

3.2.1. Topics

In our study, we used three moderately controversial and three highly controversial topics. For the selection of moderately controversial topics, we used a publicly available dataset ("search results annotated" dataset[1] in [10]), which contains human annotated search results for five moderately controversial topics. We randomly chose three from the five topics, which are obesity as a disease, cell phone radiation safety, and social networking sizes, respectively. For the selection of highly controversial topics, we did not find any public datasets, so we just chose three from ProCon[2], which are permitless carry of guns, abortion legality, and undocumented immigrants in the U.S., respectively. The chosen topics can be seen in Table 3.1.

Degree of Controversiality	Topic
Moderately Controversial	Is obesity a disease?
	Is cell phone radiation safe?
	Are social networking sites good for our society?
Highly Controversial	Should permitless carry of guns be legal?
	Should abortion be legal?
	Should the government allow undocumented immigrants to resettle in the United States?

Table 3.1: Topics Used in the Study

3.2.2. SERPs

To construct a SERP for a topic, we need to find some related search results. For moderately controversial topics, we directly used the data from the "search results annotated" dataset, which contains the URL, title, snippet, and annotated viewpoint (7-point scale, from "strongly opposing" to "strongly supporting") of the search results. For highly controversial topics, we first found some relevant sources of those topics on ProCon, then employed NotebookLM[3] to annotate the viewpoints of them (the example prompt can be seen in Table 3.2). After that, we double checked the annotations

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[1]https://osf.io/v38c5
[2]https://www.britannica.com/procon
[3]https://notebooklm.google/

to make sure they are accurate. Human annotation was not used here, as it would incur significant costs.

Besides the retrieval and annotation of the search results, we also need to find a way to rank them under different viewpoint bias conditions. To achieve this, we employed the methodology from [10], given the similarity between their experiment and ours concerning SERPs. We randomly sampled three "opposing", two "somewhat opposing", two "somewhat supporting", and three "supporting" items from the search result items that were deemed relevant to a given topic. For the supporting condition, we used the ranking with extreme bias towards the supporting viewpoint. For the opposing condition, we used the ranking with extreme bias towards the opposing viewpoint. For the neutral condition, we used the ranking with little bias (supporting viewpoint and opposing viewpoint are counter-balanced, half contained bias for the opposing viewpoint and half the supporting viewpoint).

3.2.3. AI Summaries and Podcasts

We used NotebookLM to generate the summaries and podcasts with different viewpoint biases based on the SERPs (the example prompts can be seen in Table 3.2). Specifically, we instructed the AI model to generate content from topic sources, enforcing a specific viewpoint bias.

3.2.4. Attention Check Questions

To measure the user's attention and test their understanding towards the content, we also prepared some True or False questions with NotebookLM (the example prompt can be seen in Table 3.2). We kept the question set short (five easy questions) to avoid excessive time demands on participants.

3.2.5. Experiment Platform

The experiment platform was developed using the Flask framework[4] (all the materials and code can be accessed on GitHub[5]). We deployed it on Render[6], which is a cloud application platform. Snapshots of the platform can be seen in Figure 3.1.

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[4]https://flask.palletsprojects.com/en/stable/
[5]https://github.com/wjj710/podcast-study
[6]https://render.com/

Do Cell Phones Cause Cancer? - Robert B. Laughlin
Do Cell Phones Cause Cancer? Sandy Smith ... with multiple theories stating that there is a direct correlation as well as arguments against this theory that state the signals being emitted are too low to form the carcinogenic cells. ... this may pose more of a problem, but as of now, the emitting of cell phone radiation is the least of concerns ...

Cellphone radiation poses no real harm to humans, new ...
Male rats showed a small increase in a type of heart tumor after exposure to massive amounts of cellphone radiation, a new government study reports. But don't read too much into that, experts ...

Do Cell Phones Cause Cancer? | Memorial Sloan Kettering ...
But cell phone radiation is actually very low in energy. ... The argument that cell phones cause cancer lacks biological plausibility because the energy contained in the waves is too low to cause damage. ... Current safety standards limit cell phones to a maximum of 1.6 watts per kg, which is not enough to warm the body. This safety limit ...

Cancer Risk From Cellphone Radiation Is Small, Studies ...
Cancer Risk From Cellphone Radiation Is Small, Studies Show ... Safety questions about cellphones have drawn intense interest and debate for years as the devices have become integral to most ...

Of Science, Certainty, and the Safety of Cell Phone Radiation
Davis, who has written books about tobacco and cell phone safety, described the Popular Science article as "a remarkable piece of disinformation," and expressed disappointment that Science Friday had picked it up. That was really a tragedy, as far as I'm concerned, and really irresponsible on their part," Davis said.

(a) SERP

Social networking can have positive effects on society and provides various benefits.

These benefits include:

- **Enhanced connectivity** Social media provides an effortless way to connect with like-minded individuals, revive relationships, and connect with business professionals. It helps users expand their networks, enhance their careers, and find people with scarce skills.
- **Business strategies** Social media is a primary means of expanding businesses through cheaper advertising, reaching broader demographics, promoting two-way communication, and sharing information on various platforms.
- **Benefits for students and teachers** Social media provides easy access to knowledge from experts and helps in learning various skills. Many students use social networking for educational purposes.
- **Platform for noble causes** Social media can be used to promote social welfare activities, NGOs, and create awareness about various innovations.
- **Community building** Social media helps people with shared interests, religions, and nationalities form communities to discuss and stay updated on their hobbies.
- **Mental health benefits** Social media can relieve social isolation, open new communication pathways, offer support, and develop self-expression.
- **Saving lives** Social media can spread awareness, motivate people, and assure them they are not alone, with many websites offering support through social platforms.
- **Meeting new people** Social networking sites allow users to meet new people worldwide, learn more about them through profiles, and connect more easily than through other internet channels.
- **User-friendly interface** Social networking sites are designed to be user-friendly, requiring minimal internet knowledge, and mobile versions enhance accessibility.
- **Interest-based groups** Social networks allow users to create and join groups to share interests and hobbies.
- **Job market** Professional social networks help people establish their brand, showcase skills, and get recognized by potential employers, with many companies recruiting through platforms like LinkedIn.
- **Reaching potential customers** Social networking sites help businesses reach potential customers through targeted advertising based on user profiles.
- **Encouraging creativity** Social media platforms encourage creativity through various forms of content, allowing users to participate, engage, and

(b) Summary
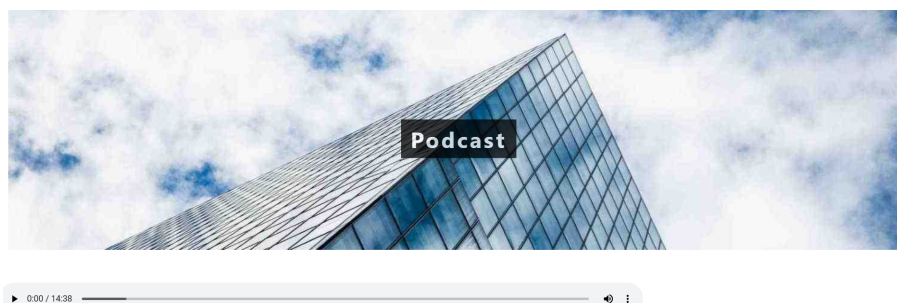
(c) Podcast

Figure 3.1: Snapshots of Content Page with Three Kinds of Presentation

Usage	Prompt	Illustration
Annotation	`Please give the viewpoint of each source about the statement that "Permitless carry of gun should be legal". You have seven choices: strongly opposing, opposing, somewhat opposing, neutral, somewhat supporting, supporting, strongly supporting.`	This prompt is used to generate the viewpoint annotations for the search results (i.e. web pages) of the gun topic.
Summary	`Generate a summary for the given sources, focus on the sources which hold the view that obesity is a disease.`	This prompt can generate a summary with supporting viewpoint bias towards the obesity topic.
Podcast	`Focus on discussing whether obesity is a disease. Make a balance between the sources which hold the view that obesity is a disease and the sources which hold the view that obesity is not a disease.`	This prompt is used with the *Audio Overview* feature, it can generate a podcast with neutral viewpoint bias towards the obesity topic.
Questions	`Generate 5 easy true or false questions for the source (the generated 5 questions should only be based on the information of this source, with correct answers distribute equally between True and False), save the questions and answers into a csv file (only give the csv format).`	This prompt is used to generate 5 True or False questions for the source (SERP/Summary/Podcast).

Table 3.2: Example Prompts for NotebookLM

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Method

4.1. Experiment Design

We employed a 3×3 **between-subjects** design for presentation mode and viewpoint bias (see Table 4.1) to mitigate carryover effects—ensuring participants' responses would not be influenced by prior exposure to the same topic under different conditions.

For degree of controversiality, we adopted a **within-subjects** design, where each participant engaged with multiple topics. This approach was justified by the independence of the selected topics; since attitudes toward one topic were unlikely to influence those toward another, interference between tasks was minimized.

	Supporting	Neutral	Opposing
SERP	Group 1	Group 4	Group 7
Summary	Group 2	Group 5	Group 8
Podcast	Group 3	Group 6	Group 9

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Table 4.1: Group Division

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4.2. Variables

All the variables that we set and measured in the study are shown in Table 4.2. We have two independent variables: presentation mode (target domain of SERP, summary and podcast) and viewpoint bias (target domain of supporting, neutral and opposing). Following the approach in [10], we used attitude change as the dependent variable, which is calculated by subtracting the first measurement (measured before being presented with the topic-related content) from the second (measured after being presented with the topic-related content). We considered the users' intellectual

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humility scale [14], familiarity of the topic, preexisting viewpoint and user engagement scale [19] as covariates. Besides that, we also measured user's familiarity and preference about the presentation ways (can be used to do further analysis), time spent and number of correctly answered questions (can be used to check their attention), as well as some behavior data (can be used to analyze other factors which may influence user's attitude change, like order effects).

Variable Type	Variable Name	Value Type	Value Scale
Independent variable	Presentation mode	Option	SERP, Summary, Podcast
	Viewpoint bias	Option	Supporting, Neutral, Opposing
Dependent variable	Opinion change	Interval	[-6,6]
Covariates	Intellectual humility scale	Likert	7-point
	Familiarity of the topic	Likert	5-point
	Preexisting viewpoint	Likert	7-point
	User engagement scale	Likert	7-point
Others	Familiarity of the presentation ways	Likert	5-point
	Preference about the presentation ways	Option	SERP, Summary, Podcast
	Time spent on the content page	Continuous	$[0,\infty)$
	Number of questions that are correctly answered	Interval	[0, 5]
	Behavior data (links clicked in a SERP and segments played in a podcast)	-	-

Table 4.2: Variables and Their Characteristics

4.3. Procedure

4.3.1. Pilot Study

To prepare for the main study, we conducted two pilot studies. In the first pilot study, we collected participants' familiarity and viewpoint about six topics, which can help us decide whether the topics are suitable for the main study and calculate the degree of controversiality. In the second pilot study, we separated the participants into nine groups (mentioned in Section 4.1) and tested the whole experiment process on one topic ("Is obesity a disease?"), the detailed procedure is as follows:

- **Pre-Task:** The participants will first be presented with an introduction about the study, then they will make an informed decision regarding their participation (the introduction and consent form can be seen in Appendix A). Before the formal task, the participants need to answer some questions about their intellectual humility (we used the "limitations-owning intellectual humility scale" in [14], the questionaire can be seen in Appendix B).

- **Task:** The task contains four steps. In the first step, the participants answer a question about their familiarity about the obesity topic. In the second step, they answer a question about their current attitude towards that topic (evaluation). In the third step, they will be presented with some content which is related to the topic (the type of content depends on the group of the participant; for example, the participants of Group 1 will be presented with a SERP which has the supporting viewpoint bias). In the fourth step, they need to indicate their attitude again (re-evaluation).

- **Post-Task:** After the task, the participants are required to answer questions about their familiarity and preference about the presentation modes, as well as the degree to which they are involved and satisfied with the study experience (we used the "user engagement scale short form" in [19], the questionaire can be seen in Appendix B). Finally, the participants give some feedback about our study (this is optional).

4.3.2. Main Study

The procedure of the main study (see Figure 4.1) is very similar to that of the pilot study, but there are some differences. The modifications we made are as follows:

- **Sessions:** We divided the task into two sessions (having one session would need too many participants, having more than two sessions would tire participants and reduce their attention), each focusing on a single topic and containing five steps. In the first session, participants were randomly assigned a moderately controversial topic, followed by a highly controversial topic in the second session.

- **Questions:** Besides the four steps mentioned in the pilot study procedure, we added another step to test the users' attention. At the end of each session, the participants need to answer some questions related to the content which has been presented before (we used 5 questions for each session in our study).

- **Tutorial:** To help the participants become familiar with the study process, we added a tutorial before the task. The tutorial introduces the five steps in a session by showing some example content and questions.
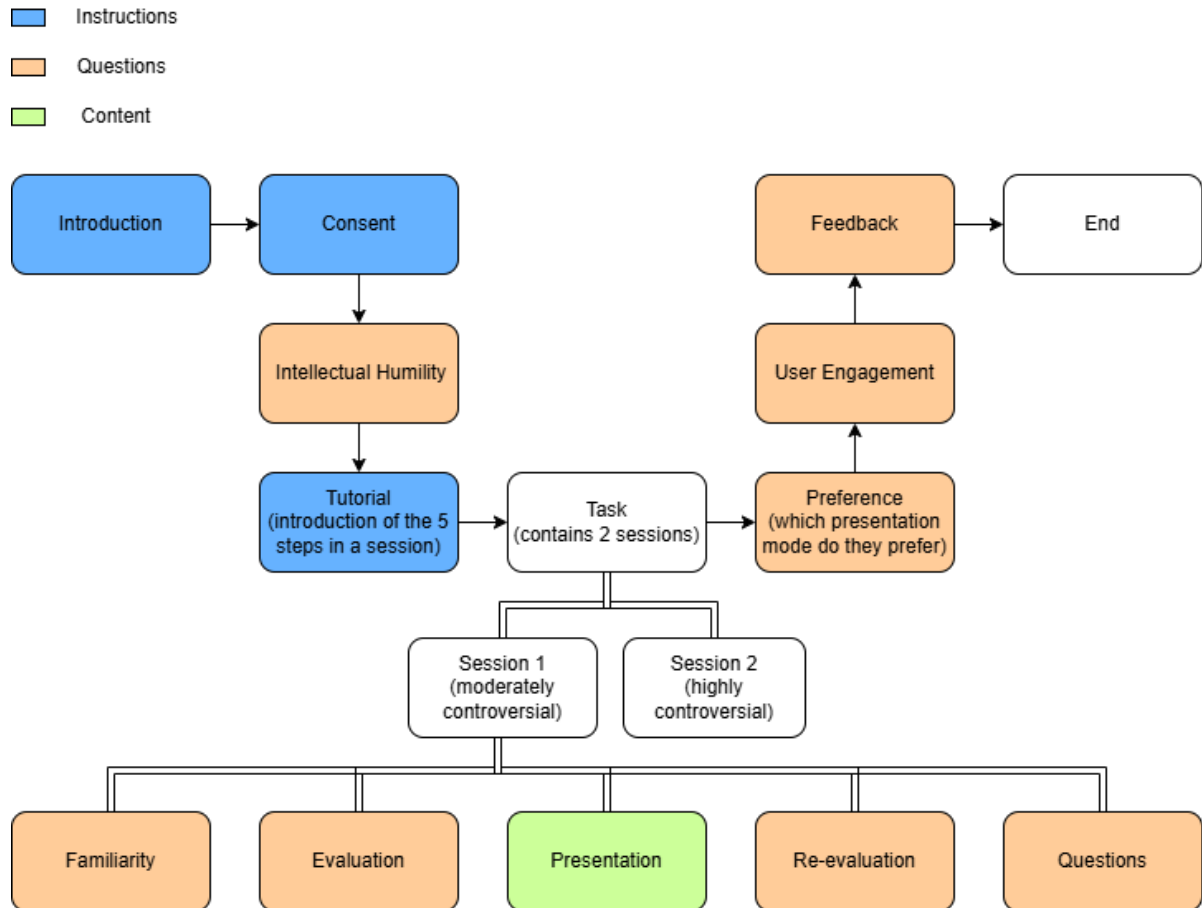

Figure 4.1: Study Procedure

4.4. Participants

4.4.1. Pilot Study

We recruited 50 participants for the first pilot study and 18 participants for the second pilot study (2 people in each group) through Prolific[1]. Participants were paid an hourly wage of around 9 GBP per hour (as per the guidelines for a 'good' payment on Prolific). We used crowd workers whose age is between 18 and 50. They should have successfully completed more than 40 tasks and maintained an approval rate of over 90%. All the workers are from the U.S.[2] and the gender ratio is 1:1.

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[1]https://www.prolific.com/
[2]We did this because some topics in our study are social issues belonging to the United States

4.4.2. Main Study

We recruited 324 participants for the main study (approximately 108 people for each topic, 12 people in a group). The hourly wage and selection criteria are the same as the pilot study. We also gave the participants 0.25 GBP as bonus if they correctly answered all the questions of a session.

4.5. Data Filtering

We used two metrics—time spent on the content page and the number of correctly answered questions—to measure participants' attention levels and filtered out data from participants who showed insufficient attention. Specifically, we first calculated the median time spent and the median correct answer rate for a specific type of content (e.g., a podcast with a supporting viewpoint bias on the topic of obesity). Next, we computed each participant's attention score for a session using the formula: (time spent / median time) + (correct answer rate / median correct answer rate). Participants whose attention scores were below 1 in both sessions were excluded from the analysis.

4.6. Analysis

We used the following statistical methods to analyze the data:

- **ANOVA (Analysis of Variance) Test:** We conducted a three-way ANOVA to analyze the influence of the two independent variables (presentation way and viewpoint bias) and degrees of controversiality on user's attitude change. We also conducted a two-way ANOVA to analyze the influence of listening time and listening style under the podcast condition.

- **ANCOVA (Analysis of Covariance) Test:** We performed two ANCOVAs (with presentation way and viewpoint bias as between factor respectively), using intellectual humility scale, familiarity of the topic, preexisting viewpoint, and user engagement scale as covariates.

- **Spearman Rank-Order Test:** We carried out four Spearman rank-order tests to analyze the correlation between user's attitude change and the four covariates.

Results

5.1. Pilot Study

5.1.1. Pilot Study 1

The participants' familiarity with the topics and their viewpoint distribution can be seen in Appendix C. The data reveals that most participants were familiar with the topics, and their viewpoints were relatively balanced, with no extreme bias toward a single perspective (e.g., entirely supporting or opposing). This indicates that our topic selection was appropriate, allowing us to proceed confidently with the experiment.

5.1.2. Pilot Study 2

The primary data collected from the 18 participants can be seen in Appendix C. We observed that participants exposed to podcasts showed no change in their attitudes toward the topic (attitude change = 0). To investigate this outcome, we analyzed their familiarity with the three presentation modes: SERP, summary, and podcast. The average familiarity scores were 1.22 for SERP, 1.22 for summary, and -0.72 for podcast. We believe that the participants' lack of familiarity with podcasts is the key reason for this result. To address this issue, we introduced a tutorial before the task to help participants become more comfortable with the presentation modes and the study process. Additionally, we included attention check questions designed to encourage them to engage more attentively with the content, whether through reading or listening.

5.2. Main Study

5.2.1. Descriptive Statistics

We used the method in Section 4.5 to filter out the data of the participants with insufficient attention, and the final number of participants in each group can be seen in Table 5.1. Overall intellectual humility (mean = 1.31, sd = 0.76), familiarity of the topic

(mean = 0.54, sd = 1.18), preexisting viewpoint (mean = 0.10, sd = 2.07), and user engagement (mean = 1.13, sd = 0.84) were moderate.

Across all conditions, 49.65% of people expressed an attitude change (i.e. they moved at least one point on the Likert scale in their post-search attitude compared to their pre-existing attitude) after being presented with the content. Specifically, the percentage for the three presentation modes (SERP, summary and podcast) are 46.88%, 46.43% and 55.79%, respectively. Besides, the mean absolute attitude change for podcast condition is 0.94 (sd = 1.14), higher than that of SERP (mean = 0.82, sd = 1.19) and summary (mean = 0.90, sd = 1.28).

To examine the impact of the three presentation modes under different viewpoint bias conditions, we created a box plot, as shown in Figure 5.1. The plot reveals that the podcast mode differs from the other two modes in the neutral condition, exhibiting a wider range of viewpoint changes. We also examined how participants' attitudes changed when their preexisting views aligned with the biased perspective presented (e.g., a participant who already agreed that "obesity is a disease" was exposed to content supporting that claim). The data in Table 5.2 shows that the podcast strengthened participants' attitudes when the content supported their initial stance. Additionally, to determine whether there are differences based on the level of controversiality, we calculated the mean absolute attitude change for both highly controversial and moderately controversial topics, as presented in Table 5.3. Overall, the results indicate that the amplitude of attitude change is greater for moderately controversial topics compared to highly controversial ones. Besides, for moderately controversial topics, podcast's influence is the highest among the three presentation modes.

We also measured the participants' familiarity and preference towards the three presentation modes, which is shown in Figure 5.2. The data indicates that users exposed to podcasts tend to prefer podcasts over other presentation modes, while those in other conditions show a stronger preference for summaries.

The average time spent on the content page of the SERP, the summary, and the podcast is 43 seconds, 67 seconds, and 602 seconds, respectively. This indicates that users tend to spend significantly more time engaging with podcasts compared to other content types. Additionally, we collected behavioral data from the participants, as illustrated in Figure 5.3. Our analysis reveals that users are more likely to focus on information presented at the beginning of the content.

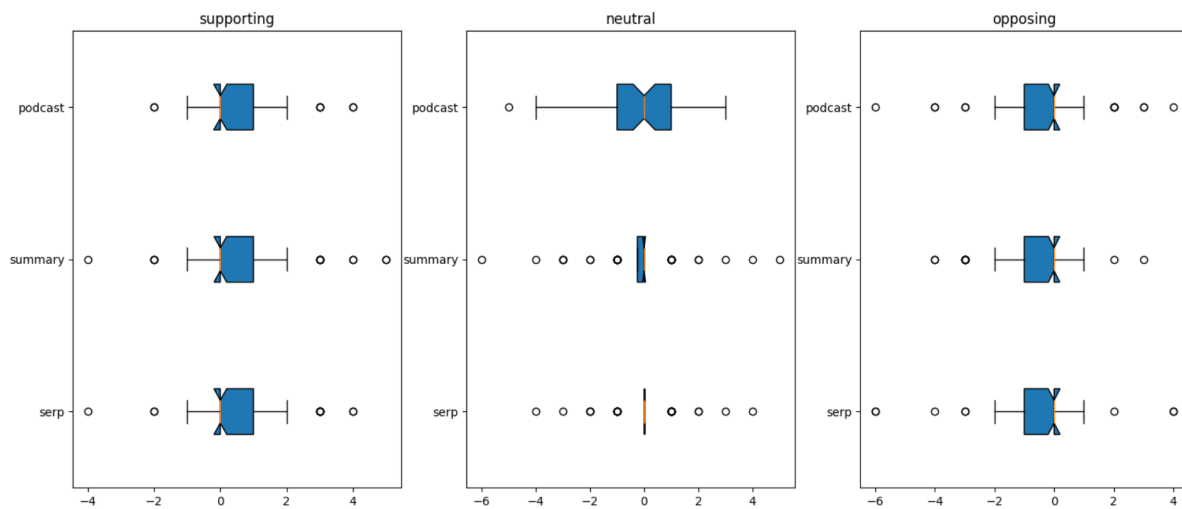| Topic	Gr 1	Gr 2	Gr 3	Gr 4	Gr 5	Gr 6	Gr 7	Gr 8	Gr 9
phone	12	12	10	10	9	10	11	13	12
social	8	12	11	12	10	12	12	12	12
obesity	13	10	10	10	11	8	8	9	10
immigration	13	10	10	10	11	8	8	9	11
gun	12	12	10	10	9	10	11	13	12
abortion	8	12	11	12	10	12	12	12	11

Table 5.1: Number of Participants in Each Group

Figure 5.1: Box Plot of User's Viewpoint Change in Three Viewpoint Bias Conditions

| Presentation	Supporting	Opposing
SERP	-0.29 (±1.16)	0.28 (±1.37)
Summary	-0.13 (±1.04)	0.00 (±0.83)
Podcast	0.22 (±0.75)	0.53 (±1.25)

Table 5.2: Mean Average Attitude Change (± std. dev.) for Participants with Supporting and Opposing Preexisting Viewpoint (under the viewpoint bias condition which aligns with the pre-viewpoint)

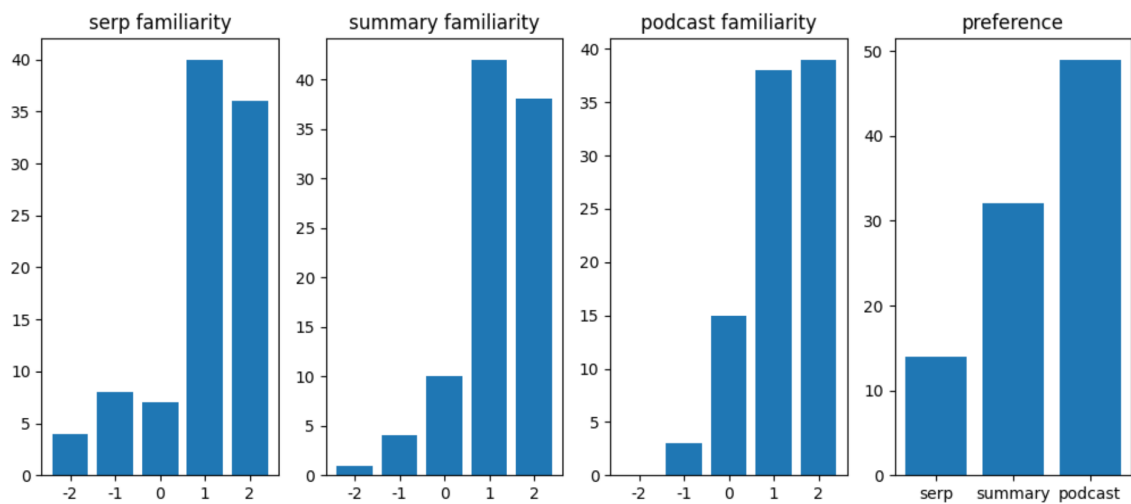| Presentation	Moderately Controversial	Highly Controversial
SERP	1.00 (±1.21)	0.64 (±1.14)
Summary	1.03 (±1.22)	0.78 (±1.33)
Podcast	1.13 (±1.29)	0.76 (±0.93)

Table 5.3: Mean Absolute Attitude Change (± std. dev.) for Moderately Controversial and Highly Controversial Topics
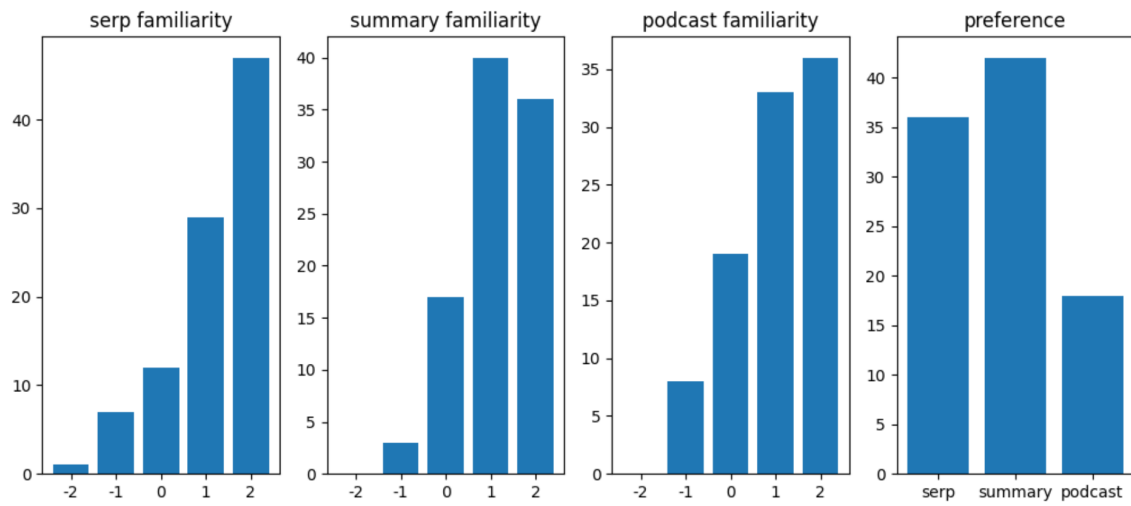
(a) SERP
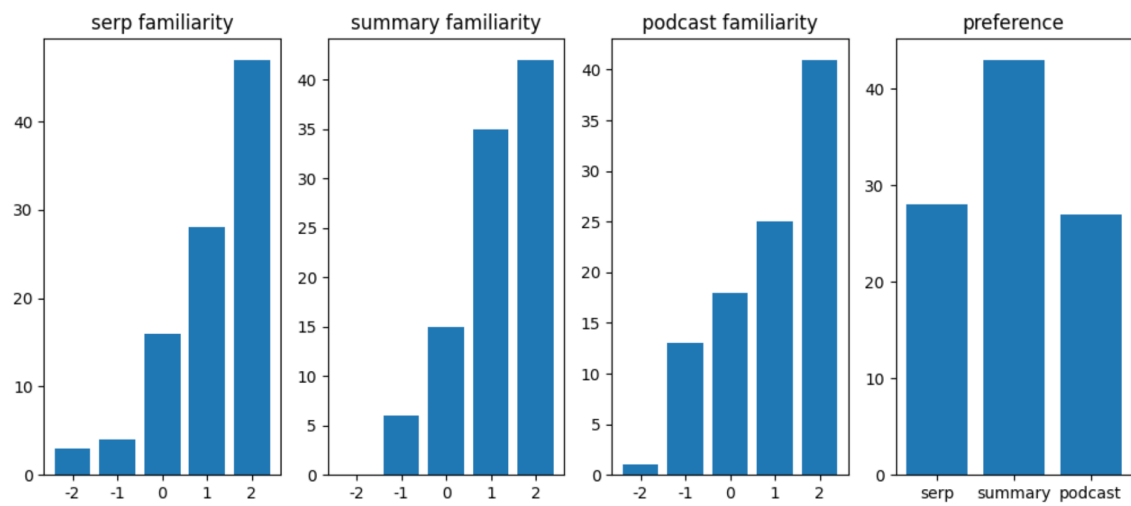
(b) Summary

(c) Podcast

Figure 5.2: Familiarity and Preference Data Under the Three Presentation Conditions
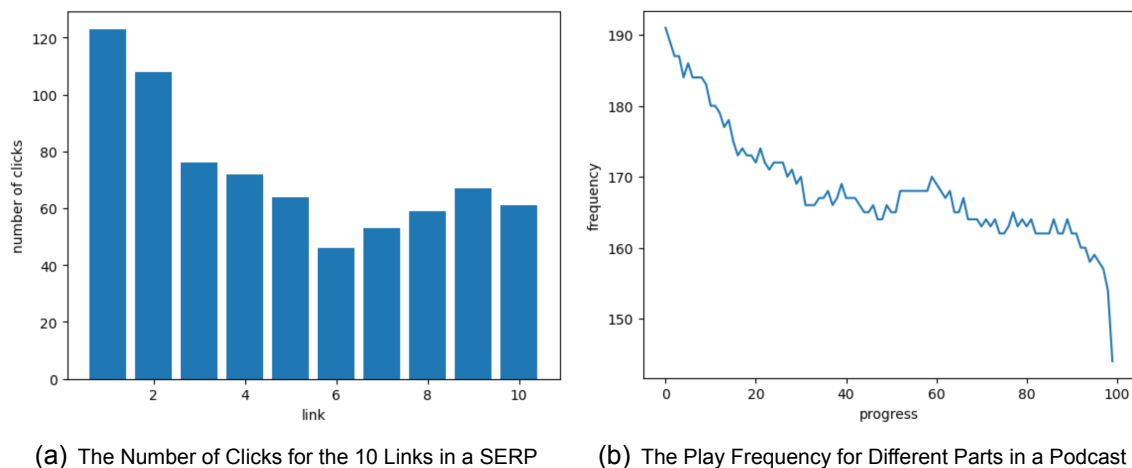
(a) The Number of Clicks for the 10 Links in a SERP   (b) The Play Frequency for Different Parts in a Podcast

Figure 5.3: Behavior Data

5.2.2. Hypothesis Tests

In this part, we will show the results of the hypothesis tests, which are obtained using the statistical methods mentioned in Section 4.6.

H1: effect of presentation mode on user's attitude change

The analysis reveals no significant difference (see Table 5.4, Source = presentation, F = 0.646, p-unc = 0.524, n2 = 0.002) in attitude change across different presentation methods, providing no support for **H1**. To account for the influence of covariates, we also conducted the ANCOVA analysis, the result for presentation mode (see Table 5.6, Source = presentation, F = 1.269, p-unc = 0.282, n2 = 0.004) still does not provide evidence for **H1**.

H2: effect of viewpoint bias on user's attitude change

A significant difference (see Table 5.4, Source = viewpoint, F = 20.192, p-unc = 0.000, n2 = 0.064) was observed between the various viewpoint bias conditions. As illustrated in Figure 5.1, the direction of attitude change aligns with the viewpoint bias across all presentation modes, supporting **H2**. To account for the influence of covariates, we also conducted the ANCOVA analysis, the result for viewpoint bias (see Table 5.5, Source = viewpoint, F = 26.644, p-unc = 0.000, n2 = 0.067) aligns with our earlier finding, further supporting **H2**.

H3: effect of degree of controversiality on user's attitude change

While there is a significant difference (see Table 5.4, Source = controversiality, F = 16.330, p-unc = 0.000, n2 = 0.026) between the two levels of topic controversiality (also shown in Table 5.3), no significant interaction effect was found between presentation methods and controversiality (see Table 5.4, Source = presentation * controversiality, F = 0.996, p-unc = 0.370, n2 = 0.003). Consequently, **H3** is not supported by the data.

Source	SS	DF	MS	F	p-unc	n2
viewpoint	82.667	2.000	41.333	20.192	0.000	0.064
presentation	2.645	2.000	1.323	0.646	0.524	0.002
controversiality	33.427	1.000	33.427	16.330	0.000	0.026
viewpoint * presentation	4.631	4.000	1.158	0.566	0.688	0.004
viewpoint * controversiality	4.781	2.000	2.390	1.168	0.312	0.004
presentation * controversiality	4.077	2.000	2.039	0.996	0.370	0.003
viewpoint * presentation * controversiality	12.793	4.000	3.198	1.562	0.183	0.010

Table 5.4: ANOVA Test Results (using independent variables and degrees of controversiality as between-subjects factors)

Source	SS	DF	F	p-unc	n2
viewpoint	86.762	2	24.644	0.000	0.067
familiarity	1.788	1	1.016	0.314	0.001
pre_viewpoint	195.447	1	111.029	0.000	0.151
humility	2.286	1	1.298	0.255	0.002
engagement	0.418	1	0.238	0.626	0.000

Table 5.5: ANCOVA Test Results (using viewpoint bias as between factor)

Source	SS	DF	F	p-unc	n2
presentation	4.834	2	1.269	0.282	0.004
familiarity	1.181	1	0.621	0.431	0.001
pre_viewpoint	191.594	1	100.638	0.000	0.149
humility	3.067	1	1.611	0.205	0.002
engagement	0.522	1	0.274	0.601	0.000

Table 5.6: ANCOVA Test Results (using presentation mode as between factor)

5.2.3. Exploratory Findings

Analysis of Listening Time and Style
The hypothesis tests indicate that AI-generated podcasts do not exert a greater influence on searchers' opinion changes compared to other presentation modes. To delve deeper into this finding, we conducted additional analyses, which are of exploratory nature. First, we examined the time participants spent listening to the podcasts, as shown in Figure 5.4. Notably, some participants listened for less than three minutes, despite the podcast exceeding ten minutes in length. We also analyzed behavior data, revealing that some individuals listened to discontinuous segments of the podcast.

To explore whether listening time and style affected attitude change, we categorized participants into groups based on listening duration (more than or less than three minutes) and the number of segments played (one segment or multiple segments). A two-way ANOVA analysis (see Table 5.7) was performed on the data under podcast condition. The results indicate no significant difference in attitude change between participants with varying listening time and styles.
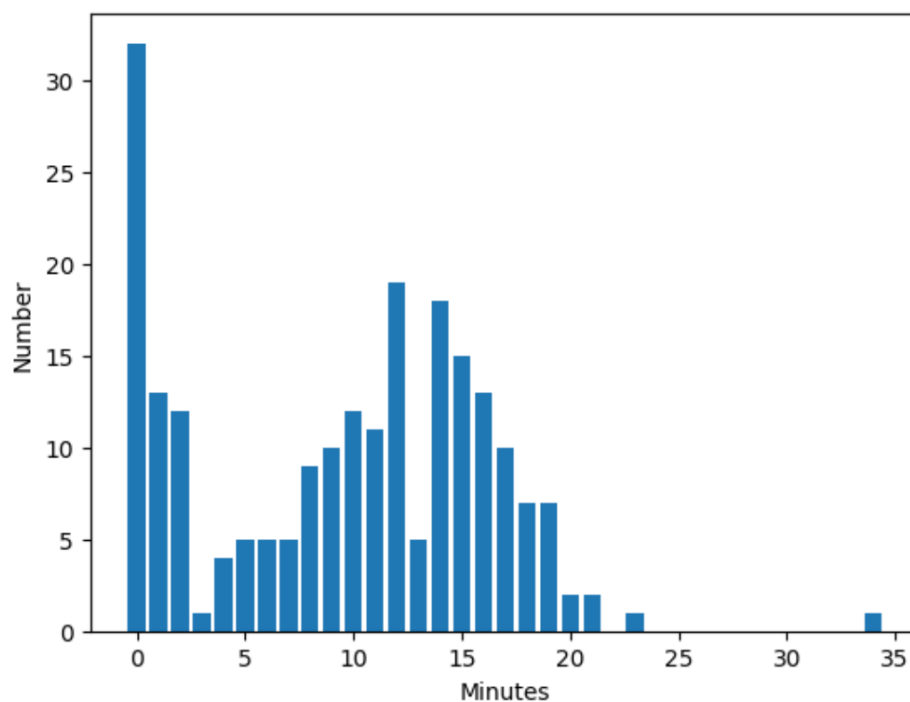

Figure 5.4: The Distribution of Time Used on Podcasts

Source	SS	DF	MS	F	p-unc	n2
time	4.401	1.000	4.401	2.022	0.157	0.011
segment	0.001	1.000	0.001	0.001	0.981	0.000
time * segment	2.519	1.000	2.519	1.157	0.283	0.006

Table 5.7: ANOVA Test Results (using time and segment as between-subjects factors)

Correlation with Covariates

We used the Spearman test to further analyze the correlation between attitude change and the four covariates (see Table 5.8). It was found that preexisting viewpoint has a negative correlation (coefficient = -0.356, p-value = 0.000) with the attitude change, but the correlations for the other three covariates (topic familiarity, intellectual humility and user engagement) are not significant.

Result	familiarity	pre_viewpoint	humility	engagement
correlation coefficient	-0.042	-0.356	-0.020	-0.005
p-value	0.311	0.000	0.637	0.898

Table 5.8: Spearman Rank-Order Test Results

6

Discussion

6.1. Interpretation

First, we observed no significant difference in attitude change effects across the various presentation modes (**RQ1**). Exploratory analysis further revealed that neither listening time (duration spent) nor listening style (number of segments played) significantly influenced attitude change. This rules out the possibility that limited exposure to podcast content explains why some participants' attitudes remained largely unchanged. Does this mean our hypothesis is entirely incorrect? Not necessarily. Upon closer examination of the data, we noticed that participants exposed to podcasts were more likely to change their opinions (a higher percentage showed attitude change), particularly in the neutral viewpoint bias condition (see Section 5.2.1). However, this difference was not as significant as anticipated. Besides, the data also shows that podcast has a strengthening effect for user's pre-existing attitudes under the supporting condition, which indicates that there may be some confirmation bias in the interaction with podcasts.

Second, we found significant differences in attitude change across the three viewpoint bias conditions (**RQ2**), which supports our hypothesis. We attribute this to exposure effects [1]. In the condition of SERPs, users tend to engage more with higher-ranked results, leading them to consume more documents reflecting a specific viewpoint [10]. Similarly, for AI-generated summaries and podcasts, users were exposed to content emphasizing a particular viewpoint, as the AI model was instructed to prioritize sources aligned with that perspective.

Third, we found no evidence of interaction effects between presentation mode and the degree of controversiality (**RQ3**). This is not very surprising, given that the presentation mode itself did not have a significant effect. However, we did observe differences between the two types of topics. For moderately controversial topics, the magnitude of attitude change was greater compared to highly controversial topics, particularly for podcasts.

Additionally, we uncovered some other intriguing findings. For instance, participants exposed to podcasts generally preferred podcasts over other presentation modes,

while those in other conditions favored summaries more. This suggests that podcasts may be more engaging or appealing than other presentation modes.

6.2. Limitations and Future Work

The first limitation of our study is the relatively small number of participants. With only 324 participants recruited, the experiment lacks the scale needed to fully realize its potential. In future work, we plan to expand the participant pool and conduct more detailed analyses for each topic. Besides, we have minimal control over the generated podcasts. Although we provided the AI model with basic prompts to guide the viewpoint bias of the content, it's unclear whether the final output accurately reflects that bias. In future research, expert validation could help assess the degree of bias more effectively. Additionally, in this work, we ran our study in different presentation modes separately and compared their effects on attitude change. In the future, we plan to investigate the interaction between different presentation modes by showing the content in two presentation ways. Furthermore, opinion formation is a gradual process, yet we measured participants' attitudes immediately after content exposure. To address this, future studies could involve participants interacting with LLM-based deliberative agents after the task and reassessing their attitudes at a later stage.

7

Conclusions

In this thesis, we conducted a comparative analysis of the effects of three distinct presentation modes—Search Engine Results Pages (SERPs), AI-generated summaries, and AI-generated podcasts—on users' attitude change. To ensure the robustness and comprehensiveness of our study, we designed a controlled experiment in which participants were exposed to content varying across three dimensions: topic, presentation mode, and viewpoint bias.

Our findings revealed that podcasts, overall, exerted a greater influence on users' attitude change, particularly in scenarios involving neutral viewpoint bias and moderately controversial topics. However, the observed differences were not statistically significant. Besides, for all presentation modes, the direction of influence consistently corresponds with the viewpoint bias. Moreover, while the attitude change between the two debated topic types shows significant variation, the degree of controversiality does not alter the impact of the presentation modes.

While the results did not fully align with our initial hypotheses, they nonetheless offer valuable insights that contribute to the broader understanding of attitude formation and change. These findings serve as a foundation for future research in this area, highlighting the nuanced interplay between presentation modes, content characteristics, and user responses.

A
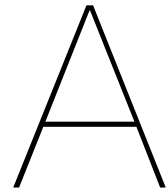
Instructions

A.1. Introduction

In this study, you will be asked about your familiarity with and attitudes toward some topics. You will also be asked to read or listen to information related to these topics and answer questions about them. (Note: You will need to answer some pre-task and post-task questions before and after the main task.)

Please answer the questions honestly. If you are ready, click "Next" to proceed.

A.2. Consent Form

You are invited to participate in a research study on some topics. Before deciding whether to participate, it is important for you to understand why the research is being conducted and what it will involve. Please read the following information carefully before deciding whether to participate.

The study will take approximately 15-30 minutes to complete. The data collected will only be used for research purposes. You will be asked to answer questions about your attitudes toward various topics, including sensitive ones such as abortion and gun control. We recognize that such topics have the potential to cause emotional discomfort.

To the best of our ability, your answers will remain confidential. We will minimize risks by using only IDs to identify users and will not store sensitive personal data.

By clicking the "Next" button on this page, you confirm that you have read this consent form, understand the procedures involved in the experiment, and freely consent to participate in the study. You also understand that your answers will be recorded for research purposes and that your data will be kept confidential. Your participation in this study is entirely voluntary, and you may withdraw at any time.

Do you understand and agree to the above terms?

- I agree.

- I disagree.

B
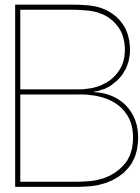
Questionaires

B.1. Intellectual Humility Scale

To what extent do you agree with the following statements?

- If I don't understand something, I try to get clear about what exactly is confusing to me.

- When I don't understand something, I try hard to figure it out.

- I love learning.

- I care about truth.

- I focus on my intellectual weaknesses too much.*

- When I know that I have an intellectual weakness in one area, I tend to doubt my intellectual abilities in other areas as well.*

- When I think about the limitations of what I know, I feel uncomfortable.*

- I tend to get defensive about my intellectual limitations and weaknesses.*

- I have a hard time admitting when one of my beliefs is mistaken.*

- When someone points out a mistake in my thinking, I am quick to admit that I was wrong.

- I am quick to acknowledge my intellectual limitations.

- I feel comfortable admitting my intellectual limitations.

(Note: * denotes item is reverse-scored.)

B.2. User Engagement Scale

To what extent do you agree with the following statements?

- I lost myself in this experience.

- The time I spent on the study just slipped away.

- I was absorbed in this experience.

- I felt frustrated during the study.*

- I found the study confusing.*

- Participating in the study was taxing.*

- The interface was attractive.

- The interface was aesthetically appealing.

- The interface appealed to my senses.

- Participating in the study was worthwhile.

- My experience was rewarding.

- I felt interested in this experience.

(Note: * denotes item is reverse-scored.)
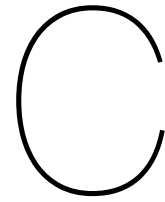
C Results of Pilot Studies

C.1. Pilot Study 1

The data collected in the first pilot study is shown in Figure C.1 and Figure C.2.
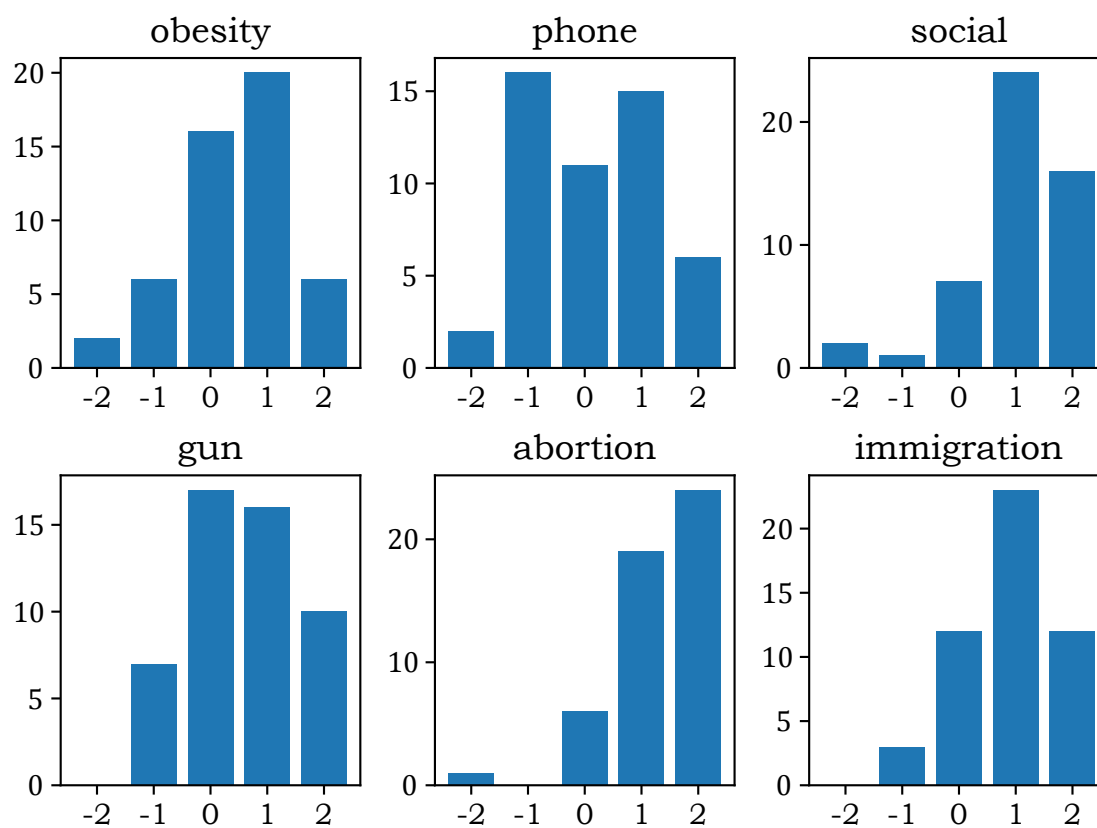

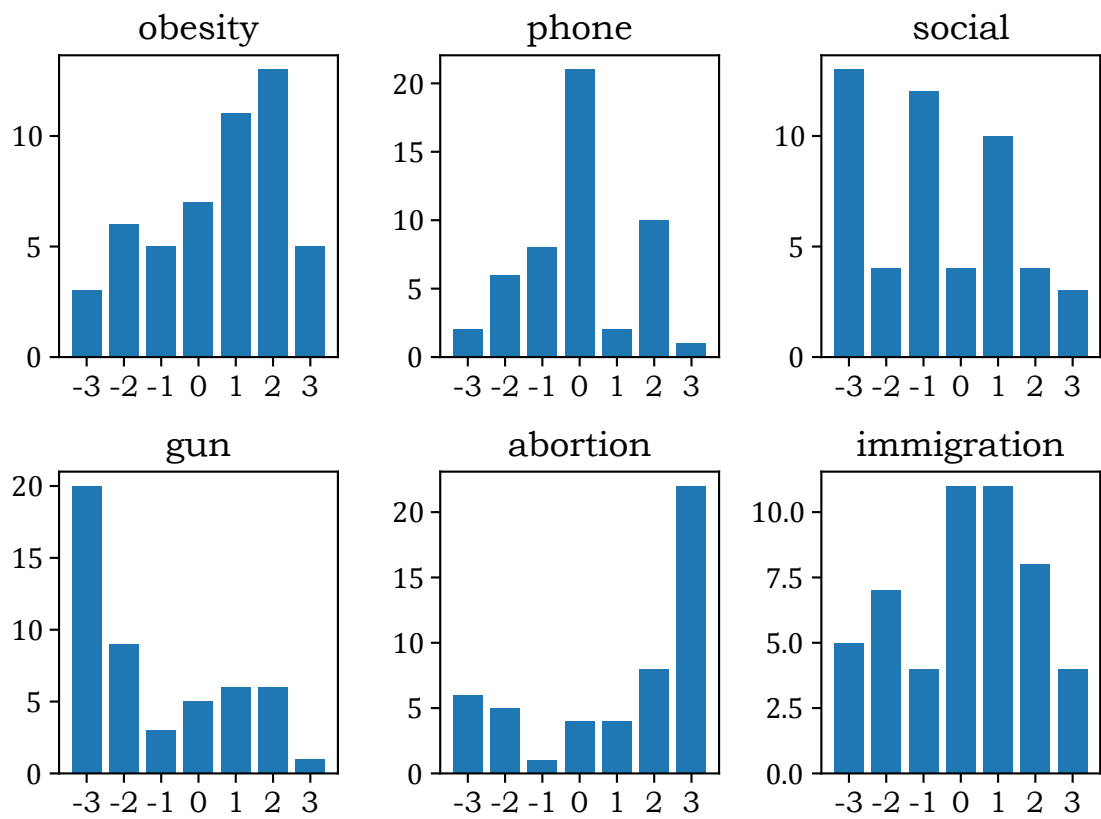Figure C.1: Familiarity Distribution of the Topics

Figure C.2: Viewpoint Distribution of the Topics

C.2. Pilot Study 2

The data collected in the second pilot study is shown in Table C.1.

Group	Condition	Pre-attitude	Post-attitude	Attitude Change
1	supporting + SERP	-1	-2	-1
1	supporting + SERP	2	3	1
2	supporting + summary	-1	-1	0
2	supporting + summary	-1	1	2
3	supporting + podcast	2	2	0
3	supporting + podcast	1	1	0
4	neutral + SERP	-3	-2	1
4	neutral + SERP	3	3	0
5	neutral + summary	2	-2	-4
5	neutral + summary	0	-2	-2
6	neutral + podcast	-2	-2	0
6	neutral + podcast	2	2	0
7	opposing + SERP	1	0	-1
7	opposing + SERP	1	-1	-2
8	opposing + summary	3	3	0
8	opposing + summary	3	3	0
9	opposing + podcast	2	2	0
9	opposing + podcast	-2	-2	0

Table C.1: User's Attitude Change in Pilot Study 2

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