

# Everyday Uncertainty: How Blind People Use GenAI Tools for Information Access

Xinru Tang  
University of California, Irvine  
Irvine, California, USA  
xinrut1@uci.edu

Darren Gergle  
Northwestern University  
Evanston, Illinois, USA  
dgergle@northwestern.edu

Ali Abdolrahmani  
University of Maryland, Baltimore County  
Baltimore, Maryland, USA  
Maryland State Department of Education  
Baltimore, Maryland, USA  
ali.abdolrahmani@maryland.gov

Anne Marie Piper  
University of California, Irvine  
Irvine, California, USA  
ampiper@uci.edu

## Abstract

Generative AI (GenAI) tools promise to advance non-visual information access but introduce new challenges due to output errors, hallucinations, biases, and constantly changing capabilities. Through interviews with 20 blind screen reader users who use various GenAI applications for diverse tasks, we show how they approached information access with *everyday uncertainty*, or a mindset of skepticism and criticality towards both AI- and human-mediated assistance as well as information itself. Instead of expecting information to be ‘correct’ and ‘complete’, participants extracted cues from error-prone information sources; treated all information as tentative; acknowledged and explored information subjectivity; and constantly adjusted their expectations and strategies considering the politics around access. The concept of everyday uncertainty situates GenAI tools among the interconnected assistive applications, humans, and sociomaterial conditions that both enable and hinder the ongoing production of access. We discuss the implications of everyday uncertainty for future design and research.

## CCS Concepts

• **Human-centered computing** → **Empirical studies in HCI; Accessibility.**

## Keywords

uncertainty, generative artificial intelligence, accessibility, blind, screen reader users

## ACM Reference Format:

Xinru Tang, Ali Abdolrahmani, Darren Gergle, and Anne Marie Piper. 2025. Everyday Uncertainty: How Blind People Use GenAI Tools for Information Access. In *CHI Conference on Human Factors in Computing Systems (CHI '25)*, April 26–May 01, 2025, Yokohama, Japan. ACM, New York, NY, USA, 17 pages. <https://doi.org/10.1145/3706598.3713433>



This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

*CHI '25, Yokohama, Japan*

© 2025 Copyright held by the owner/author(s).

ACM ISBN 979-8-4007-1394-1/25/04

<https://doi.org/10.1145/3706598.3713433>

## 1 Introduction

We are amidst a moment in which information access for blind people is increasingly bound to Generative AI (GenAI), as evidenced by the integration of GenAI models into mainstream assistive tools [40, 47, 95, 97]. Built on large language models (LLMs) and large multimodal models (LMMs), such as GPT-4 [3], emerging GenAI tools have led to a growing interest in making text, code, images, visual interfaces, audio, and videos more accessible to people with disabilities (PWD)<sup>1</sup> [44, 52, 134], particularly blind people [4, 27, 59, 83]. These emerging capabilities have accelerated research at the intersection of GenAI and accessibility [4, 27, 41, 43, 44, 59, 89] as well as commercial applications for blind people, such as Microsoft Seeing AI [97], Picture Smart AI in JAWS [40], Be My AI [38, 105], and Aira Access AI [47].

Yet, we are only just now beginning to understand how blind people use applications of generative models across diverse tasks and contexts, such as text generation [4], information seeking [4], image generation [27, 59, 83, 91], data visualization [114], and graphical user interface navigation [77]. As use cases and opportunities for AI-powered access have expanded, so have the challenges. Prior work has documented the technical limitations of generative models for access [4, 6, 44], lack of quality and representative data [41, 69, 89], inaccessible interfaces and interaction mechanisms [4, 6, 27, 44, 59], and the diverse range of accessibility needs in different contexts [45, 100, 121]. Building completely error- and bias-free models appears to be an unrealistic goal [88, 94], making it ever-important to study how blind people understand and adapt to these limits inherent in GenAI, as resonated with the growing recognition of uncertainty as a central theme in AI and machine learning (ML) scholarship [14, 18, 74, 109].

Extensive AI/ML work has explored uncertainty from a computational perspective, often focusing on the establishment of quantitative estimates of confidence that exist around model predictions and how they influence technical decisions such as algorithm choice, feature selection, and parameter tuning [1, 132]. Other work pivots to examine the human side of understanding and interpretation of model output [109]. Such work is often concerned with how

<sup>1</sup>We use person-first language when referring to people with disabilities as a larger group and identity-first language to reference specific groups (e.g., blind people), noting that people have different preferences in the usage of language [115].

to best convey uncertainty in model outcomes, such as what are the best ways to present prediction uncertainty through data visualizations [60], and whether such representations lead to more accurate inferences or simply serve to further confuse people. A related and growing area of study involves conveying the uncertainty inherent in broader applications of generative models. This research examines, for example, the extent to which transparency in the conveyance of uncertainty through various stages of the technology pipeline affects people’s trust and reliance on the information provided [18, 74, 109]. Despite these valuable insights, this line of work often neglects the broader sociomaterial context that shapes how people reason about uncertainty with respect to information-seeking and its access.

To expand our empirical and theoretical understanding of uncertainty, we analyze the practices of blind screen reader users who use GenAI applications for diverse activities, such as image understanding, document reading, online search, and visual-spatial concept learning. Studying uncertainty in the context of blindness is important and could provide valuable insights given that blind people regularly grapple with inaccessible information, such as when they navigate busy streets [136, 142], read documents [82], browse the web [20, 65, 82], and take and share photos [66]. The pervasive applications of GenAI introduces new possibilities but also complexities for blind users, particularly given the constant change, invisibility, and inscrutability of AI [8, 144, 149]. Difficulties also present for screen reader users to evaluate or verify model output when it contains inaccessible visual elements [4, 6, 27, 44]. This constellation of challenges coupled with the momentum of AI-powered accessibility tools makes it crucial to develop a more nuanced and comprehensive understanding of how blind people interact with GenAI in the context of uncertainty as well as how GenAI is shaping their information access more broadly.

Drawing on interview data with twenty blind screen reader users, we find that participants approached information access with a mindset of *everyday uncertainty*, which we define as skepticism and criticality towards both AI- and human-mediated assistance as well as information itself. That is, uncertainty associated with model output, while important, is only one small part of the process of reasoning about uncertainty in information access. Instead, everyday uncertainty arises from the ongoing and situated working out of one’s understanding through imperfect tools and variations in human assistance. Consequently, participants learned to extract meaningful cues from error-prone information sources; treated all information as tentative and progressively updated their understanding over time; acknowledged and explored information subjectivity; and constantly adjusted their expectations and strategies considering the politics around access.

This study makes three primary contributions. First, we introduce the concept of *everyday uncertainty*, which broadens how we understand the role of GenAI tools within the situated, ongoing process of information access. Expanding beyond contemporary notions of uncertainty as a quantitative metric or attribute of probabilistic models, we theorize uncertainty as an everyday mindset that blind people living in a world dominated by sighted-first thinking and inaccessible information contend with daily. The concept contributes a system-level perspective on the process of information access, which situates GenAI tools among the interconnected

assistive applications, humans, and sociomaterial conditions that both enable and hinder the ongoing production of access. Second, our analysis contributes to the growing literature on uncertainty in HCI [18, 26, 36, 113, 119], providing a novel empirical case of the experience of uncertainty among PWD that contrasts with previous contexts of study such as disaster risk, healthcare, finance, and cybersecurity [113, 119]. Third, drawing on the concept of everyday uncertainty, we provide actionable recommendations for AI-powered access technology to go beyond existing precision-oriented goals (e.g., accuracy, bias mitigation) and evaluation metrics.

## 2 Related Work

### 2.1 Blind People’s Everyday Access

Despite improved digital access with assistive technologies like screen readers [9, 39, 96, 103], inaccessibility remains a day-to-day experience for blind people [65] due to pervasive inaccessible documents [79], webpages [20], visual-based features [12, 32], images [99, 137], and mobile applications [7]. Additionally, there is still a lack of shared guidelines for essential accessibility features like alt-text [16, 34, 53] and data visualizations [35]. Even with standards such as the Web Content Accessibility Guidelines, enforcement remains inconsistent [127]. As a result, blind people often spend significant time navigating different systems [112], developing workarounds and individual solutions [117].

Beyond digital contexts, inaccessibility is also pervasive in blind people and other PWD’s everyday life, considering the lack of reliable accessibility services [126, 140], standards [55], social acceptance of disability [72], as well as the complexity and emergent nature of access needs [17, 56, 90]. For instance, for blind people, remote human assistance services such as Be My Eyes are not always reliable due to factors like unfamiliarity with blindness and technical limitations like internet issues [84, 86]. Even trained professionals like Aira visual interpreters might encounter challenges ranging from information acquisition to social engagement [85]. The poor quality or inconvenience of such assistance not only hinders task completion but can also undermine one’s sense of independence, fostering feelings of losing control over their access and hesitation in seeking human support [84].

As a result, developing creative accessibility solutions is a widely shared disability experience [104, 133, 140]. Prior work shows that access is deeply conditioned in sociomaterial contexts [101], involving constant negotiation among individuals with and without disabilities, assistive tools, and environment affordances [15, 17, 28, 33, 138]. For instance, blind people construct their living world through dynamic interactions and emergent actions [33], such as by using white canes to gather environmental cues [142], collecting embodied cues from sighted guides [33], and seeking out human assistance [84]. This interconnected nature of access makes it important to examine how GenAI tools fit into PWD’s existing practices for access. However, most research on GenAI for accessibility has focused on the utility of specific tools for isolated tasks or as standalone applications such as ChatGPT’s utility for text summarization, writing template generation, and image description [4, 44]. This model- or tool-focused approach might miss important accessibility issues or design opportunities (e.g., inconsistent standards

for accessibility [127], or combined use of multiple tools for access needs [117]). Taking a broader view, our study understands how blind people skillfully use GenAI tools alongside other resources to meet their access needs.

## 2.2 Studying AI with and for Blind People

Despite the long history of studying AI with and for blind people [129], HCI and accessibility research has primarily focused on training AI for bounded tasks like image description, object detection, and text recognition [42, 111]. This work has centered around visual question answering [129], from dataset creation [21, 49, 50, 73, 116, 128, 150] and model development [19, 24, 130] to understanding user experiences [45, 92, 143, 152]. However, these applications often fall short in meeting the dynamic and context-dependent information needs of blind people [121], such as experiential needs required for personal photos [66]. To address individual needs, personalized and teachable AI has gained increasing attention, but these applications still often operate as end-to-end systems with fixed labels [100, 116, 128].

The rapid evolution and integration of GenAI models into today's applications bring rich potential for more open-ended exploration with AI. Recent research has tried to integrate GenAI models in diverse application contexts for blind people, including graphical user interface navigation [77], image creation [59, 83], video description [135], and data visualization [114]. However, existing GenAI tools still exhibit shortcomings in serving blind people and other PWD due to inaccessible interfaces [4], embedded ableism [41, 91], shortage of training data [22, 69], and lack of robust verification mechanisms [27, 44]. While earlier research suggests blind people might overtrust AI-generated image descriptions [92], distrust towards AI systems is more common as limitations in AI models become more recognized [4, 6, 45, 58]. Blind people worry about AI errors that could cause social embarrassment or safety concerns such as in health information [4], social photo sharing [152], and recognition of bathroom gender signs [2]. Increasing research is focused on blind users' interactions with AI errors, such as their verification strategies, which uncovers blind users' abilities in detecting AI errors using contextual cues or other tools like search engines [6, 45, 58].

However, GenAI models' opacity and constant change pose additional challenges, as it is difficult to predict the models' capabilities and limitations [8, 144]. Research shows that blind users experiment with and develop knowledge of AI applications in low-risk and known settings to (con)test AI systems [6, 45, 58], a daily practice Gonzalez et al. coined as "practice ground of visual landscapes" [45]. For researchers, this ongoing updating of use can make it hard to determine how long existing findings and solutions around specific GenAI models will apply in the future. Being aware of these challenges, our study analyzes how blind people adapt imperfect information and tools into their everyday process of information access.

## 2.3 Uncertainty in HCI and Human-Centered AI/ML Research

Uncertainty is a pervasive concept in HCI and machine learning scholarship [120], leading to a 'conceptual overload', with varying

interpretations even within the same field of study [120]. Moreover, numerous related concepts, such as instability, risk, and ambiguity, are frequently used interchangeably with uncertainty, while others, like confidence, reliability, and trustworthiness, are often discussed in similar contexts [110, 118, 146]. Traditionally, uncertainty has been viewed as a problem to be solved [51, 119, 120]. This perspective is reflected in efforts to measure [13, 18], control [81, 110], visualize [36, 60, 71], and understand human perceptions of uncertainty related to computing systems [74]. Additionally, research on uncertainty has often been conducted from the lens of risk management and discussed in risk-sensitive contexts like disaster risk, healthcare, finance, and cybersecurity [113, 119]. In machine learning, uncertainty, arising from the statistical nature of model output, could occur at any stage of deployment [70, 88]. Some research acknowledges this uncertainty inherent in machine learning and focuses on design opportunities associated with model uncertainty [14], such as improving communication with end-users about model mechanisms and output [18, 25, 148]. However, these works still tend to focus on uncertainty within models and rely on a computational understanding.

Recent HCI scholarship and beyond has embraced uncertainty as a natural part of human life [31, 108, 113, 119], suggesting that statistics alone cannot fully capture the complexities. Soden et al. proposed approaching uncertainty from *political*, *generative*, and *affective* dimensions [119]. Along these three dimensions, they encourage critical reflections on the treatment of uncertainty, view uncertainty as an opportunity for design and creativity rather than something to be solved, and invite research to understand the embodied experiences of uncertainty. As one of such efforts, Devendorf et al. showed how uncertainty is a fundamental and embodied experience in parenting, shifting away from the optimization and self-improvement narratives popular in parenting tools [31]. Beyond HCI scholarship, research similarly argued for a critical reflection on the traditional treatment of uncertainty across disciplines like environmental science, healthcare, and finance (see example cases in [113]). Our analysis responds to these calls for situated studies of uncertainty and expands the existing literature with a case in the context of accessibility.

## 3 Method

We interviewed twenty blind screen reader users to understand their practices and desired GenAI experiences. We iteratively refined our interview protocol and performed a reflexive thematic analysis of the data [23].

### 3.1 Participants

Twenty blind screen reader users participated in this study (Table 1). We recruited participants through our academic and professional network, collaboration with the American Foundation for the Blind, and snowball sampling [106]. We distributed a screening survey deployed on Google Forms to help with recruitment. We set the following inclusion criteria for participants: (1) identify as legally blind, (2) use screen readers (and do not use visual magnification tools), (3) located in the U.S. when the study was conducted, (4) speak English, (5) age 18 or older, and (6) have used GenAI tools, broadly construed. We took a broad view of GenAI, covering any

AI that participants see as relevant and can generate content across modalities. We offered all participants \$50 U.S. in cash or an Amazon gift card of the same amount to compensate for their time.

### 3.2 Initial Exploration

As a first step, we informed our understanding of blind screen reader users' use of GenAI tools by analyzing transcripts and video recordings of a blind co-author's naturalistic interactions with ChatGPT, Gemini, and Be My AI. The researcher independently captured usage logs of his exploration of ChatGPT and Be My AI for understanding complex concepts like a radiator panel (with images of the appliance), the layout and components of home roofs in the U.S., details of cultivating hyacinth flowers while gardening, and a comparison of LED light bulbs of different shapes as part of a home repair project. The specific uses of these tools were determined by the researcher's personal information needs and curiosity. The researcher then reviewed the transcripts of interaction and added reflexive annotations about his intentions, goals, and reactions to various portions of activity as it was captured in the logs. Other team members reviewed and asked further questions about these interactions. Additionally, the researcher worked with a sighted collaborator to explore two specific GenAI tools, which were recorded via screen capture for later analysis. The sessions captured the researcher's first experience using (1) ChatGPT to assist in reading a PDF document and (2) Google Gemini to describe the visual layout of a poster. Three researchers read the transcripts, reviewed the videos, and reflected on the interactions together with the blind co-author. Based on this preliminary analysis, we created interview questions to understand blind people's use of GenAI tools, their prompting and evaluation strategies, their suggestions for improvement, and how they understand the opportunities and challenges of various GenAI tools alongside other options they have for access (e.g., human assistance).

### 3.3 Semi-Structured Interviews

The lead author conducted all interviews remotely via Zoom from April to September 2024. This study was qualified as self-exempt and approved by the Institutional Review Board (IRB) of the University of California, Irvine. Before the interviews, the lead author emailed each participant a digital copy of the study information sheet. At the beginning of each interview, she briefed participants on the study procedure and obtained their verbal consent. Participants were informed that they could skip questions or stop the interview at any time. They were also assured of their right to turn off their camera during the interview. Each interview lasted approximately one hour. We focused on the most typical use cases as well as those they perceived as relevant to blindness. As follow-up questions, we asked about their workflows, the change brought by GenAI tools for the task, etc. While initially centered on use strategies and experiences, the interview protocol evolved to include questions about GenAI tools' impact on their relationships for access, e.g., how GenAI tools changed their ways of getting access. All interviews were video recorded and transcribed for analysis by the lead author.

### 3.4 Data Analysis

We adopted reflexive thematic analysis for both interview and transcript data as we sought to have a qualitative understanding of participants' lived experiences. Our analysis entails iterative and ongoing theme development along with data collection based on patterns of shared meaning among the data [23]. The lead author conducted open inductive coding of the cumulative interview data after each interview and regularly discussed the results with the research team. In the initial stages, we focused on the surface meaning of the data to familiarize ourselves with the data, e.g., identifying use cases, GenAI tools' limitations perceived by participants, etc. We informed our analysis with critical reflections on AI [8, 94], the sociomaterial nature of access and disability [15, 17, 28, 68, 101, 138], and socio-cognitive theories or methods in HCI and related fields [57, 61, 80, 123].

Through continued interviews, iterative coding, and analytic memoing, we began to identify the broader sociomaterial context of our participants' use of GenAI applications and the pervasive and ongoing nature of uncertainty. At various stages of the research, all researchers met to discuss the key themes, iterate on our findings, and reach a consensus. Subsequently, our thematic analysis identified the practices of (1) extracting meaningful cues from error-prone information sources; (2) treating all information as tentative and progressively updating understandings over time; (3) acknowledging and exploring information subjectivity; and (4) constantly adjusting expectations and strategies considering the politics around access. Across these themes, participants demonstrated a mindset of skepticism and criticality towards AI- and human-mediated assistance and information itself. We termed this mindset *everyday uncertainty* to call attention to the pervasive, ongoing, and routine nature of contending with uncertainty in information access experienced by blind people living in a world dominated by sighted-first thinking, imperfect access tools, and variations in human support.

### 3.5 Positionality Statement

Our research team has four researchers based in the U.S. The primary author, who led the interview protocol design, data collection, and analysis, is sighted and has been exposed to blind communities through ongoing volunteer work. The second author is blind and contributed to the early and ongoing exploration of various GenAI tools. His usage, personal reflections, and interactions with the research team have greatly shaped the team's understanding of information access through GenAI applications. The third and fourth authors are sighted and contributed to data analysis and theorizing alongside the other researchers. All authors contributed to interpreting the findings and the implications of the study. Our academic backgrounds in computer science, communication, cognitive science, and philosophy as well as our empirical orientations towards interpretive qualitative research and inferential statistical analyses influenced our research.

## 4 Findings

Across our data, participants detailed many use cases where they sought information about artifacts, environments (digital and/or physical), and concepts that were otherwise inaccessible to them.

| P#  | Age        | Gender | Self-reported Blindness   | Blindness Onset | GenAI Tools Discussed in Interviews  |
|-----|------------|--------|---|-----------------|--|
| P1  | 25-34      | Man    | 100% blind  | Since birth     | OpenAI ChatGPT, Be My AI, Microsoft Seeing AI, DALL-E, Midjourney                                |
| P2  | 25-34      | Man    | fully blind   | Later in life   | Google Gemini, OpenAI ChatGPT, Be My AI  |
| P3  | 25-34      | Man    | I have some vision but very little. My right eye is just light perception and my left eye is something like 20/350. | Later in life   | OpenAI ChatGPT, Be My AI   |
| P4  | 35-44      | Man    | totally blind   | Later in life   | Google Gemini, OpenAI ChatGPT, Be My AI, Microsoft Seeing AI, Anthropic Claude.ai, Adobe Express |
| P5  | 35-44      | Man    | no eyesight at all  | Later in life   | Google Gemini, OpenAI ChatGPT, Be My AI, Microsoft Seeing AI                                     |
| P6  | 35-44      | Woman  | light perception  | Since birth     | Google Gemini, OpenAI ChatGPT, Be My AI  |
| P7  | 35-44      | Woman  | fully blind   | Since birth     | Google Gemini, OpenAI ChatGPT, Be My AI, Microsoft Seeing AI                                     |
| P8  | 25-34      | Man    | Blind   | Later in life   | OpenAI ChatGPT, Be My AI   |
| P9  | 45-54      | Man    | totally blind   | Since birth     | OpenAI ChatGPT, Be My AI, Picture Smart AI in JAWS, Aira Access AI                               |
| P10 | 45-54      | Woman  | totally blind   | Since birth     | Google Gemini, OpenAI ChatGPT, Be My AI, Microsoft Seeing AI, Picture Smart AI in JAWS           |
| P11 | 55-64      | Woman  | totally blind   | Since birth     | Be My AI, Picture Smart AI in JAWS, Aira Access AI   |
| P12 | 25-34      | Woman  | total blindness   | Since birth     | OpenAI ChatGPT, Microsoft Seeing AI, DALL-E, Stable Diffusion                                    |
| P13 | 55-64      | Woman  | No usable vision. Light perception with some strange shadow vision.   | Later in life   | OpenAI ChatGPT, Be My AI, Microsoft Seeing AI  |
| P14 | 45-54      | Woman  | Blind, light perception only with some shadows.   | Later in life   | Be My AI, Microsoft Seeing AI, Facebook's Automatic Alt Text                                     |
| P15 | 18-24      | Man    | I can see some light, shapes if it's close, and some colors if they are bright and close.                           | Since birth     | OpenAI ChatGPT, Be My AI, Microsoft Seeing AI, Udio, Suno  |
| P16 | 45-54      | Woman  | I have no usable vision.  | Since birth     | Be My AI, Microsoft Seeing AI, Zoom AI Companion   |
| P17 | 65 or over | Man    | totally blind   | Since birth     | Be My AI, Picture Smart AI in JAWS, Aira Access AI   |
| P18 | 35-44      | Man    | I am totally blind though I have light perception.  | Since birth     | OpenAI ChatGPT, Be My AI   |
| P19 | 35-44      | Man    | blind   | Since birth     | Be My AI, PiccyBot   |
| P20 | 25-34      | Woman  | totally blind   | Since birth     | OpenAI ChatGPT, Be My AI, Aira Access AI   |

**Table 1: Participant demographics.**

They used a range of GenAI applications (see GenAI tools discussed in interviews in Table 1) alongside other tools (e.g., search engines,

PDF readers) and human assistance to make information in myriad forms more accessible. Specific use cases of GenAI tools included extracting both high-level structures and details of digital and physical artifacts, such as inaccessible PDFs (P2, P7, P8, P17, our member researcher), legal documents (P15, P17), restaurant menus (P12), product assembly instructions (P6), and personal photos or public images (P2, P4, P7, P10, P13, P14, P19, P20). Participants also used GenAI tools to understand the layout of desktop screenshots and the arrangements of elements such as in web pages (P11, P14, P17), data tables (P11, P16), presentation slides (P11), questionnaires (P14, P17), and charts (P16). Additionally, they used GenAI tools to satisfy diverse curiosities such as understanding historical figures (P5), emojis (P3), visual arts (P7), sporting events (P1, P3), and building structures (our member researcher).

Across these use cases, we observed that participants approached information access with a mindset of *everyday uncertainty*, which is characterized by skepticism and criticality towards both AI- and human-mediated assistance as well as the information itself. Rather than expecting information to be ‘correct’ or ‘complete’, they learned to extract meaningful cues from error-prone information sources; treated all information as tentative and progressively updated their understanding over time; acknowledged and explored information subjectivity; and constantly adjusted their expectations and strategies considering the politics around access.

#### 4.1 Extracting Meaningful Cues from Error-prone Information Sources

Model hallucination, i.e., false or misleading content generated by AI, is a known concern in using GenAI applications for accessibility [4, 6, 44], and as such, blind people use a variety of strategies to test and verify output (e.g., turning to search engines, sighted assistance, trying another model, re-prompting, testing with known settings) [4, 6, 45]. Our findings extend this prior work, as we found that working with model hallucinations, or otherwise error-prone output, was often an assumed part of using GenAI tools for access among our participants. Their use shifted from simply verifying output to skillfully making use of error-prone output as part of information access. They developed a tolerance for certain kinds of errors, learning to integrate error-prone GenAI tools into their situated practices and workflows, such as reasoning in environments with rich contextual cues (e.g., personal photos, or physical objects, in both digital and physical environments), extracting outlines to facilitate document reading, and identifying terminology before conducting an online search.

The situated nature of information access was central to participants’ tolerance towards errors in information, affording them the ability to draw on contextual cues and extract meaningful cues from erroneous outputs. This was evident when they reasoned about items with rich contextual cues such as personal photos. In these cases, participants drew on a range of contextual information, such as image metadata and their memories, to work with erroneous model output. When we asked P2 how he dealt with AI hallucination in image description, he told us based on his experience the AI models he used usually do not make mistakes in terms of high-level image structures or categories of the objects. As such, he developed a way to use AI for selecting photos for his online

sharing because “*misrecognizing a palm tree into another type of tree wouldn’t affect*” as long as he gets the cues to know if it is a photo of scenery or people. As another example, P9, who worked as an accessibility engineer, often used Picture Smart AI to check screenshots of test cases provided by his client. While the output was expected to have errors, his work experience equipped him with certain anticipations toward the output. As he said,

“*Typically in the screenshots there’ll be a highlight or pointer, pointing at the code in question. And usually, AI is able to tell something like the focus or whatever they’re using to point to this code snippet. Tell me what code snippets are being focused or emphasized.*”

As seen from this quote, P9 actively directed his attention to where he should focus and had more confidence. Additionally, he told us, out of concerns about AI hallucinations, he would only use GenAI tools on tasks where he had a clue about the output like the workplace screenshots. Likewise, other participants said they “*never use [GenAI tools] for anything important*” (P4) or “*won’t hang a life on [AI-generated descriptions]*” (P14).

Similarly, participants drew on knowledge of their local material environment to extract meaningful cues from erroneous outputs related to physical objects (P9, P11, P13, P15, P17). For instance, P11 frequently combined information from merchant labels with Seeing AI descriptions to refine her understanding when shopping for clothing. As she stated, “*I’d like to get information from at least 2 different sources to decide.*” Similarly, P15 remained conscious of potential errors from AI output. He once identified an error when Seeing AI misrecognized a mac and cheese package as a hot pie when he almost put it in his microwave, explaining, “*I’m glad I checked...You have to kind of trust your instinct.*” Instead of approaching this as a one-time verification process as often discussed in the literature [6, 58], we found that participants iteratively checked their understanding using environmental cues, developing “*instincts*” towards pervasive errors and a readiness to adjust their reasoning accordingly.

Another common context of appropriating erroneous output involved using various GenAI tools (ChatGPT, Gemini) to extract structured outlines from documents (described by five participants), given that document reading is typically an attention-demanding task for screen reader users and often rife with inaccessibility [79]. While GenAI models are far from perfect in summarizing long documents [44], participants found it useful to generate a rough structure to help them preview content and know what to attend to when reading. P2 and P8 shared that, before using ChatGPT, they frequently needed to read through substantial portions of a paper to understand the structure, even when they were generally familiar with common paper structures. P2’s experience represented a typical reading experience with ChatGPT or similar text-based GenAI tools. “*I’ll have a rough understanding of the structure of the article, the main view, and the key points [with the outline GPT generated]. I know there may be three main points in the article’s main body, and I will know when it comes to the first one.*” He emphasized that “*every time after the summarization, I’ll read the article because I don’t totally believe it.*” In this example, P2 fully expected the possibility of AI hallucination, and thus he only sought a structured

overview and a preview of content to guide his reading at places of interest.

Extending beyond AI model outputs, anticipating and managing errors is an inherent part of the process of information access for participants, due to widespread inaccessibility of web resources and the nature of the information-seeking process [78]. For instance, participants remained mindful of potential errors in both the AI outputs and their subsequent searches when they used GenAI tools as an initial search tool (noted by four participants). P5, for instance, shared how he gathered keywords from erroneous output to help narrow down and focus his web search.

*“Sometimes I ask Gemini to summarize, for example, the U.S. national strategy on a certain thing. It sounds ridiculous, right?...Gemini would see a lot of things and it’ll probably mention a few documents. It may even provide some links. I think 50% of the links are either wrong or dead...(However,) I get a very nice bunch of keywords, and I can put the things into Google. If I don’t use AI, I’m not sure what the keywords would be.”*

In this example, he was not turning to search engines for verification [4], but instead, he assumed errors in the output and shifted focus to information that he could use to narrow down his search space. The advantage of Gemini’s summarizing ability is evident for him as a screen reader user as opposed to search engines, because “for every item on the web page, you have to verify, like if this source is reliable or not, or if this title is interesting or not. A lot of judgments came in.” Likewise, P20 described prompting ChatGPT for example items and associated links to narrow her search on Amazon for online shopping, an activity known to be inaccessible because of pervasive inaccessible links and visual elements [122]. In these two instances, participants treated GenAI tools as resources to support their situated activities on inaccessible web pages and resources. They constantly adjusted their expectations about the tools’ limits and actively worked out the ongoing uncertainty they experienced arising from the process, such as frequent dead links, untrustworthy sources, and misinformation from associated resources.

## 4.2 Progressive Updating of Information and Understanding Over Time

The experience of everyday uncertainty is also reflected in participants’ sense of incompleteness in using AI for access. In contrast to errors and hallucinations, the sense of incompleteness arises from the richness of the information itself, combined with the opaque and ever-evolving nature of GenAI models. Consequently, rather than seeing verification as a one-time task, participants treated all information and understanding as tentative, gradually refining their understanding of both the information they were exploring and the tools used in their process.

This ongoing updating of understanding is evident when participants used GenAI tools to understand complex concepts and topics out of curiosity, such as visual-spatial concepts (P1, P3, P5, P8). In such cases, GenAI models were perceived as good at providing visual layouts and drawing relations between elements for concepts requiring spatial understanding. For example, P1 described using ChatGPT to generate a granular understanding of American football,

*“When I said explain it to a blind person it gave me a more detailed description of the field. Things like what is on the left-hand side of the field or what is on the right-hand side of the field...it gave me a bunch of new terms and then I picked each one by one and I said, okay, explain tackle to me. Explain other things to me.”*

As with other participants, P1 did not care if ChatGPT gave a completely accurate explanation in this request because he would not use the information for serious purposes at this particular moment (similar to findings from [4, 58]). Along with him, participants commonly recognized potential opportunities for expansion of understanding, indicating a longer-term process of working out uncertainty.

We observed many similar examples of this ongoing process of updating understanding in the transcripts of our member researcher’s use of ChatGPT. In one instance, he was learning about the physical structure and terminology of a single-family home’s roof to prepare for his conversations with a repair person. The researcher started with a general query about roof components: “can you teach me different names in the context of the exterior of a house?” He further prompted for relationships between the elements and explanations tailored to a blind person, such as “since i am legally blind and not able to see these, can you describe, Fascia, Soffit, Flashing, and eaves better so that I understand what relates to what and how they look like?” With general descriptions in outputs (e.g., “fascia boards are the horizontal boards located along the lower edge of the roof, just behind the gutters.”), he iteratively refined his understanding of local elements (e.g., “what do you mean that fascia is behind the gutters”), and shifted attention to aspects that were important to him (e.g., “let’s forget about the flashing. and focus on the other items”).

As he was uncertain about the model’s capability and his own understanding of the concepts, he iteratively sought verification as a way to build up his understanding and test the model’s consistency (e.g., “so eaves are like an extension to the roof which is parallel with the ground, and perpendicular with the wall, correct? like the edge of a hat”), to which ChatGPT replied “Yes, that’s a good way to describe it!” While ChatGPT sometimes failed to capture the intended meaning of the prompts, the researcher was impressed by its ability to choose appropriate words like “U-shaped” and how it provided information after he disclosed his blindness. For instance, ChatGPT connected the elements following a brief explanation,

*“To help you relate these elements, envision the following sequence from top to bottom: at the highest point, you have the roof covering, which consists of shingles or roofing materials. Just below the roofline, you have the eaves, which are the horizontal extensions of the roof...”*

Still viewing this understanding as tentative, he refined it further through conversations with a repair person several days later. This example, along with other cases, highlights that while incompleteness is pervasive in information access with GenAI tools, blind people actively experimented with strategies to mitigate uncertainty

through ongoing interaction with various information sources, including GenAI tools, humans, and the material world they live in.

The need for ongoing updating of one’s understanding also stems from the opaque and constantly evolving nature of GenAI tools, which makes it difficult for users to fully understand and reason about models’ capabilities. P6 noted that she iteratively experimented with various prompting strategies to understand the limits and reliability of various GenAI tools. For example, she kept collecting her sighted friends’ top three photos and the reasons behind the choice to learn how to elicit specific details from Be My AI about visual aesthetics. Through constant experimentation, she learned some specific questions she could ask, such as if her finger shows up in the photo. However, her use of Be My AI still involves a lot of exploration and improvisation,

*“It really depends on what it is and what I’m trying to get, the piece of information. There are times I asked very specific questions like ‘are the leaves brown on this plant?’ The other day I asked it ‘do these plants look healthy?’”*

While others have shown similar exploration and prompting strategies [4, 6, 45], here we find that even with greater familiarity, she remained uncertain about whether her understanding would be accurate in the future, given her sense that the models were changing almost daily alongside the information she wanted to explore (the state of her plant). Given this varying and evolving nature of outputs, participants often described combining results from multiple models to complement one another. As P11 said,

*“[Picture Smart AI] usually gives you 2 choices. I’m not choosing which one to use, but they give different results. Sometimes Claude tends to be more general, and ChatGPT tends to be more detailed.”*

We observed several similar cases of ongoing reasoning about model and output in the transcripts we analyzed. In one case, our member researcher kept checking his understanding and Be My AI’s reliability when he asked the application to describe a radiator panel. He turned on/off the buttons on the panels several times, and kept modifying his prompts to see if Be My AI could capture the change and if it was consistent in outputs. However, later when he checked with his partner, he realized that Be My AI kept providing details that did not match the actual scene (e.g., stating the power button was green when it had no light). This moment became a “turning point” for him. He found that he could not “100% trust the result.” As this example shows, reasoning about models and their output was inherently part of using GenAI tools. This process extends beyond just one tool, individual, or interaction. Similar to our member researcher, participants leveraged all available resources, including AI-powered tools, access applications, and human assistance as part of grappling with uncertainty brought by model opacity and constant change. They iteratively explored model capabilities and updated their understandings of information and tools through situated uses within particular social and material contexts.

### 4.3 Acknowledging and Exploring Information Subjectivity

Beyond errors and the perceived incompleteness of information, participants recognized subjectivity as an indispensable aspect of information acquisition. They did not describe their goal as seeking a single ‘correct’ interpretation as often implied in the process of verification [6, 45, 58] and the concept of (in)accuracy (as seen in decades of efforts to classify visual needs and train end-to-end models accordingly [21, 150]). Instead, they moved between various AI models and human sources to deepen their understanding, whether by making information structures clearer, seeking verification on specific details, or comparing opinions (e.g., on visual aesthetics). That is, participants saw GenAI tools as one of many sources of interpretation they could draw on to build a more complete understanding during their process of information access. As P5 noted, “everyone interprets information differently, and AI simply adds another layer of interpretation.”

One way participants embraced subjectivity is evident in their exploration of different prompting strategies that solicit multiple perspectives and ways of thinking about information. For example, they typically refined their grasp of visual-spatial concepts by following up general prompts to GenAI tools (e.g., “explain American football to a blind person”) with requests for comparisons and additional details about concepts and objects. They explored diverse prompting strategies that allowed them to use their embodied knowledge (e.g., “draw a baby”), perform analogical reasoning (e.g., comparing Persian cats vs. Siamese cats), make spatial inferences (e.g., asking for neighboring states of a state), or tap into their broader social understanding (e.g., learned about buoyant colors like neon colors by asking what clothing people wear for music events). These strategies demonstrate how they anticipated and leveraged the subjectivity of information, exploring various perspectives and interpretations generated by GenAI tools.

However, not all instances of subjectivity are desirable, making contending with subjectivity a routine experience for access. Participants cited the “cheesy” descriptions AI tools generated, such as always describing a room as “beautiful” or a sofa as “cozy” regardless of the actual scene or object in question (P7, P9, P10, P11, P12, P14, P16). P16 provided an example, “when I was outside, walking in my backyard, sometimes it describes things as lush and breathtaking. They might not be all that incredible.” While the partiality in this example might be perceived as obvious, other instances are more subtle and difficult to detect. For example, ordinary clothing in one culture might be perceived as costume-like in another (P12). As a result, participants raised concerns that the partiality of information creates perpetual uncertainty with using GenAI for access, particularly when the information carries criticality. As P9 said, “what happens if [GenAI tool] influence the way I vote?”

While sighted people are often treated as robust for verification [6, 47, 95, 151], participants explained that contending with subjectivity also extends to information provided by humans, echoing the subjectivity of “seeing” reported by one participant in [6]. Some told us that few sighted people are good at describing visuals to blind people if they are not familiar with blindness, because sighted people tend to focus on what visually stands out to them and lack order in descriptions (P1, P5, P6). P5 found descriptions sighted people



provided often confusing because they overly focused on precision: “if the room is not a perfect square, they would say ‘it’s an oval-like square room,’ to what extent it’s oval, to what extent it’s square.” Even when asking for information from close ties (e.g., one’s partner or parent), they may follow different styles in descriptions, such as being minimalist, detailed, interjecting strong opinions, or including details unnecessary to the request like colors (P6, P10, P13, P19, P20). Subjectivity even existed in explanations provided by trained professionals such as Aira agents. P19 recounted a post he found online to highlight the subjectivity inherent in human perception, “The Aira agent agreed that the AI’s description was correct, but it turned out to be misleading when I shared it on my group. The AI had described a person’s hands as being on a braille book, but it looked more like a sheet of candy buttons.” In this case, a trained Aira agent and an AI tool may “agree” on an interpretation and yet that interpretation will still be partial, calling into question what constitutes verification and correctness.

Given the inherent subjectivity in information access among AI and humans, participants described intentionally choosing certain sources according to perceived strengths. On the whole, participants typically found value in GenAI tools’ consistent comprehensive descriptions, which usually follow a systematic top-to-bottom, left-to-right approach (P1, P18) and setting a framework first (P5)<sup>2</sup>. This systematic approach allowed participants to have greater access to incidental information, e.g., unexpected elements on webpages like logos (P13). Participants explained that GenAI tools could even capture visual nuances often overlooked by sighted individuals, such as a small taint on a wall, and a blurred, small bird in a photo of an airplane (P6, P16). Based on reasoning about different expertise of AI and humans, P15 described a hybrid approach to have more control over his access,

*“Be My AI drastically cut down the amount that I’ve had to call a volunteer to help me...I can just have my VoiceOver describe everything for me, and it’ll speak it much faster than a human. It’ll be very unbiased. It’ll usually be pretty descriptive. Then I guess you could ask a more specific question to the volunteer.”*

As seen from this quote, Be My AI was perceived as “unbiased” because it followed a consistent method of description, making it more standardized and predictable than human assistance, even though its descriptions are still shaped by design choices and data.

Participants also described intentionally choosing specific people as information sources according to their relationships and backgrounds (P1, P3, P4, P12). For instance, P12 would strategically choose information sources based on their expertise, asking her mother about color, her father about automobiles, and her artist friend for arts, as she is familiar with each person’s unique strengths in describing and explaining visual-spatial information. In some instances, participants intentionally looked for opinions from certain people, such as advice on fashion and home decorations (P4, P6, P12, P20). P3 further illustrated the situated and relational nature of understanding that close social contacts can bring to information access. He compared how his sister and ChatGPT might explain animal size to him using known frames of reference,

*“My cousin has a pet pig that is like 140 pounds. And so she might say it’s like 4 times the size of the pig. Or if it’s something smaller she might compare it to the cat that we grew up with. We have the same frames of reference that ChatGPT couldn’t have...The only cat that I interacted with and that I actually touched, that’s basically just my cat. ChatGPT will interpret an average cat to be an actual average cat, whereas I don’t really have that in my brain.”*

“Average” and “size” proved to be elusive concepts for the participant, as the understanding of both concepts was deeply influenced by individual experiences. Only people who were intimately familiar with him, like his sister, could comprehend these concepts in a way that aligns with his thinking. Not only did they share common knowledge, but the participant’s sister was also aware of the nuances of his blindness (“she knows what I can see”) and needs (“what I want out of the question”). In this example, the way his sister explained the concepts was deeply subjective, as it was influenced by both of their experiences and relationships, yet it offered an ideal perspective that he could easily use to build his own understanding. However, such an intimate understanding is born from years of shared experiences and cannot be easily replicated.

This subjective nature of information, especially when complicated by the mediation of AI or human assistance of varying qualities, underpins participants’ experience with everyday uncertainty in access. Due to this assumed subjectivity in information, the way participants shifted between human and AI tools to access information and manage uncertainty goes beyond the typical focus on verification, as often discussed in the literature [4, 6, 45, 58] and media [47, 95]. Instead, they accepted and adapted to the subjective nature of information, synthesizing insights from diverse sources and perspectives, teasing out the parts they found useful, and building their own understanding. Additionally, as we will show next, even when it is with participants’ close ties, an ideal interpretation is not always easy to have because of politics around access.

#### 4.4 Anticipating the Politics Around Information Access

Not only did participants experience uncertainty due to the error-prone, incomplete, and subjective nature of information access, they also confronted politics of access that further contributed to the lived experience of everyday uncertainty. This included not knowing whether GenAI models and applications would respond to their requests, or how they might respond, as well as grappling with the costs and tradeoffs of moving between AI systems and humans for access.

The most evident way in which GenAI models wield power over access and create uncertainty is through the use of ‘guardrails’ built into applications — the programmed limitations on the types of questions applications will answer and the kind of responses they provide. While designed to avoid doing harms to user values, societal norms, and company interests, the restrictive nature of guardrails complicated the ongoing working out of uncertainty blind people experienced, and such experiences with guardrails made them question whether GenAI applications can truly serve blind people. For example, some participants observed GenAI tools

<sup>2</sup>See Adnin and Das’s work for examples of GPT-generated visual descriptions [4].

trying to avoid making judgments such as on race and gender (P6, P14, P18). P14 found the AI applications she used “*seems to have backed off on guessing gender even, or ethnicity,*” and she could only “*guess who’s in the picture.*” P18 noted his concerns about how these guardrails restricted his access,

*“It tries to keep itself out of trouble, but it does come up with a certain way of filtering the world just because they’re trying to make it as least offensive as possible. Sometimes you just have to prompt in a certain way to get around the filters that are put in place.”*

For him, the focus on “*identity politics*” could overshadow the more pressing issue of inclusivity and access,

*“Could we make the arguments in terms of all humanity? Not fighting for the assertion of a supposed blind identity, which should really be a small part of who you are. It’s difficult to come up with real-world results that include all of us when you’re arguing for only your own identity.”*

Others described cases where their access requests were denied due to unexpected guardrails. This occurred, for example, when participants requested details about photos of a shooting incident, male body parts, or privacy-sensitive scenarios (e.g., bathrooms), which AI might deem inappropriate (P6, P10, P12). P10 stated,

*“That bothers me because I don’t know if I want to see it, but I know that everybody else in my world can see it. So why can’t I have that described to me? I feel like we’re limited on what we can see because of what it’s allowed to tell us, and I think that’s not right.”*

These quotes surface the challenges in negotiating the politics around different values and norms around access. As P6 pointed out, “*there’s been a debate in the blindness community about facial descriptions. There are places where it’s not allowed for AI to process faces, and at the same time, that’s a valuable piece of information for a blind person. How do you balance?*” As yet another example, P18 provided a case in which Be My AI initially refused to describe a bathroom but provided the information when prompted for safety concerns about bumps on the ground in the bathroom. The uncertainty brought by the political nature of information access is salient in these examples, with what is a ‘sanctioned’ request for access constantly changing as social norms, guardrail implementation, and underlying models evolve.

The political nature of access also manifests in participants’ contending with societal biases in AI models and outputs [4, 44, 91]. While participants were often unsurprised by such biases, these encounters could disrupt their access experiences and introduce uncertainty about how well GenAI tools could meet their needs. For example, P10 was frustrated by one interaction with ChatGPT in which the system responded “I’m sorry” when she disclosed her blindness to the application.<sup>3</sup> P1 found that ChatGPT exhibited bias in frequently using “touch” and tactile cues in explanations, neglecting other descriptive modalities and strategies he might prefer.

<sup>3</sup>Chancey Fleet reported a similar response from GenAI models in a recent talk [37]. She mentioned that she closed the application after Microsoft CoPilot responded “Sorry to hear that you’re blind” to her prompt about blindness.

The politics of information access becomes even more complicated when participants negotiated the trade-offs between AI systems and humans; both sources were perceived as having certain advantages (as acknowledged in participants’ triangulation of different information sources for their understanding), while both entail cognitive, social, and emotional costs. The challenges in tradeoffs were obvious in participants’ hesitation to use the volunteer option within the Be My AI application even if they were aware of the feature [95]. While many appreciate human assistance, participants typically expressed concerns about the variance of assistance quality [84] and the socio-cognitive demands involved in the transition from a GenAI model to a random person, especially after investing time and efforts into using AI (P7, P11). Others noted pervasive bias or anxiety sighted people have in helping blind people (P13, P20). For instance, P13 told us sometimes people assume she cannot do things due to age-related stereotypes (e.g., describing everything when she asked for “*even the slightest amount of information*”). As a result, many participants only considered online human assistance services when the benefit is clear, such as efficiently finding a specific piece of information over a large space (P5, P6, P8, P15, P16, P17, P18, P20).

The trade-offs between using AI versus human assistance in social contexts became more complicated and nuanced when considering the emergent situation and individuals involved. For example, P11 noted her concerns in using AI for access in group settings, “*I would feel weird if I was in a group of people. And I was like talking to my phone saying ‘Hey, what kind of drink is this?’ People around me might be like, well, ‘I could just tell you.’*” Because of these social concerns, she tended to reserve more casual or enjoyable tasks for human assistance (e.g., aesthetics or general descriptions) while using AI for structural or detailed information, such as when asking about a quilt with complex patterns. We observed similar efforts in making AI a natural participant in a social setting. P16 shared an example where she used Be My AI as a conversation starter around her access needs when talking about a painting,

*“They [her colleagues and friends] were trying to interpret an artist’s rendering of some people, and their facial expressions. I thought to myself, ‘wow, everybody’s talking about this, and I have no idea what it is.’ So I took out my Be My AI. And then, I got their attention and said, ‘Hey, guys, look at this! What do you think?’ They were impressed because the description didn’t really give anything away. And then I could be in the conversation. It’s just a nice dinner conversation we were all having.”*

Several transcripts we analyzed captured such exploratory, collaborative interactions in real-time, everyday settings (e.g., discussing flowers during gardening or local bridges while traveling with a partner, creating cocktail recipes at a party). In these interactions, the researcher described being able to contribute to their shared goal in more meaningful ways by having a GenAI tool at his fingertips (e.g., to understand a gardening process or the bridge in question) while his partner focused on other aspects of the task (e.g., performing manual aspects of a gardening task or driving). As he reflected, “*when my wife was helping me, making that rosemary syrup, she was following my instructions because I knew all the*

steps, because I asked GPT to summarize it in my way of understanding.” In these instances, the availability of GenAI tools shifted the power dynamics of what each person contributed to a collaborative task, making the researcher feel “*more engaged and involved in the conversations.*” As seen from these scenarios, a satisfying access experience with GenAI tools involved constant sensitivity to the emerging power relationships and dynamics regarding who and how to contribute to access, particularly in interactions involving unfamiliar individuals. While influenced by personal relationships, such dynamics are tied to broader politics of information accessibility, including the structural challenges of making information accessible in the first place.

## 5 Discussion

Across HCI scholarship and beyond, there has been an insurgence of research aiming to understand how people interact with, interpret, and navigate the capabilities of GenAI models and applications [63, 141, 149]. Related accessibility research similarly focused on the usability or accessibility of GenAI tools [4] and the capabilities and limitations of various models for specific tasks or use cases [43, 44, 59, 83, 135]. Others have focused on the types of errors and biases blind people experience with AI tools and verification strategies [6, 45, 58]. Expanding on prior work, we introduce the concept of everyday uncertainty to conceptualize the situated, ongoing working out of understandings in the context of the error-prone, incomplete, subjective, and political nature of information access, whether achieved through human or AI-powered support. Our analysis expands beyond uncertainty as a quantitative metric and theorizes uncertainty as an everyday mindset that blind people living in a world dominated by sighted-first thinking and inaccessible information contend with on a daily basis. We now discuss the conceptual and practical implications of everyday uncertainty for accessible computing and HCI more broadly.

### 5.1 Uncertainty as a Situated, Ongoing, Life-long Process in an Ableist World

While our analysis focuses on the case of blindness and uncertainty, especially when accessing primarily visual-spatial information, the concept of everyday uncertainty can help understand AI-augmented information access for PWD more broadly and their situated, ongoing, and life-long working out of uncertainty in an ableist world. As a day-to-day experience, uncertainty can be understood as an ontological reality of disability, as is evidenced in d/Deaf signers’ life-long experience of understanding different signing styles of varying quality, including machine translations [29, 147]; autistic people’s constant balancing between the cost of “unmasking” and “masking” when taking communication advice, including AI-generated ones [62]; and negotiated use of assistive technologies out of social, environmental, and technical considerations commonly observed with PWD, such as real-time captioning tools [93] and spellcheckers [139]. By reframing uncertainty as an inherent and routine part of PWD’s lived experience with access, we connect scholarship on uncertainty, accessibility, and AI/ML, contributing to the critical discussion of how uncertainty should be addressed across these domains [119].

Viewing uncertainty as a situated, ongoing, and life-long process for PWD calls into question the focus on precision-oriented goals, such as accuracy and mitigating bias, and discrete tasks and evaluation metrics that pervade HCI, accessibility, and AI/ML scholarship. The concept of everyday uncertainty shifts analytic attention beyond quantifying, reducing, and communicating uncertainty toward the socially and materially situated process of working through uncertainty. While recent work considers the limits of one-size-fits-all approaches to accessibility tasks like alt-text creation [121], our analysis shows that information access is a far more contextualized and adaptive process. Information access was not only situated in one’s environment, where people could readily draw on knowledge of familiar objects and context cues; the process was also shaped by the availability of various tools, accessibility of artifacts, human support, broader sociomaterial contexts, and the nature of information being questioned — all of which are inherently non-deterministic, changing, connected, and characterized by pervasive imperfections.

Due to these complexities, information access could result in a sense of ‘ontological uncertainty,’ as seen in participants’ assumptions about ableism and imperfections rooted in models and human assistance, as well as their readiness to adjust to the politics around access. Consequently, rather than expecting a definite correct answer, participants typically aimed for a ‘good enough’ result that met their minimum requirements for understanding at that moment, with what constitutes “good enough” varying across task types (focused questions vs. exploring concepts), purposes of understanding (syntax vs. semantics of a document), temporal constraints, criticality (e.g., real-world outcomes such as safety and recoverability), and associated cost (e.g., time, cognitive demands, social norms). Additionally, they accepted and held onto some uncertainty for the future, making space for refined understanding in the future (e.g., as seen in our member researcher’s reasoning about roof elements).

As such, rather than seeking a single truth as implied by ground-truth labels [21, 150], participants’ approach to information access emphasized plurality (recognizing different ways of knowing), skepticism (acknowledging potential inaccuracy, incompleteness, and bias), dissent (actively seeking alternative perspectives), and humility (accepting ignorance). These practices echo the principles of virtue epistemology, which shifts the epistemological emphasis from the qualities of knowledge to the knower, prioritizing the intellectual virtues important to acquiring, maintaining, and applying knowledge over time [131]. In the following section, we explore how future research and AI applications for accessibility can take action based on these insights and the concept of everyday uncertainty to foster further advancements.

### 5.2 Implications of Everyday Uncertainty

In response to calls to a more critical and broad treatment of uncertainty [113, 119], we identify three key areas in which everyday uncertainty can advance research on AI for accessibility.

*5.2.1 Beyond the Focus on Error and Bias.* The concept of everyday uncertainty encourages critical reflection on how uncertainty should be managed in GenAI models, and from whose perspectives. Accessibility research often associates AI limitations with

ground-truth labels [21, 49, 50, 73, 116, 128, 150], model hallucinations [4, 6, 44], and biased outputs [41, 91]. Yet, recent studies show that blind people’s rating of AI-generated descriptions go beyond a binary classification of “correct” versus “incorrect”, especially when they could infer useful information from the erroneous output [45] or have contextual information to help with reasoning [6]. As disability activist John Lee Clark once recounted a “biased” yet “best” interpreter he worked with, “you don’t want his bigotry, but you want his talent for not thinking twice...the problem isn’t accuracy, per se, but whose accuracy” [65]. Our findings extend these prior accounts, suggesting that errors and biases are inherent to information access. Participants in our study treated all information, particularly visual-spatial description, as subjective. Given this, they triangulated across accounts from AI models, web resources, and people with different expertise, knowing that any one perspective is incomplete and their understanding is subject to revision over time.

To center PWD’s perspectives in addressing uncertainty, we recommend that future accessibility research shift its focus from model prediction and control to supporting users in continuous engagement and reasoning. This approach aligns with the established tradition of sense-making and CSCW research, such as user-centered misinformation interventions [54]. In other words, greater certainty can come from ongoing practice, reflection, and communication, rather than being solely reliant on rigid prediction and control by specific models.

Consider the development pipeline of GenAI assistive tools. A practice-oriented approach would involve training different models across diverse benchmarks and data sources, including those that may offer “biased” perspectives [46]. Ultimately, users should have the ability to triangulate information from various sources and viewpoints. The integration of multiple models in tools like Picture Smart AI in JAWS represents a step forward, but current GenAI applications still limit blind users’ ability to effectively compare outputs from different models and human support. Similar to participants seeking information from sources with different expertise, enhanced features could support requests for descriptions of elements in images or concepts in documents, comparing consistency and difference among outputs generated from multiple models [48], diverse cultural and linguistic sources [10], as well as viewpoints taking different perspectives [107]. Additionally, tools could be designed to help users cultivate epistemic virtues over time, such as framing model outputs in ways that encourage skepticism [92]. While demanding further investigation, similar approaches could be applied to enhance other assistive systems, such as sparking skepticism and supporting cross-referencing in sign language translation systems [22] and communication advice tools for autistic individuals [62].

**5.2.2 *Recontextualizing Task Design and Evaluation.*** The concept of everyday uncertainty also broadens the design and evaluation space of GenAI tools for accessibility. Accessibility research has a long history of classifying blind people’s visual needs [21, 45], often framing accessibility tasks as de-contextualized, isolated, and time-bounded activities. Typical examples in the context of blindness include image or scene descriptions [24, 45, 92, 143, 152] and object

recognition [49, 67, 100, 116, 128, 130], with a tendency to emphasize end-to-end solutions. This siloed approach, however, stands in contrast to the many situated use cases our findings uncovered, such as expanding on web search using keywords extracted from AI output, using AI-generated outlines to locate places of interests during reading, and cross-referencing visual descriptions when interpretation, rather than verification, is the goal. A similar gap between discrete research tasks and nuanced user practices was reflected in other accessibility contexts, such as the typical focus on end-to-end sign language systems [22] compared to the wide range of communication methods d/Deaf signers piece together [138].

As a discipline, accessibility research must rethink the design and evaluation of accessibility tasks such that they better preserve the complexity of real-world usage, actual workflows, and broader information spaces in which PWD use GenAI tools or features. A crucial next step is to evaluate GenAI models and design tools in naturalistic, real-world scenarios. For example, consider how participants extracted keywords from GenAI responses to facilitate web search. Evaluations should be conducted within users’ actual search flows, ensuring that other information tools, like search engines, are easily available. Similarly, design should consider the user’s entire workspace. For instance, to optimize the search experience, tools could help users quickly identify named entities in AI responses and link them directly to relevant web search results (e.g., see recent work on interactive LLMs as potential examples [64, 124]). A thoughtful design process must also consider the political and social dynamics of real-world use. For example, model errors that could cause social embarrassment should be addressed as a priority [2]. This calls for long-term studies that explore how GenAI tools operate within broader societal contexts and affect users’ experiences over time.

To truly embrace interconnectedness, developers should treat all access opportunities equally as key parts of users’ access experiences. For instance, previous research often aimed to differentiate use cases for AI versus human assistance, with varying findings over which is more robust and ‘unbiased’ [45, 151]. However, our participants’ frequent shift between different information sources suggests that the boundary between human and AI-powered access is not always clear-cut. To help users integrate information from diverse sources, future research should explore strategies to streamline the transitions between different information sources. For example, rather than requiring users to initiate a separate call after using AI, as is the case in the current version of Be My AI [95], Aira Access AI offers a promising alternative by allowing users to share their conversation history with AI to human agents for quick additional descriptions [47]. Enabling users to call on AI agents during live interactions with human agents could be another way to enhance the experience.

**5.2.3 *Mitigating Uncertainty at Its Core.*** The concept of everyday uncertainty further encourages structural efforts to mitigate uncertainty. Disability activist Mia Mingus coined “access intimacy” [98] to describe the ideal access to her: “access intimacy is that elusive, hard to describe feeling when someone else ‘gets’ your access needs.” However, this ideal is difficult to achieve as uncertainty pervades nearly all aspects of access – AI models, documents, tables, visuals, web pages, and human interactions alike, manifesting

as an everyday, affective, embodied, irrational experience. Mitigating this deep feeling of uncertainty demands long-term, systemic, and infrastructural change to build a foundation for public trust among PWD. As Knowles et al. noted, the deep distrust in computing systems among marginalized communities often arises from a shared experience of betrayal in a world not designed with them in mind [75].

Bringing in the political dimension of uncertainty could be the first step towards structural efforts, as resonated in the growing call for “studying up” in AI research communities — focusing on the broader structural influences on AI rather than just on statistical de-biasing methods [11, 94]. A key direction for future work would be to explore how guardrails are constructed within AI models and how they may affect access. Several cases in our findings show that biases are embedded through guardrails that carry assumptions of who is using the system and how, which completely restrict access to certain information (e.g., refusing to describe a bathroom). While some of these tensions surfaced in prior research on visual descriptions [16, 53] and privacy concerns around camera-based assistive technologies [5], it remains unclear how practitioners navigate the tradeoffs and make decisions regarding these tensions. Similar challenges may arise across various disabilities, including neurodiversity [62] and d/Deafness [102], where communities have long debated appropriate ways to gain access. Understanding these nuanced challenges could be a crucial step in developing a more negotiable framework to address uncertainty in access. For example, negotiating visual access needs with bystanders in family or workplace settings may be possible.

Further, to drive systemic change, it is crucial to adopt a governance perspective in building foundational trust in AI-powered access technologies [76]. While policies have long been central to promoting accessibility, policymaking research has received less attention in accessibility studies compared to technological solutions [127]. Mitigating uncertainty at its core requires the development of robust regulatory frameworks [87], ensuring active participation of PWD in agenda-setting [30] and in the development of foundational models [125]. For designers and practitioners, this offers an opportunity to consider policy implications or collaborate with policymakers on how uncertainty should be represented throughout the process and to consider the types of information and involvement PWD may need to reduce uncertainty in access. For example, besides dataset quality and model accuracy as often discussed in research [6, 69], blind users may seek transparency about who is represented in training data [46], what standards are followed in visual descriptions, and who is responsible for the information provided by tools like visual description applications. Although influencing policy is a complex task, incorporating a policy perspective into accessibility research could serve as an important first step [145].

## 6 Conclusion

We present a qualitative study based on semi-structured interviews with 20 blind screen reader users to understand their practices with GenAI tools. We introduce the concept of *everyday uncertainty* to articulate the core experience of blind people’s use of GenAI tools

for access, reframing uncertainty as a situated, ongoing, and life-long process. Drawing on the concept of everyday uncertainty, we articulate future directions to advance AI research for accessibility. We call to go beyond precision-focused objectives like accuracy and bias mitigation, addressing the limitations of model-specific approaches to design and evaluation of AI, and developing strategies to mitigate uncertainty at its core.

## Acknowledgments

We thank the anonymous reviewers for their valuable feedback. We also acknowledge the Accessibility Research Collective for their insights throughout various stages of this research and extend our thanks to Sanika Bhamare for her assistance during the initial exploration of this work. This work was supported by NSF Award #2326023.

## References

- [1] Moloud Abdar, Farhad Pourpanah, Sadiq Hussain, Dana Rezazadegan, Li Liu, Mohammad Ghavamzadeh, Paul Fieguth, Xiaochun Cao, Abbas Khosravi, U Rajendra Acharya, et al. 2021. A review of uncertainty quantification in deep learning: Techniques, applications and challenges. *Information fusion* 76 (2021), 243–297.
- [2] Ali Abdolrahmani, William Easley, Michele Williams, Stacy Branham, and Amy Hurst. 2017. Embracing errors: Examining how context of use impacts blind individuals’ acceptance of navigation aid errors. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 4158–4169.
- [3] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Alvenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774* (2023).
- [4] Rudaiba Admin and Maitraye Das. 2024. “I look at it as the king of knowledge”: How Blind People Use and Understand Generative AI Tools. In *Proceedings of the 26th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–14.
- [5] Taslima Akter, Tousif Ahmed, Apu Kapadia, and Manohar Swaminathan. 2022. Shared privacy concerns of the visually impaired and sighted bystanders with camera-based assistive technologies. *ACM Transactions on Accessible Computing (TACCESS)* 15, 2 (2022), 1–33.
- [6] Rahaf Alharbi, Pa Lor, Jaylin Herskovitz, Sarita Schoenebeck, and Robin Brewer. 2024. Misfitting With AI: How Blind People Verify and Contest AI Errors. In *Proceedings of the 26th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–17.
- [7] Abdulaziz Alshayban, Iftekhar Ahmed, and Sam Malek. 2020. Accessibility issues in android apps: state of affairs, sentiments, and ways forward. In *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering*. 1323–1334.
- [8] Callen Anthony, Beth A Bechky, and Anne-Laure Fayard. 2023. “Collaborating” with AI: Taking a system view to explore the future of work. *Organization Science* 34, 5 (2023), 1672–1694.
- [9] Apple. Retrieved August, 2024. Use VoiceOver in apps on iPhone. <https://support.apple.com/en-lb/guide/iphone/iphe4ee74be8/ios>.
- [10] Patti Bao, Brent Hecht, Samuel Carton, Mahmood Quaderi, Michael Horn, and Darren Gergle. 2012. Omnipedia: bridging the wikipedia language gap. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1075–1084.
- [11] Chelsea Barabas, Colin Doyle, JB Rubinovitz, and Karthik Dinakar. 2020. Studying up: reorienting the study of algorithmic fairness around issues of power. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*. 167–176.
- [12] Natā M Barbosa, Jordan Hayes, Smirity Kaushik, and Yang Wang. 2022. “Every Website Is a Puzzle!”: Facilitating Access to Common Website Features for People with Visual Impairments. *ACM Transactions on Accessible Computing (TACCESS)* 15, 3 (2022), 1–35.
- [13] Edmon Begoli, Tanmoy Bhattacharya, and Dimitri Kusnezov. 2019. The need for uncertainty quantification in machine-assisted medical decision making. *Nature Machine Intelligence* 1, 1 (2019), 20–23.
- [14] Jesse Josua Benjamin, Arne Berger, Nick Merrill, and James Pierce. 2021. Machine learning uncertainty as a design material: A post-phenomenological inquiry. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–14.
- [15] Cynthia L Bennett, Erin Brady, and Stacy M Branham. 2018. Interdependence as a frame for assistive technology research and design. In *Proceedings of the 20th*

- international acm sigaccess conference on computers and accessibility*. 161–173.
- [16] Cynthia L Bennett, Cole Gleason, Morgan Klaus Scheuerman, Jeffrey P Bigham, Anhong Guo, and Alexandra To. 2021. "It's complicated": Negotiating accessibility and (mis) representation in image descriptions of race, gender, and disability. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–19.
  - [17] Cynthia L Bennett, Daniela K Rosner, and Alex S Taylor. 2020. The care work of access. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–15.
  - [18] Umang Bhatt, Javier Antorán, Yunfeng Zhang, Q. Vera Liao, Prasanna Sattigeri, Riccardo Fogliato, Gabrielle Melançon, Ranganath Krishnan, Jason Stanley, Omesh Tickoo, Lama Nachman, Rumi Chunara, Madhulika Srikumar, Adrian Weller, and Alice Xiang. 2021. Uncertainty as a Form of Transparency: Measuring, Communicating, and Using Uncertainty. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society (Virtual Event, USA) (AI/ES '21)*. Association for Computing Machinery, New York, NY, USA, 401–413. <https://doi.org/10.1145/3461702.3462571>
  - [19] Jeffrey P Bigham, Chandrika Jayant, Hanjie Ji, Greg Little, Andrew Miller, Robert C Miller, Robin Miller, Aubrey Tatarowicz, Brandyn White, Samuel White, et al. 2010. Vizwiz: nearly real-time answers to visual questions. In *Proceedings of the 23rd annual ACM symposium on User interface software and technology*. 333–342.
  - [20] Jeffrey P Bigham, Irene Lin, and Saiph Savage. 2017. The Effects of "Not Knowing What You Don't Know" on Web Accessibility for Blind Web Users. In *Proceedings of the 19th international ACM SIGACCESS conference on computers and accessibility*. 101–109.
  - [21] Erin Brady, Meredith Ringel Morris, Yu Zhong, Samuel White, and Jeffrey P Bigham. 2013. Visual challenges in the everyday lives of blind people. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 2117–2126.
  - [22] Danielle Bragg, Naomi Caselli, Julie A Hochgesang, Matt Huenerfauth, Leah Katz-Hernandez, Oscar Koller, Raja Kushalnagar, Christian Vogler, and Richard E Ladner. 2021. The fate landscape of sign language ai datasets: An interdisciplinary perspective. *ACM Transactions on Accessible Computing (TACCESS)* 14, 2 (2021), 1–45.
  - [23] Virginia Braun and Victoria Clarke. 2021. Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling and Psychotherapy Research* 21, 1 (2021), 37–47.
  - [24] Chongyan Chen, Samreen Anjum, and Danna Gurari. 2022. Grounding answers for visual questions asked by visually impaired people. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 19098–19107.
  - [25] Hao-Fei Cheng, Ruotong Wang, Zheng Zhang, Fiona O'connell, Terrance Gray, F Maxwell Harper, and Haiyi Zhu. 2019. Explaining decision-making algorithms through UI: Strategies to help non-expert stakeholders. In *Proceedings of the 2019 chi conference on human factors in computing systems*. 1–12.
  - [26] Kara Combs, Adam Moyer, and Trevor J Bihl. 2024. Uncertainty in Visual Generative AI. *Algorithms* 17, 4 (2024), 136.
  - [27] Maitraye Das, Alexander J. Fiannaca, Meredith Ringel Morris, Shaun K. Kane, and Cynthia L. Bennett. 2024. From Provenance to Aberrations: Image Creator and Screen Reader User Perspectives on Alt Text for AI-Generated Images. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 1–21.
  - [28] Maitraye Das, Darren Gergle, and Anne Marie Piper. 2019. "It doesn't win you friends" Understanding Accessibility in Collaborative Writing for People with Vision Impairments. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–26.
  - [29] Maartje De Meulder. 2021. Is "good enough" good enough? Ethical and responsible development of sign language technologies. In *Proceedings of the 1st International Workshop on Automatic Translation for Signed and Spoken Languages (AT4SSL)*. 12–22.
  - [30] Fernando Delgado, Stephen Yang, Michael Madaio, and Qian Yang. 2023. The participatory turn in ai design: Theoretical foundations and the current state of practice. In *Proceedings of the 3rd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization*. 1–23.
  - [31] Laura Devendorf, Kristina Andersen, and Aisling Kelliher. 2020. The fundamental uncertainties of mothering: Finding ways to honor endurance, struggle, and contradiction. *ACM Transactions on Computer-Human Interaction (TOCHI)* 27, 4 (2020), 1–24.
  - [32] Bryan Dosono, Jordan Hayes, and Yang Wang. 2015. {"T'm"} {"Stuck!"}: A Contextual Inquiry of People with Visual Impairments in Authentication. In *Eleventh Symposium On Usable Privacy and Security (SOUPS 2015)*. 151–168.
  - [33] Brian L Due. 2021. Distributed perception: Co-operation between sense-able, actionable, and accountable semiotic agents. *Symbolic Interaction* 44, 1 (2021), 134–162.
  - [34] Emory J Edwards, Michael Gilbert, Emily Blank, and Stacy M Branham. 2023. How the Alt Text Gets Made: What Roles and Processes of Alt Text Creation Can Teach Us About Inclusive Imagery. *ACM Transactions on Accessible Computing* 16, 2 (2023), 1–28.
  - [35] Frank Elavsky, Cynthia Bennett, and Dominik Moritz. 2022. How accessible is my visualization? Evaluating visualization accessibility with Chartability. In *Computer Graphics Forum*, Vol. 41. Wiley Online Library, 57–70.
  - [36] Michael Fernandes, Logan Walls, Sean Munson, Jessica Hullman, and Matthew Kay. 2018. Uncertainty displays using quantile dotplots or cdfs improve transit decision-making. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–12.
  - [37] Fleet, Chancey. Retrieved August, 2024. Keynote Talk by Chancey Fleet, New York Public Library. [https://www.youtube.com/watch?v=yUTpK\\_HOGmo](https://www.youtube.com/watch?v=yUTpK_HOGmo).
  - [38] Forbes. Retrieved March, 2024. Meta Announces Voicebox Generative AI Model, Touting Accessibility Implications. <https://www.forbes.com/sites/stevenaquinio/2023/06/20/meta-announces-voicebox-generative-ai-model-touting-accessibility-implications/?sh=44d0ee3569c6>.
  - [39] Freedom Scientific. Retrieved August, 2024. JAWS. <https://www.freedomscientific.com/products/software/jaws/>.
  - [40] Freedom Scientific. Retrieved August, 2024. New and Improved Features in JAWS. <https://www.freedomscientific.com/training/jaws/new-and-improved-features/>.
  - [41] Vinitha Gadiraju, Shaun Kane, Sunipa Dev, Alex Taylor, Ding Wang, Emily Denton, and Robin Brewer. 2023. "I wouldn't say offensive but...": Disability-Centered Perspectives on Large Language Models. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*. 205–216.
  - [42] Bhanuka Gamage, Thanh-Toan Do, Nicholas Seow Chiang Price, Arthur Lowery, and Kim Marriott. 2023. What do Blind and Low-Vision People Really Want from Assistive Smart Devices? Comparison of the Literature with a Focus Study. In *Proceedings of the 25th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–21.
  - [43] Kate Glazko, Yusuf Mohammed, Ben Kosa, Venkatesh Potluri, and Jennifer Mankoff. 2024. Identifying and Improving Disability Bias in GPT-Based Resume Screening. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*. 687–700.
  - [44] Kate S Glazko, Momona Yamagami, Aashaka Desai, Kelly Avery Mack, Venkatesh Potluri, Xuhai Xu, and Jennifer Mankoff. 2023. An Autoethnographic Case Study of Generative Artificial Intelligence's Utility for Accessibility. In *Proceedings of the 25th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–8.
  - [45] Ricardo E Gonzalez Penuela, Jazmin Collins, Cynthia Bennett, and Shiri Azenkot. 2024. Investigating Use Cases of AI-Powered Scene Description Applications for Blind and Low Vision People. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–21.
  - [46] Mitchell L Gordon, Michelle S Lam, Joon Sung Park, Kayur Patel, Jeff Hancock, Tatsunori Hashimoto, and Michael S Bernstein. 2022. Jury learning: Integrating dissenting voices into machine learning models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–19.
  - [47] Griffin, Hannah. Retrieved August, 2024. Aira Announces New Access AI Feature at CSUN! <https://aira.io/aira-announces-new-access-ai-feature-at-csun/>.
  - [48] Ziwei Gu, Ian Arawjo, Kenneth Li, Jonathan K Kummerfeld, and Elena L Glassman. 2024. An AI-Resilient Text Rendering Technique for Reading and Skimming Documents. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–22.
  - [49] Danna Gurari, Qing Li, Chi Lin, Yanan Zhao, Anhong Guo, Abigale Stangl, and Jeffrey P Bigham. 2019. Vizwiz-priv: A dataset for recognizing the presence and purpose of private visual information in images taken by blind people. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 939–948.
  - [50] Danna Gurari, Qing Li, Abigale J Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P Bigham. 2018. Vizwiz grand challenge: Answering visual questions from blind people. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 3608–3617.
  - [51] Ian Hacking. 1990. *The taming of chance*. Number 17. Cambridge University Press.
  - [52] Alieh Hajizadeh Saffar, Laurianne Sitbon, Maria Hoogstrate, Ahmed Abbas, Sirinithip Roomkham, and Dimity Miller. 2024. Human and Large Language Model Intent Detection in Image-Based Self-Expression of People with Intellectual Disability. In *Proceedings of the 2024 ACM SIGIR Conference on Human Information Interaction and Retrieval*. 199–208.
  - [53] Margot Hanley, Solon Barocas, Karen Levy, Shiri Azenkot, and Helen Nissenbaum. 2021. Computer vision and conflicting values: Describing people with automated alt text. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*. 543–554.
  - [54] Katrin Hartwig, Frederic Doell, and Christian Reuter. 2024. The Landscape of User-centered Misinformation Interventions-A Systematic Literature Review. *Comput. Surveys* 56, 11 (2024), 1–36.
  - [55] Tina Helle, Aase Brandt, Björn Slaug, and Susanne Iwarsson. 2011. Lack of research-based standards for accessible housing: Problematisation and exemplification of consequences. *International Journal of Public Health* 56 (2011), 635–644.

- [56] Megan Hofmann, Devva Kasnitz, Jennifer Mankoff, and Cynthia L Bennett. 2020. Living disability theory: Reflections on access, research, and design. In *Proceedings of the 22nd International ACM SIGACCESS Conference on Computers and Accessibility*. 1–13.
- [57] James Hollan, Edwin Hutchins, and David Kirsh. 2000. Distributed cognition: toward a new foundation for human-computer interaction research. *ACM Transactions on Computer-Human Interaction (TOCHI)* 7, 2 (2000), 174–196.
- [58] Jonggi Hong and Hernisa Kacorri. 2024. Understanding How Blind Users Handle Object Recognition Errors: Strategies and Challenges. In *The 26th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–15.
- [59] Mina Huh, Yi-Hao Peng, and Amy Pavel. 2023. GenAssist: Making Image Generation Accessible. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–17.
- [60] Jessica Hullman, Xiaoli Qiao, Michael Correll, Alex Kale, and Matthew Kay. 2018. In pursuit of error: A survey of uncertainty visualization evaluation. *IEEE transactions on visualization and computer graphics* 25, 1 (2018), 903–913.
- [61] Edwin Hutchins. 1995. *Cognition in the Wild*. MIT press.
- [62] JiWoong Jang, Sanika Moharana, Patrick Carrington, and Andrew Begel. 2024. "It's the only thing I can trust": Envisioning Large Language Model Use by Autistic Workers for Communication Assistance. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–18.
- [63] Ellen Jiang, Edwin Toh, Alejandra Molina, Kristen Olson, Claire Kayacik, Aaron Donsbach, Carrie J Cai, and Michael Terry. 2022. Discovering the syntax and strategies of natural language programming with generative language models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–19.
- [64] Peiling Jiang, Jude Rayan, Steven P Dow, and Hajjun Xia. 2023. Graphologue: Exploring large language model responses with interactive diagrams. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–20.
- [65] John Lee Clark. Retrieved September, 2024. Against Access. [https://audio.mcsweeneys.net/transcripts/against\\_access.html](https://audio.mcsweeneys.net/transcripts/against_access.html).
- [66] Ju Yeon Jung, Tom Steinberger, Junbeom Kim, and Mark S Ackerman. 2022. "So What? What's That to Do With Me?" Expectations of People With Visual Impairments for Image Descriptions in Their Personal Photo Activities. In *Proceedings of the 2022 ACM Designing Interactive Systems Conference*. 1893–1906.
- [67] Hernisa Kacorri, Kris M Kitani, Jeffrey P Bigham, and Chieko Asakawa. 2017. People with visual impairment training personal object recognizers: Feasibility and challenges. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 5839–5849.
- [68] Alison Kafer. 2013. *Feminist, queer, crip*. Indiana University Press.
- [69] Rie Kamikubo, Lining Wang, Crystal Marte, Amnah Mahmood, and Hernisa Kacorri. 2022. Data representativeness in accessibility datasets: A meta-analysis. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–15.
- [70] Shivani Kapania, Alex S Taylor, and Ding Wang. 2023. A hunt for the Snark: Annotator Diversity in Data Practices. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [71] Matthew Kay, Tara Kola, Jessica R Hullman, and Sean A Munson. 2016. When (ish) is my bus? user-centered visualizations of uncertainty in everyday, mobile predictive systems. In *Proceedings of the 2016 chi conference on human factors in computing systems*. 5092–5103.
- [72] Stephanie L Kerschbaum, Laura T Eisenman, and James M Jones. 2017. *Negotiating disability: Disclosure and higher education*. University of Michigan Press.
- [73] Jiho Kim, Arjun Srinivasan, Nam Wook Kim, and Yea-Seul Kim. 2023. Exploring chart question answering for blind and low vision users. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [74] Sunnie S. Y. Kim, Q. Vera Liao, Mihaela Vorvoreanu, Stephanie Ballard, and Jennifer Wortman Vaughan. 2024. "I'm Not Sure, But...": Examining the Impact of Large Language Models' Uncertainty Expression on User Reliance and Trust. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency (Rio de Janeiro, Brazil) (FAccT '24)*. Association for Computing Machinery, New York, NY, USA, 822–835. <https://doi.org/10.1145/3630106.3658941>
- [75] Bran Knowles, Jasmine Fledderjohann, John T Richards, and Kush R Varshney. 2023. Trustworthy AI and the Logics of Intersectional Resistance. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*. 172–182.
- [76] Bran Knowles and Vicki L Hanson. 2018. Older adults' deployment of 'distrust'. *ACM Transactions on Computer-Human Interaction (TOCHI)* 25, 4 (2018), 1–25.
- [77] Satwik Ram Kodandaram, Utku Uckun, Xiaojun Bi, IV Ramakrishnan, and Vikas Ashok. 2024. Enabling Uniform Computer Interaction Experience for Blind Users through Large Language Models. In *Proceedings of the 26th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–17.
- [78] Carol C Kuhlthau. 1993. A principle of uncertainty for information seeking. *Journal of documentation* 49, 4 (1993), 339–355.
- [79] Anukriti Kumar and Lucy Lu Wang. 2024. Uncovering the New Accessibility Crisis in Scholarly PDFs. In *Proceedings of the 26th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–16.
- [80] Bruno Latour. 2007. *Reassembling the social: An introduction to actor-network-theory*. Oup Oxford.
- [81] Edith Law, Krzysztof Z Gajos, Andrea Wiggins, Mary L Gray, and Alex Williams. 2017. Crowdsourcing as a tool for research: Implications of uncertainty. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*. 1544–1561.
- [82] Jonathan Lazar, Aaron Allen, Jason Kleinman, and Chris Malarkey. 2007. What frustrates screen reader users on the web: A study of 100 blind users. *International Journal of human-computer interaction* 22, 3 (2007), 247–269.
- [83] Seonghee Lee, Maho Kohga, Steve Landau, Sile O'Modhrain, and Hari Subramonyam. 2024. AltCanvas: A Tile-Based Image Editor with Generative AI for Blind or Visually Impaired People. In *Proceedings of the 26th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–22.
- [84] Sooyeon Lee, Madison Reddie, and John M Carroll. 2021. Designing for Independence for people with visual impairments. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–19.
- [85] Sooyeon Lee, Madison Reddie, Chun-Hua Tsai, Jordan Beck, Mary Beth Rosson, and John M Carroll. 2020. The emerging professional practice of remote sighted assistance for people with visual impairments. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–12.
- [86] Sooyeon Lee, Rui Yu, Jingyi Xie, Syed Masum Billah, and John M Carroll. 2022. Opportunities for human-AI collaboration in remote sighted assistance. In *Proceedings of the 27th International Conference on Intelligent User Interfaces*. 63–78.
- [87] Gabriel Lima, Nina Grgić-Hlača, Jin Keun Jeong, and Meeyoung Cha. 2022. The conflict between explainable and accountable decision-making algorithms. In *Proceedings of the 2022 ACM conference on fairness, accountability, and transparency*. 2103–2113.
- [88] Cindy Kaiying Lin and Steven J Jackson. 2023. From bias to repair: Error as a site of collaboration and negotiation in applied data science work. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023), 1–32.
- [89] Kelly Mack, Emma McDonnell, Dhruv Jain, Lucy Lu Wang, Jon E. Froehlich, and Leah Findlater. 2021. What do we mean by "accessibility research"? A literature survey of accessibility papers in CHI and ASSETS from 1994 to 2019. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–18.
- [90] Kelly Mack, Emma McDonnell, Venkatesh Potluri, Maggie Xu, Jaily Zabala, Jeffrey Bigham, Jennifer Mankoff, and Cynthia Bennett. 2022. Anticipate and adjust: Cultivating access in human-centered methods. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–18.
- [91] Kelly Avery Mack, Rida Qadri, Remi Denton, Shaun K Kane, and Cynthia L Bennett. 2024. "They only care to show us the wheelchair": disability representation in text-to-image AI models. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–23.
- [92] Haley MacLeod, Cynthia L Bennett, Meredith Ringel Morris, and Edward Cutrell. 2017. Understanding blind people's experiences with computer-generated captions of social media images. In *proceedings of the 2017 CHI conference on human factors in computing systems*. 5988–5999.
- [93] Nora McDonald and Nazanin Andalibi. 2023. "I Did Watch 'The Handmaid's Tale'": Threat Modeling Privacy Post-roe in the United States. *ACM Transactions on Computer-Human Interaction* 6, 4 (2023), 1–34.
- [94] Milagros Miceli, Julian Posada, and Tianling Yang. 2022. Studying up machine learning data: Why talk about bias when we mean power? *Proceedings of the ACM on Human-Computer Interaction* 6, GROUP (2022), 1–14.
- [95] Michele Paris. Retrieved August, 2024. Introducing: Be My AI. <https://www.bemyeyes.com/blog/introducing-be-my-ai>.
- [96] Microsoft. Retrieved August, 2024. Narrator. <https://www.microsoft.com/en-us/windows/tips/narrator>.
- [97] Microsoft. Retrieved March, 2024. Seeing AI App Launches on Android - Including new and updated features and new languages. <https://blogs.microsoft.com/accessibility/seeing-ai-app-launches-on-android-including-new-and-updated-features-and-new-languages/>.
- [98] Mingus, Mia. Retrieved August, 2024. Access Intimacy: The Missing Link. <https://leavingevidence.wordpress.com/2011/05/05/access-intimacy-the-missing-link/>.
- [99] Meredith Ringel Morris, Annuska Zolyomi, Catherine Yao, Sina Bahram, Jeffrey P Bigham, and Shaun K Kane. 2016. "With most of it being pictures now, I rarely use it" Understanding Twitter's Evolving Accessibility to Blind Users. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 5506–5516.
- [100] Cecily Morrison, Martin Grayson, Rita Faia Marques, Daniela Massiceti, Camilla Longden, Linda Wen, and Edward Cutrell. 2023. Understanding Personalized Accessibility through Teachable AI: Designing and Evaluating Find My Things for People who are Blind or Low Vision. In *Proceedings of the 25th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–12.

- [101] Ingunn Moser. 2006. Disability and the promises of technology: Technology, subjectivity and embodiment within an order of the normal. *Information, communication & society* 9, 3 (2006), 373–395.
- [102] Karen Nakamura. 2006. *Deaf in Japan: Signing and the politics of identity*. Cornell University Press.
- [103] NV Access. Retrieved August, 2024. About NVDA. <https://www.nvaccess.org/about-nvda/>.
- [104] Aisling Ann O’Kane, Abdinasir Aliomar, Rebecca Zheng, Britta Schulte, and Gianluca Trombetta. 2019. Social, cultural and systematic frustrations motivating the formation of a DIY hearing loss hacking community. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–14.
- [105] OpenAI. Retrieved March, 2024. Be My Eyes uses GPT-4 to transform visual accessibility. <https://openai.com/customer-stories/be-my-eyes>.
- [106] Charlie Parker, Sam Scott, and Alistair Geddes. 2019. Snowball sampling. *SAGE research methods foundations* (2019).
- [107] Savvas Petridis, Nicholas Diakopoulos, Kevin Crowston, Mark Hansen, Keren Henderson, Stan Jastrzebski, Jeffrey V Nickerson, and Lydia B Chilton. 2023. Anglekindling: Supporting journalistic angle ideation with large language models. In *Proceedings of the 2023 CHI conference on human factors in computing systems*. 1–16.
- [108] Sarah Pink, Yoko Akama, and Shanti Sumartojo. 2018. *Uncertainty and possibility: New approaches to future making in design anthropology*. Bloomsbury Publishing.
- [109] Snehal Prabhudesai, Leyao Yang, Sumit Asthana, Xun Huan, Q. Vera Liao, and Nikola Banovic. 2023. Understanding Uncertainty: How Lay Decision-makers Perceive and Interpret Uncertainty in Human-AI Decision Making. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (Sydney, NSW, Australia) (IUI ’23). Association for Computing Machinery, New York, NY, USA, 379–396. <https://doi.org/10.1145/3581641.3584033>
- [110] Reid Priedhorsky, Aron Culotta, and Sara Y Del Valle. 2014. Inferring the origin locations of tweets with quantitative confidence. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. 1523–1536.
- [111] Emanuele Pucci, Isabella Possaghi, Claudia Maria Cutrupi, Marcos Baez, Cinzia Cappiello, and Maristella Matera. 2023. Defining Patterns for a Conversational Web. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [112] Abir Saha and Anne Marie Piper. 2020. Understanding audio production practices of people with vision impairments. In *Proceedings of the 22nd International ACM SIGACCESS Conference on Computers and Accessibility*. 1–13.
- [113] Ian Scoones and Andy Stirling. 2020. Uncertainty and the politics of transformation. *The politics of uncertainty: Challenges of transformation* (2020), 1–30.
- [114] JooYoung Seo, Sanchita S. Kamath, Aziz N. Zeidieh, Saairam Venkatesh, and Sean McCurry. 2024. MAIDR Meets AI: Exploring Multimodal LLM-Based Data Visualization Interpretation by and with Blind and Low-Vision Users. In *Proceedings of the 26th International ACM SIGACCESS Conference on Computers and Accessibility*.
- [115] Ather Sharif, Aedan Liam McCall, and Kianna Rocas Bolante. 2022. Should I say “disabled people” or “people with disabilities”? Language preferences of disabled people between identity-and person-first language. In *Proceedings of the 24th international ACM SIGACCESS conference on computers and accessibility*. 1–18.
- [116] Tanusree Sharma, Abigale Stangl, Lotus Zhang, Yu-Yun Tseng, Inan Xu, Leah Findlater, Danna Gurari, and Yang Wang. 2023. Disability-first design and creation of a dataset showing private visual information collected with people who are blind. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [117] Kristen Shinohara, Murtaza Tamjeed, Michael McQuaid, and Dymen A Barkins. 2022. Usability, accessibility and social entanglements in advanced tool use by vision impaired graduate students. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–21.
- [118] Ben Shneiderman. 2020. Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human-Computer Interaction* 36, 6 (2020), 495–504.
- [119] Robert Soden, Laura Devendorf, Richmond Wong, Yoko Akama, Ann Light, et al. 2022. Modes of Uncertainty in HCI. *Foundations and Trends® in Human-Computer Interaction* 15, 4 (2022), 317–426.
- [120] Robert Soden, Laura Devendorf, Richmond Y Wong, Lydia B Chilton, Ann Light, and Yoko Akama. 2020. Embracing uncertainty in HCI. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–8.
- [121] Abigale Stangl, Nitin Verma, Kenneth R Fleischmann, Meredith Ringel Morris, and Danna Gurari. 2021. Going beyond one-size-fits-all image descriptions to satisfy the information wants of people who are blind or have low vision. In *Proceedings of the 23rd International ACM SIGACCESS Conference on Computers and Accessibility*. 1–15.
- [122] Abigale J Stangl, Esha Kothari, Suyog D Jain, Tom Yeh, Kristen Grauman, and Danna Gurari. 2018. Browsewithme: An online clothes shopping assistant for people with visual impairments. In *Proceedings of the 20th International ACM SIGACCESS Conference on Computers and Accessibility*. 107–118.
- [123] L Suchman. 1987. *Plans and situated actions: e problem of human-machine communication*. Cambridge University Press.
- [124] Sangho Suh, Bryan Min, Srishti Palani, and Haijun Xia. 2023. Sensecape: Enabling multilevel exploration and sensemaking with large language models. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–18.
- [125] Harini Suresh, Emily Tseng, Meg Young, Mary Gray, Emma Pierson, and Karen Levy. 2024. Participation in the age of foundation models. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (Rio de Janeiro, Brazil) (FAccT ’24). Association for Computing Machinery, New York, NY, USA, 1609–1621. <https://doi.org/10.1145/3630106.3658992>
- [126] Murtaza Tamjeed, Vinita Tibdewal, Madison Russell, Michael McQuaid, Tae Oh, and Kristen Shinohara. 2021. Understanding disability services toward improving graduate student support. In *Proceedings of the 23rd international ACM SIGACCESS conference on computers and accessibility*. 1–14.
- [127] Xinru Tang. 2024. Why is Accessibility So Hard? Insights From the History of Privacy. In *Companion Publication of the 2024 Conference on Computer Supported Cooperative Work and Social Computing*.
- [128] Lida Theodorou, Daniela Massiceti, Luisa Zintgraf, Simone Stumpf, Cecily Morrison, Edward Cutrell, Matthew Tobias Harris, and Katja Hofmann. 2021. Disability-first dataset creation: Lessons from constructing a dataset for teachable object recognition with blind and low vision data collectors. In *Proceedings of the 23rd International ACM SIGACCESS Conference on Computers and Accessibility*. 1–12.
- [129] Yong-Joon Thoo, Maximiliano Jeanneret Medina, Jon E Froehlich, Nicolas Ruffieux, and Denis Lalanne. 2023. A large-scale mixed-methods analysis of blind and low-vision research in ACM and IEEE. In *Proceedings of the 25th international ACM SIGACCESS conference on computers and accessibility*. 1–20.
- [130] Yu-Yun Tseng, Alexander Bell, and Danna Gurari. 2022. Vizwiz-fewshot: Locating objects in images taken by people with visual impairments. In *European Conference on Computer Vision*. Springer, 575–591.
- [131] John Turri, Mark Alfano, and John Greco. 2021. Virtue Epistemology. In *The Stanford Encyclopedia of Philosophy* (Winter 2021 ed.), Edward N. Zalta (Ed.). Metaphysics Research Lab, Stanford University.
- [132] Hristos Tyrallis and Georgia Papacharalampous. 2024. A review of predictive uncertainty estimation with machine learning. *Artificial Intelligence Review* 57, 4 (2024), 94.
- [133] Ovidiu-Ciprian Ungurean and Radu-Daniel Vatavu. 2021. Coping, hacking, and DIY: reframing the accessibility of interactions with television for people with motor impairments. In *Proceedings of the 2021 ACM International Conference on Interactive Media Experiences*. 37–49.
- [134] Stephanie Valencia, Richard Cave, Krystal Kallarackal, Katie Seaver, Michael Terry, and Shaun K Kane. 2023. “The less I type, the better”: How AI Language Models can Enhance or Impede Communication for AAC Users. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–14.
- [135] Tess Van Daele, Akhil Iyer, Yuning Zhang, Jalyn C Derry, Mina Huh, and Amy Pavel. 2024. Making Short-Form Videos Accessible with Hierarchical Video Summaries. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–17.
- [136] Beatrice Vincenzi, Alex S Taylor, and Simone Stumpf. 2021. Interdependence in action: people with visual impairments and their guides co-constituting common spaces. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–33.
- [137] Violeta Voykanska, Shiri Azenkot, Shaomei Wu, and Gilly Leshed. 2016. How blind people interact with visual content on social networking services. In *Proceedings of the 19th acm conference on computer-supported cooperative work & social computing*. 1584–1595.
- [138] Emily Q Wang and Anne Marie Piper. 2018. Accessibility in action: Co-located collaboration among deaf and hearing professionals. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–25.
- [139] Emily Q Wang and Anne Marie Piper. 2022. The invisible labor of access in academic writing practices: A case analysis with dyslexic adults. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW1 (2022), 1–25.
- [140] David Wästerfors. 2021. Required to be creative. Everyday ways for dealing with inaccessibility. *Disability & Society* 36, 2 (2021), 265–285.
- [141] Justin D Weisz, Jessica He, Michael Muller, Gabriela Hoefler, Rachel Miles, and Werner Geyer. 2024. Design Principles for Generative AI Applications. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–22.
- [142] Michele A Williams, Caroline Galbraith, Shaun K Kane, and Amy Hurst. 2014. “just let the cane hit it” how the blind and sighted see navigation differently. In *Proceedings of the 16th international ACM SIGACCESS conference on Computers & accessibility*. 217–224.
- [143] Shaomei Wu, Jeffrey Wieland, Omid Farivar, and Julie Schiller. 2017. Automatic alt-text: Computer-generated image descriptions for blind users on a social network service. In *proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*. 1180–1192.



- [144] Qian Yang, Aaron Steinfeld, Carolyn Rosé, and John Zimmerman. 2020. Re-examining whether, why, and how human-AI interaction is uniquely difficult to design. In *Proceedings of the 2020 chi conference on human factors in computing systems*. 1–13.
- [145] Qian Yang, Richmond Y Wong, Steven Jackson, Sabine Junginger, Margaret D Hagan, Thomas Gilbert, and John Zimmerman. 2024. The Future of HCI-Policy Collaboration. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–15.
- [146] Ming Yin, Jennifer Wortman Vaughan, and Hanna Wallach. 2019. Understanding the effect of accuracy on trust in machine learning models. In *Proceedings of the 2019 chi conference on human factors in computing systems*. 1–12.
- [147] Alys Young, Jemina Napier, and Rosemary Oram. 2019. The translated deaf self, ontological (in) security and deaf culture. *The Translator* 25, 4 (2019), 349–368.
- [148] Bowen Yu, Ye Yuan, Loren Terveen, Zhiwei Steven Wu, Jodi Forlizzi, and Haiyi Zhu. 2020. Keeping designers in the loop: Communicating inherent algorithmic trade-offs across multiple objectives. In *Proceedings of the 2020 ACM designing interactive systems conference*. 1245–1257.
- [149] JD Zamfirescu-Pereira, Richmond Y Wong, Bjoern Hartmann, and Qian Yang. 2023. Why Johnny can't prompt: how non-AI experts try (and fail) to design LLM prompts. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–21.
- [150] Xiaoyu Zeng, Yanan Wang, Tai-Yin Chiu, Nilavra Bhattacharya, and Danna Gurari. 2020. Vision skills needed to answer visual questions. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–31.
- [151] Zhuohao Jerry Zhang, Smirity Kaushik, JooYoung Seo, Haolin Yuan, Sauvik Das, Leah Findlater, Danna Gurari, Abigale Stangl, and Yang Wang. 2023. {ImageAlly}: A {Human-AI} Hybrid Approach to Support Blind People in Detecting and Redacting Private Image Content. In *Nineteenth Symposium on Usable Privacy and Security (SOUPS 2023)*. 417–436.
- [152] Yuhang Zhao, Shaomei Wu, Lindsay Reynolds, and Shiri Azenkot. 2017. The effect of computer-generated descriptions on photo-sharing experiences of people with visual impairments. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW (2017), 1–22.