# Towards Detecting and Mitigating Cognitive Bias in Spoken Conversational Search

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## ABSTRACT

Spoken Conversational Search (SCS) poses unique challenges in understanding user-system interactions due to the absence of visual cues, and the complexity of less structured dialogue. Tackling the impacts of cognitive bias in today's information-rich online environment, especially when SCS becomes more prevalent, this paper integrates insights from information science, psychology, cognitive science, and wearable sensor technology to explore potential opportunities and challenges in studying cognitive biases in SCS. It then outlines a framework for experimental designs with various experiment setups to multimodal instruments. It also analyzes data from an existing dataset as a preliminary example to demonstrate the potential of this framework and discuss its implications for future research. In the end, it discusses the challenges and ethical considerations associated with implementing this approach. This work aims to provoke new directions and discussion in the community and enhance understanding of cognitive biases in Spoken Conversational Search.

## CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; • **Information systems → Users and interactive retrieval**.

## KEYWORDS

Cognitive Bias, Spoken Conversational Search, Information Seeking, Physiological Signals, Wearable Sensors, Experimental Design

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## 1 INTRODUCTION

The rapid advancement of generative AI has been swiftly integrated into our everyday systems and acted as our personal assistants. For example, Bing Chat on search engines. This advancement marks a transition from traditional query-list-examine to conversational question-answering in information searches. Although such interaction is primarily text-based with limited access, the trend is evolving towards multimodal capabilities in personal devices, exemplified by the partnership between GPT-4o and Apple.[1] This offers broader accessibility through voice-based interaction, paving the way for Spoken Conversational Search (SCS). While this advancement can benefit various groups with limited access (e.g., visually impaired) [33] and those in situations where reading isn't feasible (e.g., driving or exercising) [80], delivering user-friendly yet relevant responses remains a challenge, especially due to limitations in cognition (in processing, analyzing, and interpreting information) and that of the voice channel itself [77, 115, 122]. Search engines act as intermediaries of knowledge making it crucial for such systems to curate relevant yet diverse content to foster balanced viewpoints (avoid "echo chambers" [8]) and overcome cognitive limitations and biases.[2]

However, screen-based web search benefits from well-defined tools and standard protocols to visualize and study bias behaviors, such as eye-tracking [17, 22, 42, 129] and click-through logs [26,

[1]OpenAI and Apple announce partnership to integrate ChatGPT into Apple experiences. Retrieved 10 June, 2024 from https://openai.com/index/openai-and-apple-announce-partnership/

[2]For instance, researchers have already raised concerns about biases in personalized informatics [124], or Conversational Search [100].

59, 106]. Such methodologies are not established for SCS, which calls for instruments, methodology, and protocols that go beyond the visual paradigm [35]. Regarding this, our contributions in this position paper are three-fold: (i) discuss the applicability of behavior analysis tools used for web search to SCS and identify research opportunities for exploring cognitive biases in SCS, (ii) propose approaches to design experiments, from setup formats to measurements, with preliminary results demonstrating the potential of using multimodal physiological signals as a voice channel equivalent to eye-tracking in web search, (iii) outline challenges with suggestions and ethical considerations for adopting our approach to achieve accurate and representative results from multimodal signals.

# 2 BACKGROUND

## 2.1 Spoken Conversational Search

Conversational information seeking (CIS), the process of obtaining information through conversations (text, audio/voice, or multimodal), is a fast-developing research area [91, 128]. CIS supports users to search for information through natural language. It enables users to ask questions, refine their questions, ask follow-up questions, or provide relevant feedback in a natural manner. The interaction of such systems could either be single-turn or multi-turn. In contrast to a single-turn, a multi-turn setting typically maintains the conversational context (e.g., co-reference resolution)[3] in a back-and-forth information exchange with the user [128]. Some advantages of multi-turn CIS include alleviating the cognitive burden on the user by breaking down the information, assisting with information need formulation, or providing highly personalized information for a given context [113]. While context management may be relatively trivial for a CIS system, users also have to perform context management subconsciously. This would require significant cognitive effort from the user, particularly when the conversation gets longer, and the task gets more complex. This paper focuses on SCS, a type of CIS, where communication between the user and system is entirely mediated verbally through audio [109]. Visual CIS interfaces often use screen-based cues like boldfacing important sections of text [20], or attributing sources within the responses of text-based CIS [61], large language model (LLM) based conversational agents [11, 62, 99]. These cues aid users in effortlessly finding information. However, in linear channels like SCS, users may struggle to keep up with presented information, due to limited cognitive capacity and audio features (e.g., prosody) that can affect their understanding [20].

## 2.2 Cognitive Biases in Information Seeking

Cognitive biases "are systematic errors in judgment and naturally occurring tendencies that skew information processes, due to limitations in cognitive, motivational, or environmental factors, which lead to sub-optimal or fundamentally wrong outcomes" [121]. It is based on the cognitive load theory [107] that humans have limited cognitive capacity, so they tend to favor mental shortcuts of other judgments (e.g., system ranking, or crowd opinions) [8, 104]. Information seekers often rely on perceived trustworthiness when accessing information, constructing mental models to link various pieces of information [59]. This process may influenced by cognitive biases [8]. In particular, the information cherry-picking will likely be affected by the order (rank) (*Order Effect*), imbalanced viewpoints (*Exposure Effect*), a prior judgment (*Confirmation Bias*), the first piece of information (*Anchoring Bias*) or *Misinformation* [18, 59, 82, 104]. This can lead to uncritical support for partisans, reinforce stereotypes, and spread misinformation [8, 21, 59]. Conversely, it can also help users effectively navigate overwhelming information. Therefore, the impacts of these biases must be studied to provide accurate in situ information in SCS. Common methods for measuring cognitive bias in web search include web-logging metrics like sentiment analysis, dwell time, clicks [26, 30, 59, 106], and eye-tracking [17, 22, 42, 129].

However, there is a lack of research on biases in voice-based systems. Eye-tracking is unavailable on these systems, and web logging has limitations in providing granular data [21, 106]. Additionally, recent work found inconsistent results using NASA-TLX for mental load [37], suggesting traditional self-reports may be unreliable. These emphasize the need for fine-grained data, such as physiological data from wearable technology.

## 2.3 Neural Activities for Cognitive Bias

The human brain is divided into several regions in charge of different functionalities. For example, the frontal lobe handles decision-making, motivation, and focus, while the temporal lobe is responsible for auditory and language processing [66]. Investigating how neural activities traveled across regions provides a window look into the flow and processing of information within the brain [64, 71]. For example, researchers have measured the workload change in web browsing [47] and understood search intentions [75, 76] or keyword relevance [123]. Listening effort refers to the cognitive resources people spend on listening [34, 89]. The audio information is first stored as a "buffer" in working memory, then processed for comprehension, and then potentially stored in long-term memory [89, 93]. During this process, information that is discrepant with the current mental model or perceived as irrelevant will not be [93], or requires more effort [94] to interpret further. Compared to visually impaired individuals, sighted users generally have a diminished ability to understand and interpret audio information [16] as evidenced by increased cognitive effort in audio-only scenarios [97]. This heightened effort may hinder their capacity for reasoning and critical thinking, that is essential for mitigating cognitive bias [8]. By understanding such cognitive activities involved, we can understand if users encounter bias - e.g., if information only reaches language regions or proceeds to memory retrieval.For instance, users expend more cognitive effort and attention when assessing information aligned with their beliefs [74]. Additionally, initial judgments during utterances can shape final decisions on a voice's believability [46].These results suggest a hypothesized process where language regions activate first, followed by comprehension and working memory assessment. If the information is deemed irrelevant or dissident, it will be discarded without further processing across brain regions, leading to biased decisions [71]. Advances in wearable devices have enabled physiological sensing to detect cognitive bias in web searches, relying on grounded theories

[3]By "context", we mean the information exchanged during the conversation necessary to interpret the users' response, e.g., the history, preferences, and so on.

(e.g.,cognitive load theory [107], orienting responses [103], cognitive dissonance [28, 90], and dual-thinking system theory [24]). Multi-modal data are discussed later in Section 5.1.

## 3 RESEARCH OPPORTUNITIES

Exploring cognitive biases in SCS offers research avenues, such as characterizing search stages, understanding user behavior, and developing bias detection or mitigation approaches.

**How to Characterize Cognitive Bias at the Different Stages of the SCS Process?** Cognitive bias may occur at each stage of a visual-based search process [8], i.e., querying, consuming the search results, and judging relevance and satisfaction. Previous work suggests variations in search stages or actions [67] (e.g., query formulation/reformulation, results scanning, selection, and assessment) and user behaviors between screen and audio-only channels [113]. Similarly, cognitive biases manifest differently in these search stages for screen and audio-only channels [50]. For instance, users can review and refer back to their query more easily on screens than with voice queries [96]. In SCS, queries are often in natural language [23, 40], and the arrangement of words may reveal user intent [102] and perhaps even reveal any underlying biases. For instance, a user's choice of query formulation between, "Why is renewable energy inefficient?" and "What are the efficiencies of renewable energy?" may indicate preconceived beliefs, potentially leading to biased search results. Furthermore, detecting cognitive biases in the query stage can be complicated by users' false memories(misremembered attributes of searched items), as they may not easily accept misremembering [52]. To this end, we highlight the significance of investigating cognitive processes at various stages of SCS interaction (e.g., detecting false memories at the query stage).

**What Is the Role of Clarifying Questions in SCS? How Is It Related to Cognitive Bias?** In CIS, the dialogic nature makes query reformulation and clarifying questions more critical and frequent, supporting conversational actions [3, 112, 128]. Users often iteratively refine queries by referring to previous responses to narrow down or expand their initial query [128]. Cognitive biases may influence this iterative process. For example, if the information aligns with users' beliefs they may accept it without further questioning. Conversely, if it opposes their beliefs, they may reformulate the query to find results that align with their expectations. This means that considering a user's reformulation/clarifying questions can help to detect potential bias. Consequently, presenting strategies for clarifying options becomes as important as providing relevant responses in SCS. Different presentation strategies may affect user satisfaction and their arrangement and format may reinforce certain types of biases (e.g., confirmation bias). this is a research challenge that has not been explored in SCS.

**Can Voice Modulation Be Used to Characterize Cognitive Bias?** While eye-tracking is not feasible in voice interactions, audio attributes (e.g., pitch and speed) from both the system and user reveal information about motivations, emotions, and personal traits [58]. For instance, Jiang et al. [46] indicated that perceived *information believability* is affected by the confidence in the voice of the system. Additionally, a recent work, found higher trust in female-voice agents that higher pitch reduces participants' decision-making reliance on the provided information [38]. These examples illustrate how voice modulation in systems affects information perception. Currently, we lack understanding of how system voice modulations might influence user beliefs or reinforce biases like *confirmation bias*, presenting an open research challenge. One potential solution is to slow down the system when discussing controversial opinions, allowing users ample time to absorb and consider. Besides, an important direction is the relationship between biases and user voice modulation. For instance, a skeptical tone and higher pitch when querying, "Is climate change REALLY [accentuate] happening?" may indicate *confirmation bias* towards the belief that climate change is not a real issue.

**How to Leverage Content Manipulation to Mitigate Harms of Cognitive Bias?** Cognitive bias does not always have a negative effect [69]. While it can skew perceptions and decisions, it also helps balance perspectives [53]. For instance, *Availability Bias* refers to placing greater importance on readily available or easily recalled information. A way to counteract it is by presenting less readily available information first. However, this solution may raise concerns about group fairness and misinformation spread. Recognizing and understanding the impact of cognitive bias helps address potential pitfalls and leverage its potential to create effective and user-friendly search experiences. Furthermore, audio interventions in voice-based conversations (e.g., nudging for clarifying questions [37], or warning users of presence of misinformation in a voice-based setting [19]) offer a potential solution to inform users of potential biases in SCS.

## 4 CASE STUDY: ARGUMENT SEARCH

Expanding on our identified research opportunities, we introduce a SCS specific use case called Spoken Conversational Argumentative Search (SCAS) and discuss its implications, data, topics, and methodology for experimentation (see Section 5). SCAS systems respond to a user's spoken query on controversial topics with multiple argument stances or viewpoints (i.e., PRO and CON). Users can rely on SCAS to provide them with balanced arguments on topics of interest. Let us consider an example in which, a user asks "is universal basic income good for society?". If the system only provides one side (i.e., PRO) of the issue, the user tends to be blind-sided by not having any information about other perspectives [36]. Such a biased exposure of perspectives is an important open challenge [85] if left unaddressed, may negatively impact society [12, 26, 114, 126]. Biases can arise from data itself as much as they can from algorithms [86] and presentation strategy in voice-only settings. Hence, choosing appropriate data is crucial when studying cognitive biases in SCS to control for unknown effects (from the data).

**Data.** For our specific case study, designing experiments requires argumentative topics (e.g., "should zoos exist?") and documents/passages supporting (PRO) and opposing (CON) the topics. A crowdsourced study by Draws et al. [26] collected opinions from 100 participants on 18 topics from the ProCon.org debate portal[4]; only a few topics identified with mild pre-existing viewpoints. Incorporating these topics into future experiments on cognitive bias is crucial to avoid heavily polarized subjects and better detect the effects of cognitive bias. The current dataset, with only 280 search results, may be insufficient for longer conversations. Therefore,

[4] https://www.procon.org/debate-topics/ [Accessed: 9 Feb 2024]

we propose expanding the collection with the args.me corpus [2], which not only includes arguments with stances (PRO or CON) but also offers additional granularity by providing sub-topical perspectives (e.g., Capitalism, Healthcare, and Poverty) for each document. This increased granularity will also aid in mitigating unknown effects in future experiments.

# 5 METHODOLOGY

This section outlines an experimental framework for studying cognitive biases in SCS, covering potential experimental setups and data collection, including behavioral and physiological data. Additionally, we showcase preliminary results from an information-seeking experiment as an example of this approach and the potential of physiological data. The less structured nature of conversational interactions and the lack of clear indicators of comprehension or focus, i.e., listening effort (see Section 2.3), make it challenging to identify and measure specific biases in SCS. This section outlines an experimental framework for studying cognitive biases in SCS, including possible setups and measurements. Table 2 categorizes applicable measurements into Behavioral and Physiological Responses. It also showcases preliminary results as an example of this approach and the potential of physiological data. To accommodate the various needs of research questions and their associated experiments, including feasibility, scalability, research method (qualitative, quantitative, mixed), Table 1 covers potential experiment set-ups, including their advantages and disadvantages.

## 5.1 Measurements

**Behavioral Responses.** In SCS, *natural language utterances* function as queries [96] and the **Voice modulation** (see Section 3) of these raised queries distinguishes it from traditional screen-based search. In a case of rectifying system errors[5], users typically adjust volume, rephrase commands, or change pronunciation [120]. When the system's response contradicts their beliefs, users, especially those less tech-savvy, might confuse cognitive biases with system errors. They may then try familiar methods used for system errors to get preferred outcomes, potentially introducing bias. Speaking of querying, users' listening habits can also be used to investigate biases in SCS. Listening effort or speech intelligibility is assessed by the recalled accuracy, as indicators of attention and language-related cognitive processing [93], in **recall/recognition tasks** like word/sentence recognition and sentence comprehension [16]. This may also reveal biases, as users often comprehend biased information more easily due to lower cognitive load [10], but it still lacks granularity. It is worth noting that confounding variables like language proficiency [51] and working memory capacity [32, 89] can also impact listening performance [16] potentially introducing biases in information comprehension. A potential solution to address these pitfalls is adapting Brief-IAT [105] – a version of the Implicit Association Test (IAT) [39] designed to assess bias [25] . However, implementing a reliable bias assessment in the SCS remains an open challenge and requires more attention from the community.

**Physiological Responses.** Cognitive bias can be measured by examining differences in cognitive processes, emotions, and engagement. For instance, a user may be more engaged and emotionally aroused at the end of an audio segment. Multi-modal sensing with wearables can capture these responses, offering a scalable and comprehensive way to 'visualize' cognitive bias in SCS, analogous to using eye-tracking for screen-based IR systems. **Electroencephalography (EEG)** gathers brain electrical activity, aiding in studying cognitive and emotional processes such as memory, attention, and responses to stimuli [15, 55, 64]. EEG has shown promising results in web search, detecting relevance judgment at both article level [4, 41] and word level [123], and identifying information needs in Q&A scenarios [70]. Two common ways EEG signals are analysed [73] are Event-Related Potentials (ERP) and Frequency Band Analysis. **ERP** is a time-locked analysis describing cognitive activity after an event's onset [64]. Typically analyzing signals within a short time window (e.g., 1 second) [31, 70, 123], which may potentially help with detecting biases in each turn of a conversation in SCS. On the other hand, **Frequency Band Analysis** is typically used with longer stimuli durations (e.g., 1 minute) and can potentially help explore biases at the whole session level, rather than just per turn of the conversation. The latter explores various wave frequencies linked to cognitive states (e.g., alpha for attention [71, 74], theta for memory [72], beta for active thinking engagement [125]) [55]. The works above focus on brain waves in the frontal cortex related to human attention, memory, decoding, and retrieval. While they were explored in a screen-based IR context, we emphasize their potential in SCS as well, to explore cognitive biases. With current wearable EEG devices (e.g., headbands [78] and earbuds [29]) being integrated ubiquitously into earphones [1, 7], we foresee opportunities to expand research on biases in SCS through crowdsourced studies, thus lowering barriers for many researchers. Additionally, **peripheral signals** from commercial wearables, such as Electrodermal Activity (EDA), Photoplethysmography (PPG), and Skin Temperature (SKT), can complement EEG [6, 15]. **EDA** measures the variations in skin's electrical conductance driven by sweat gland activity. **PPG** uses light to measure blood volume changes and to derive heart rate, blood oxygen levels, and other related metrics. **SKT** reflects the balance between the body's heat production and heat loss. These data indicate emotional responses from different aspects. For example, high arousal triggered by stressful events, often increase perspiration (sweating), leading to elevated EDA levels [9, 15, 54], or a rapid increase in heart rate (manifests as shorter intervals between PPG peaks [15, 54, 88]). Besides, EDA decreases when individuals are highly engaged (and thus less aroused) [54] and SKT generally decreases in low valence [54]. Furthermore, **pupillary responses** have been used to investigate selective attention [93], auditory distraction [65], and listening efforts [89]. For voice interaction, wearable eye-tracking glasses, e.g., Pupil Labs Neon glasses [56], can provide such a channel. However, pupil data is most suitable for lab studies with consistent lighting.

[5] A *system error* occurs when the system fails to provide users with the desired results, regardless of whether it is caused by an incorrect response or lack of a response.

**Table 1: A breakdown of different experiment set-ups (i.e., Lab, Field, and Crowdsourced) in *SCS*. LLM: large language model**

| Features | Lab Study | Field Study | Crowdsourced Study |
|---|---|---|---|
| **Control** | High | Low; unobserved factors in real-world | Moderate; depends on the design of platform or task |
| **Data Quality** | High and detailed; due to highly controlled and optimal environment | Low; real-world noise and factors may affect data | Moderate; less controlled than lab studies. |
| **Scalability** | Low; requires physical attendance on both participants and researchers | Moderate; enables more participants than lab studies but still limited | High; enables larger participant pool from diverse locations. LLM applications like Retrieval Augmented Generation (RAG) [61] show potential for controlled studies [83, 87] |
| **Ecological Validity** | Low; the artificial setting may influence behavior | High; since participants are in natural environments | Moderate; the absence of a physical entity (e.g., smart speaker) may influence user information perception [57] |
| **Setup** | Wizard of Oz (WOZ) [27, 111, 116] | Participants are provided with pre-configured voice agents and wearable devices to take home [120]. Comfortable and portable devices may facilitate longitudinal studies. | Crowdsourcing platforms like Prolific enable simulating always-on voice assistants for hypothetical scenarios. Consumer products like Apple AirPods with EEG [7] will make crowdsourced studies more feasible. |
| **Related Works** | [13, 45, 79, 109, 111, 113] | [118–120] | [43, 108] |

**Table 2: A Breakdown of studied measures by data type (Behavioral vs. Physiological) and user interaction mode (screen-based vs. voice). Bold text highlights studies on cognitive biases, emphasizing the limited research on cognitive biases in voice search (i.e., SCS).**

| | Data Type | Screen-based | | Voice | |
|---|---|---|---|---|---|
| | | Construct | Related Work | Construct | Related Work |
| **Behavioral** | Web-logging (e.g., dwell time, clicks) | **Cognitive Bias** | [26, 59, 106] | – | |
| **Behavioral** | Transcripts & Voice Modulation (e.g., pitch, speed) | – | | Perceived Trust | [38, 63] |
| **Behavioral** | Task Performance (e.g., sentiments of query/utterance, recall rate) | **Cognitive Bias**<br>Search Experience | [30]<br>[68, 98] | Listening Effort<br>Search Experience | [16, 49, 51, 89, 97]<br>[49, 98] |
| **Behavioral** | Motion, Facial Expression, Gaze | – | | Engagement | [81, 84, 84] |
| **Physiological** | Brain Signals (e.g., EEG) | Cognitive Workload<br>Search Experience<br>**Cognitive Bias** | [47, 72]<br>[4, 41, 70, 75, 123]<br>[10, 71, 74, 125] | Perceived Trust | [46] |
| **Physiological** | Peripheral Sensing (e.g., EDA, PPG) | **Cognitive Bias** | [14, 71, 90] | – | |
| **Physiological** | Pupillary Responses | Selective Attention | [41, 93] | Selective Attention<br>Distraction<br>Listening Effort | [93]<br>[65]<br>[89] |

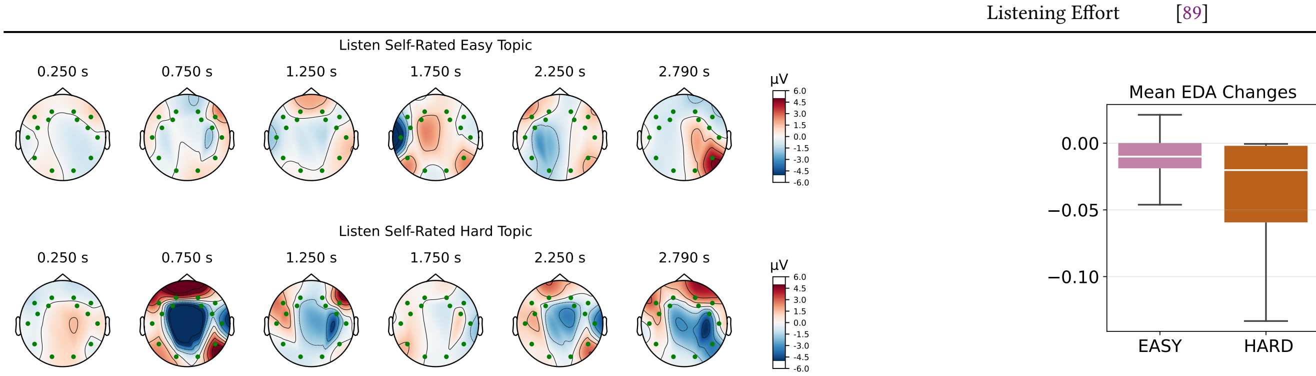


**Figure 1: Preliminary EEG (left) and EDA (right) results ($N = 7$) of grand average on listening to search results (about 1 minute) on self-rated *easy* (Antarctica exploration – R03.353) and *hard* topics (Freighter ship registration – T04.743). In the left figure, deeper colors indicate greater neural activity. Cool colors (negative voltage) represent inhibitory, i.e., suppressing or restricting neural responses, while warm colors (positive) represent excitatory, i.e., promoting or enhancing responses [64]. The dots represent the placement of 14 electrodes.**

### 5.2 Preliminary Results

We used the EEG and EDA data collected by Ji et al. [44] for illustration purposes.[6] They collected various physiological signals from wearable devices in a lab study with simulated information search settings. Each participant completed a search task and rated the perceived difficulty in understanding the provided information on 12 topics. We analyzed data from 7 participants who received search results in audio formats on both most *easy* ($\overline{\mu}$ 1.3/5.0) and *hard* ($\overline{\mu}$ 3.0/5.0) topics (according to self-ratings). Although bias was not the target manipulation, the difficulty reveals changes in cognitive efforts required to receive the information. Figure 1 demonstrates clear differences between the *easy* and *hard* topics in both results. Overall, there was less neural activation on *easy*. Increased positive voltages around 1.75s in most regions suggest focused attention and engagement. Meanwhile, the left temporal negative may indicate reallocating cognitive resources from auditory processing to other areas needing more processing power. On *hard*, heightened activation was observed early at 0.75s. Pronounced prefrontal/frontal peaks suggest deeper processing and working memory load related to understanding the information. Enhanced activation at temporal regions, which handles the auditory and language processing, indicates increased comprehension effort and knowledge recall. EDA exhibits more consistency on *easy*, while much greater variability and fluctuation on *hard*. This suggests increased arousal or stress when absorbing difficult information in the audio. **In summary**, these preliminary results suggest that observing users' auditory information consumption is viable and warrants further exploration. Multi-modal signals may offer insights into fast and slow thinking systems [24, 48], and combining behavioral data with wearable signals could accurately identify user behavior, preferences and biases in SCS.

## 6 LESSONS LEARNED & ETHICAL CONSIDERATIONS

SCS interactions are less structured than screen-based interactions, which complicates analysis. Physiological data show distinct changes in receiving audio search results but interpreting cognitive biases is still complex. To ensure collect reliable data, these factors should be considered when designing the experiment: (i) data with more channels (e.g., 14+ channel EEG) offers direct insights but involves noise and requires specialized designs and expertise, while with fewer channels (e.g., peripherals) is easier to analyze, (ii) longer activities provide more reliable data, but SCS often involves short tasks, (iii) confounding variables like fatigue, interest, health, and specific activities (e.g., speech) may significantly impact. It is important to ensure optimal contact between sensors with specific body areas (e.g., see [9]). Furthermore, given biases are abstract concepts, the related hypotheses should be deconstructed into specific constructs, like engagement or cognitive load, and further into direct indicators that are measurable, reliable, and objective [95, 117], such as skin conductance or reaction time. During analysis, the requirements of signal processing on frequency can make certain features unavailable or distorted, especially those associated with high frequency in PPG [88]. Besides, analyzing SCS transcripts requires extensive effort and qualitative approaches as demonstrated in earlier works (see [110, 113]). For **ethical considerations**, it is crucial that informed consent and participant awareness of the exposure levels as physiological data could compromise privacy by revealing thoughts and emotions [127]. For example, the protocol used by Arnau-González et al. [5] could be adopted in this case. To protect cognitive liberty [92], caution is essential when developing strategies to mitigate biases using multi-modal signals for real-time content manipulation. It is also crucial to account for individual variations (e.g., minority groups, neurological conditions) for accurate and representative results [101].

*Authors' Positionality.* This paper reflects the perspectives shaped by the interdisciplinary backgrounds and views of our author team, which includes computer science researchers in information retrieval, conversational search, human-computer interaction, and pervasive computing. Some of the authors have significantly influenced these perspectives from their work on exploring cognitive bias in screen- or voice-based search, and personal experience as members of the neurodiverse community. The authors acknowledge the complexities surrounding cognitive biases. This paper aims to support a comprehensive discussion on understanding and utilizing biases in SCS. We acknowledge the gap in including perspectives from minority groups, First Nations peoples [60, 126], or people with disabilities.

## 7 CONCLUSIONS

Drawing insights from information-seeking, psychology, cognitive science, and wearable sensors, this paper highlights the underexplored area of cognitive biases in sophisticated voice-only systems like SCS, and advocates further research. We argue that traditional web search instruments are insufficient for studying cognitive biases and envision further research opportunities. Furthermore, we propose a general experimental approach for studying cognitive biases in SCS and report preliminary results demonstrating the feasibility and significance of using physiological responses. Additionally, we discuss the challenges and ethical considerations in adopting this approach.

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[6] EEG are cleaned following Eugster et al. [31], divided into 3sec segments. EDA are cleaned, baseline-corrected following Bota et al. [15], aggregated with a 1sec window.

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