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Emerging Trends in Artificial Intelligence and Blindness: A Delphi Study

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Abstract

Introduction: This research article describes anticipated directions of future artificial intelligence (AI) research and development and potential concerns and barriers associated with development as it relates to individuals with disabilities, particularly individuals who are visually impaired (i.e., those who are blind or have low vision). **Methodology:** A Delphi method was used to identify experts' opinions and predictions around future AI developments focused around individuals who are blind or visually impaired. A combination of semistructured interviews and web-based surveys were utilized to identify consensus statements regarding the future of AI. **Results:** In the first round of semistructured interviews, 32 AI experts participated and shared their views on the future of AI and how it will affect individuals with disabilities. From the interviews, 72 common themes and insights were identified. Through 2 web-based surveys, the 72 common themes were narrowed down to 32 statements that reached consensus amongst the expert participants. The statement with the strongest support by the experts was: "A human in the loop is necessary for candidate screening"; which had a rating of 6.76 and a standard deviation of 0.44. The statement with the weakest support was: "AI-driven prenatal screening tools will create actions of eugenics"; which had a rating of 4.69 and a standard deviation of 0.95. **Discussion:** Experts discussed the careful balance between pushing AI development to support individuals' lives and the potential harms of development without careful consideration. These findings point to a need for caution in the implementation of AI technologies and tools without proper dedication to fair representation and involvement of individuals with disabilities. **Implications for Practitioners:** Practitioners should acknowledge and explore the potential benefits that AI can provide for individuals with disabilities but also be aware of the bias and discrimination that is inherent in these tools.

Keywords

blind, low vision, artificial intelligence, assistive technology, advocacy, public policy, Delphi study

Introduction

According to the Civil Rights Division of the U.S. Department of Justice, artificial intelligence (AI) systems are "machine-based systems that can make predictions, recommendations, or decisions influencing real or virtual environments"

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(Civil Rights Division, 2024, p. 1). Research and development around AI has become increasingly prominent in academia, industry, and government. Much of this growing attention relates to the potential of AI to offer people greater efficiency, including individuals with disabilities (Wu et al., 2022). A few areas that stand to be affected by AI development include accessibility, education, employment, and transportation. As analysts have previously described, disability legal protections are dispersed across sector-specific laws, and effective advocacy must work directly in those domains individually (Blanck, 2024; Kanter, 2015).

Although there is significant interest in the development of AI and increased usage in individuals' daily lives, AI presents several challenges and concerns. Some of the key concerns include ensuring AI is used ethically and responsibly, as well as the representation of diverse communities in AI dataset development (Jiang et al., 2022; Kamikubo et al., 2022; Lewicki et al., 2023). The datasets that are being used to train AI have been shown to have bias and can lead to discrimination against marginalized communities (Kamikubo et al., 2022; Lewicki et al., 2023; Shelby et al., 2023).

This paper presents expert panel findings on AI accessibility and fairness, with a focus on people who are blind or have low vision. Practitioners can use these findings to understand the unfolding AI landscape, and its effects on their clients. This understanding is essential to preparing clients to navigate emerging technology, leveraging what are productive tools in the AI space, and being proactive in avoiding harms and accessing reasonable accommodations. Advocates will find this paper informative on the areas of regulation that can influence equitable access and participation for people who are blind or have low vision. Neither AI technology nor disability policy can be addressed as just abstract, singular ideas: Each are multifaceted. This study asks how AI systems, when adopted in specific domains like education, employment, and transportation, create both risks and opportunities for people who are blind or have low vision. This inquiry serves to develop a sector-informed map of emerging trends that practitioners and policymakers can use to advance equity and accessibility.

Literature Review

This portion of the paper will summarize current literature around several AI domains: Assistive technology, education, employment, health care, and transportation. The benefits and the potential harms of AI use in these domains will be discussed in order to provide context to the current study.

Emerging Uses and Benefits of AI

In the transportation sector, there are many opportunities for AI to be incorporated that would increase access and independence (Hampshire, 2024). For example, AI can increase the efficiency of public transit and support more flexibility when traveling. It can also be used to increase the efficiency of infrastructure maintenance for roads, sidewalks, and other public transportation stations. Autonomous vehicles pose significant benefits for the general public, but especially for individuals with disabilities (Hampshire, 2024; Ray, 2023). Developments in autonomous vehicles can increase independence and freedom for individuals who might not otherwise be able to drive because of their disabilities (Hampshire, 2024).

The use of AI also has the potential to be used in educational settings in various ways including activity monitoring, alternate learning modalities, content filtering, and more (Morrison et al., 2021; Tyson, 2024; Woelfel et al., 2023). Some of the benefits of these applications of AI include a reduced workload for teachers and educators and the ability for curriculum to meet the individualized learning needs of all students (Morrison et al., 2021). Individualizing instruction can increase accessibility for individuals with disabilities and make learning materials available in modalities that work best for students.

The employment sector has increasingly been using AI as a job-screening tool (Wiessner, 2024). Roughly 25% of current Human Resource (HR) teams are using AI to screen job applicants (Society for HR Management (SHRM, 2024)). It can also be used to increase productivity for employees by completing tedious or mundane tasks and is being used by managers to monitor employees job performance (Scherer & Shetty, 2022). These types of tools can reduce stress and workload on all employees—from the managers reviewing job applications to anyone who would benefit from an AI-generated summarization of information (Partnership on Employment & Accessible Technology, 2023).

In the health care industry, AI is being increasingly used for decision-making (Brown et al., 2020; Edwards & Machledt, 2023). It is being used, for example, to support physicians in making medical diagnoses and determining treatment plans as well as deciding who is eligible to access certain medical coverage. These types of algorithmic tools are appealing to health care providers, since they can help reduce the amount of time that physicians need to spend on these details. Insurance companies similarly benefit from the decrease in the amount of time it takes their staff members to process medical requests (Edwards & Machledt, 2023). Patients also stand to benefit from the use of AI in health care with the early detection of health conditions through the use of AI.

Assistive technology stands to benefit from the development of AI by increasing the accessibility of previously inaccessible experiences for individuals with disabilities (Bennett et al., 2021; Bianchi et al., 2023). Some examples of assistive technology AI that are currently being developed include visual image description, captioning, and other communications support (Bennett et al., 2021; Bianchi et al., 2023; Gamage et al., 2023; Theodorou et al., 2021). Using AI to automate these processes increases the access of people with disabilities to environments and communications. Individuals in disability communities have also demonstrated an interest in the use of AI to support increased access to social interactions (Morrison et al., 2017; Phutane et al., 2023).

Harms of AI

Similar to the benefits that are possible with AI across all areas of daily living, there are also concerns raised by AI becoming ubiquitous in our digital interactions. In the transportation domain, there are several challenges to the implementation of autonomous vehicles that relate specifically to individuals with disabilities (Moura, 2022; Ray, 2023). Concerns include the ability of the autonomous vehicle to detect pedestrians who might not look or act like typical pedestrians (Moura, 2022). Individuals with disabilities, for example, might utilize a mobility device that the autonomous vehicle might not recognize. Another challenge with autonomous vehicles is access to the vehicle itself and ensuring individuals with any disabilities have complete access to all the available features and facilities of the vehicle itself. Such features include fully accessible communication systems within the vehicle, as well as information about drop-off and pick-up locations.

The use of AI in educational settings poses significant concerns around privacy and accessibility rights of students with disabilities (Tyson, 2024; Woelfel et al., 2023). The types of privacy concerns that already exist for many students with disabilities in the educational setting are automatically amplified with the increased use of AI for activity monitoring and remote proctoring (Tyson, 2024). Many of the applications used in educational settings require intense monitoring of students and comparison of the students' performance against "average" students who are represented in training data (Woelfel et al., 2023).

For students with disabilities, the "average" dataset might not encompass their diverse range of capabilities, increasing the risk of discrimination by the AI tool. For example, a blind student who is not looking at their computer screen during class could be mislabeled as being inattentive (Tyson, 2024).

Within the employment sector, there are several civil rights concerns around the biases AI might demonstrate in job screenings. Reviews of AI job-screening applications have already demonstrated that they have significant racial, age, gender, and disability biases (Glazko et al., 2024). Similar to the concerns of AI use in the education system, individuals are concerned about the bias in AI job-monitoring systems and how individuals with disabilities will be disproportionately flagged for "unproductive" behaviors (Partnership on Employment & Accessible Technology, 2023; Scherer & Shetty, 2022; Wiessner, 2024).

One of the largest concerns with AI use in health care is the training of AI on "average" characteristics. Individuals with disabilities, by definition, fall outside the "average," which would disproportionately identify individuals with disabilities in any AI systems being used in health care (Disability Rights Education & Defense Fund, 2022). Bringing increased attention to individuals with disabilities could harm their access to services and delay recovery times (Edwards & Machledt, 2023). Similarly, inadequate training data could suggest treatments that are not effective or appropriate for certain individuals (National Artificial Intelligence Advisory Committee, n.d.).

Regarding assistive AI, people with disabilities are often not fully included in product design (Gamage et al., 2023; Zia, 2024). The best way to design assistive technology so it meets the needs and wants of individuals with disabilities is to include individuals from the target user population in the entire design process (Morrison et al., 2017; Stangl et al., 2018). Furthermore, when the data sets used to train assistive AI are not properly representative of the population, these AI models may not actually meet the needs of disabled people (Bennett et al., 2021).

The Current Study

The current study used a Delphi method to examine experts' opinions about how AI affects people with disabilities now, as well as their predictions about how it will affect them in the next 5–10 years, with a particular focus on the effects on people who are blind or have low vision. The experts included people who work at companies that produce AI (industry experts), disability policy analysts who study the effects of technology on people with disabilities (policy experts), and academic researchers who study AI-human interaction (academic experts). Rather than focusing on the experiences of blind users, who may not yet know how AI will change over time or how "hidden AI" (such as the technology used in job screenings) may have affected them, this initial study was designed to capture predictions from those who develop AI and those who study AI and its policy implications. These experts brought a "behind-the-scenes" look at how AI will evolve, what effects it has already had on people with disabilities, and how those impacts are expected to change over time.

Methodology

This study utilized a Delphi methodology to achieve consensus among experts from various sectors, including academia, industry, and policy. The Delphi technique is a well-established iterative research method designed to collect insights and refine expert opinions through a structured series of data collection and analysis stages (Falzarano & Zipp, 2013). In this instance, the study comprised three rounds: An initial qualitative phase with semistructured interviews, followed by two rounds of quantitative web-based surveys. Ethical approval was obtained from the institutional review board (IRB) of the American Foundation for the Blind, and informed consent was secured from all participants at the start of each round. During each round, the experts were assured that their data would remain anonymous, and they were encouraged to share their own opinions, rather than those of their employer or employers. These assurances promoted candid responses.

The first round involved semistructured interviews that were intended to identify key themes and issues pertinent to the research topic. An initial group of experts was chosen based on their specialized knowledge of AI-human interaction within either academic, industry, or policy fields. These experts were then invited to share the study information with other experts in their networks through snowball sampling. All experts confirmed on the intake survey that they had specialized knowledge related to at least one domain of AI usage. This broad expertise ensured the inclusion of diverse perspectives. During the interviews, each expert was asked to share their opinions about how AI is likely to evolve in the next 5–10 years and how AI could benefit or harm (or both) people with disabilities in the areas of education, employment, health care, transportation, and when used as assistive technology. These 60-min interviews followed a semistructured format to encourage both guided discussion and exploration of emerging ideas. Interviews were transcribed verbatim, and real-time notes were taken to ensure that these data were captured accurately. Thematic analysis of the interview data was conducted, with the identified themes serving as the foundation for the subsequent survey rounds. This qualitative synthesis was essential for developing contextually relevant questions for the surveys.

The second and third rounds of the Delphi process were conducted using web-based surveys via Qualtrics, an online survey and data collection software platform, and data analysis was carried out in *R*, a statistical computing and graphics tool. Themes from the interviews were adapted into opinion statements, with modifications made to ensure anonymity and mitigate potential biases related to participants' reputations. The same group of experts from the interview phase was invited to participate in these rounds, ensuring consistency and continuity throughout the iterative process.

The second-round survey aimed to quantify the degree of agreement with the themes and insights identified in the interviews. Each of 72 opinion statements was adapted into a survey question with a seven-point Likert scale for responses, allowing participants to express their level of agreement with each opinion statement. The survey also included open-ended fields, enabling participants to provide explanations or elaborations on their ratings. This qualitative input was valuable in understanding the reasoning behind expert opinions and contributed to the design of the subsequent round.

Following the second round, statements were designated as achieving consensus if the participants' ratings on those statements had a standard deviation of 1.0 or less on the 7-point scale, in line with the latest best practices for Delphi analysis (Franc et al., 2023). This criterion was chosen to ensure a rigorous and statistically robust measure of agreement while accommodating a diversity of perspectives. If statements achieved a standard deviation of 1.80 or higher, their response distributions were examined for any bimodal trends, suggesting a split opinion amongst the panel between strong endorsement and strong opposition. If no bimodal distributions were observed, those statements with a standard deviation of greater than 1.80 were removed from the pool. The statements with standard deviations between 1.0 and 1.80 were advanced to a third round of analysis. In this phase, participants were provided with aggregated data from the previous survey, including the mean Likert scores for each item. This information allowed participants to consider their peers' collective responses while preserving anonymity. Additionally, anonymized justifications from the second round were shared to provide context for differing opinions. This iterative process promoted reflection and refinement of responses, ultimately leading to a deeper consensus.

Table 1. Expert Demographics.

Variables	Number of participants
Employment sector	
Academia	7
Contractor	1
Federal government	2
For-profit or private industry	13
Nonprofit	9
Expertise area	
Generative AI	21
LLMs	17
AI use in school settings	9
Education of students with disabilities in K-12 or postsecondary settings	12
Employment issues affecting people with disabilities	13
AI in the workplace	17
Autonomous vehicles	6
Transportation policy	6
AI used for visual descriptions (image or video descriptions) or visual interpretation	18
Algorithmic decision making in healthcare settings	9
AI use for determining benefits eligibility	3
Policy issues around regulation of AI technologies	13
Other	4
Gender	
Cisgender female or woman	13
Cisgender male or man	15
Genderqueer, gender-nonbinary, or gender fluid	3
Preferred to not answer	1
Race	
Asian or Asian American	7
Black or African American	2
Preferred to not answer	3
ME/NA	1
White non-Hispanic	19
Number of years in role	
Less than 1 year	4
1–2 years	3
2–5 years	13
6–10 years	4
11–20 years	5
More than 20 years	3
Location	
California	4
Colorado	1
England	1
Florida	2
Kansas	1
Maryland	3
Massachusetts	4
Michigan	1
Minnesota	1
New York	2
Texas	1
Toronto	2
Virginia	2
Washington	1
Washington, D.C.	6

(continued)

Table 1. Continued.

Note. LLM = large language models; AI = artificial intelligence; ME/NA = Middle Eastern or North African.

Results

A total of 32 experts across academia, industry, and policy completed the first-round interviews. Of these, 26 completed the second-round survey and 17 completed the third-round survey. The expert panel was still well balanced by the end, with 5 experts from academia, 10 from industry, and 5 from policy backgrounds. Table 1 shows the sample demographics.

After the second round, 7 statements achieved consensus with standard deviations of less than or equal to 1.0. Another 13 statements achieved standard deviations of greater than 1.80. These statements were examined for bimodal distributions, but none were found, suggesting that responses were widely distributed across the 7-point scale spectrum. These 13 statements were thus removed from the pool. The remaining 52 statements advanced to the third round of testing. After the third round, 32 of the statements achieved standard deviations of less than or equal to 1.0.

Table 2 shows the 32 opinion statements that reached consensus amongst the panel. The statements are ranked in order of agreement strength

Table 2. Consensus on AI.

Variable		Descriptive statistics: Standard deviation	Descriptive statistics: Mean	Respondents *n*
Q43	A human in the loop is necessary for candidate screening. (6.5)	0.44	6.76	17
Q79	The tech industry needs more diversity in its own employees to be able to spot and guard against the many types of bias that AI can generate. (6.4)	0.44	6.76	17
Q7	AI auditing must account for anti-disabled biases in addition to racial and gender biases.	0.53	6.73	26
Q3	AI needs to focus on expanding access and inclusion; it is not enough to only avoid harm to PWDs.	0.68	6.69	26
Q19	AI should be a partner, not a replacer, in writing IEPs for students with disabilities. (6.2)	0.51	6.59	17
Q75	There should be strong privacy laws at the federal level that are informed by the disabled community.	0.80	6.50	22
Q6	Automation bias (belief that if it comes from the algorithm it must be true and unbiased) leads to an over trust of AI for tasks it is not particularly accurate for. (6.0)	0.51	6.47	17
Q72	Balancing privacy standards with accessibility needs is critical in AI development for PWD. (6.3)	0.62	6.47	17
Q76	Regulation needs to ensure individuals with disabilities are proactively considered in AI development.	0.98	6.43	21
Q42	AI used in resume screeners or hiring decisions need to be disclosed to all applicants.	0.93	6.42	24
Q16	AI should not replace interactions with human educators. (6.2)	0.80	6.41	17
Q78	PWD should be involved at every stage of creating, procuring and deploying algorithmic decision-making. (6.0)	0.80	6.41	17
Q10	Skills like curiosity, empathy, and critical thinking will remain the most relevant after AI adoption. (6.0)	0.86	6.35	17
Q65	Training methods for AI literacy, such as drag-and-drop interfaces, pose barriers for people with disabilities.	0.97	6.25	20
Q84	Reactionary regulation, where actions are taken only after something bad happens, is common in AI. (5.8)	0.44	6.24	17
Q74b	There is a gap between technology development and user experience as it relates to disability needs. (alt question 5.9)	0.54	6.19	16
Q30	For patients who have a "non-average" characteristic, AI could fail in ways that are difficult to detect. (5.9)	0.64	6.18	17
Q74a	There is a lack of involvement of PWDs in research. (alt question 5.9)	0.86	6.12	17
Q5	Businesses that deploy AI solutions are accountable for the bias when AI makes biased decisions. (6.2)	0.83	6.06	17
Q85	Regulation of AI should come sooner rather than later and specifically protect individuals with disabilities. (5.9)	0.94	6.00	17
Q82	The NIST risk management framework should be applied to educational AI software before adoption (evaluates privacy, security, etc).	1.00	6.00	15
Q52	AI can be used to track sidewalk accessibility to create better routes.	1.00	5.95	22

(continued)

Table 2. Continued.

Variable		Descriptive statistics: Standard deviation	Descriptive statistics: Mean	Respondents *n*
Q73	Blind users may perceive AI for reading as more private than a human reader, if images are not stored in the cloud. (5.6)	0.96	5.93	15
Q70	AI tools oversimplify disability and miss the variability within the disabled community. (5.7)	0.96	5.88	16
Q61	Text-to-image tools are currently not accessible as blind users are unable to review generated images non visually. (5.6)	0.55	5.85	13
Q27	Many people with disabilities need more unusual healthcare, which is likely to get flagged by AI for denial. (5.4)	0.86	5.80	15
Q51	AI will revolutionize wayfinding accessibility for blind people in the next 5 years. (5.6)	0.86	5.80	15
Q60	AI models often sound confident when making mistakes, making it almost impossible for blind users to identify if an image description is wrong. (5.9)	0.93	5.75	16
Q83	There is a cumulative harm from things viewed as too minor to need regulation—death by a million small cuts. (5.4)	0.89	5.56	16
Q22	Many AI tools coming to classrooms will be inaccessible. (4.6)	0.80	5.53	17
Q44	New job categories, like AI supervision, could be inaccessible to PWD. (5.0)	0.91	5.40	15
Q31	AI-driven prenatal screening tools will create actions of eugenics. (4.1)	0.95	4.69	13

Note. PWD = people with disability; IEP = Individualized Education Plan; AI = artificial intelligence; NIST = National Institute of Standards and Technology.

(mean rating). Statements with means near 7.0 were very strongly endorsed by the panel.

Discussion

Experts in this study reached a consensus on many statements reflecting a balanced evaluation of AI's capabilities and potential harms. As a tool that enhances computing power and extends technological capabilities, AI offers both opportunities and risks for individuals with disabilities. For instance, AI-driven applications like image description software and navigation devices can promote greater independence in daily activities. However, experts concurred that these tools remain imperfect—blind users often cannot verify the accuracy of image descriptions (Q60, mean = 5.75), and text-to-image tools are largely inaccessible to them (Q61, mean = 5.85). Still, AI may revolutionize wayfinding accessibility for blind people in the next 5 years (Q51, mean = 5.80), suggesting optimism for at least some assistive technology or universally designed products.

Conversely, AI models employed in areas such as employment screening and health care decision-making may inadvertently perpetuate biases against people with disabilities, often in ways that are not transparent to end users. For example, many people with disabilities require nonstandard health care, which may be flagged by AI systems for denial by insurance carriers (Q27, mean = 5.80). Similarly, résumé screeners pose serious fairness risks to candidates unless human oversight is built into screening processes (Q43, mean = 6.76), and universal disclosure of AI use in hiring is critical to enable candidates to request appropriate accommodations (Q42, mean = 6.42). The risks are compounded when AI fails in ways that are hard to detect, which affects health care users with "non-average" characteristics (Q30, mean = 6.18). Therefore, it is crucial for both developers and implementers of AI technologies to proactively validate these models to ensure accurate and fair representation of individuals with disabilities. To address these concerns, experts in the study strongly agreed that auditing must include antidisabled bias, not just antiracial and antigender bias (Q7, mean = 6.73), and that regulation must ensure proactive consideration of people with disabilities during AI development (Q76, mean = 6.43). Businesses deploying AI were also seen as being responsible for biased decisions made by their tools (Q5, mean = 6.06). Moreover, human oversight remains essential in setting parameters, boundaries, critically reviewing outputs, and authorizing final decisions informed by AI tools (Q43, mean = 6.76; Q10, mean = 6.35). Providing skill development opportunities for AI users is necessary to prevent systematic discrimination. Experts emphasized that soft skills like curiosity, empathy, and critical thinking will remain highly relevant even as AI tools become more sophisticated (Q10, mean = 6.35). Actively recruiting and training individuals with disabilities for roles in AI development and deployment across various contexts is a proactive step toward high-quality AI tool development. Involving people with disabilities at every stage of AI creation, procurement, and deployment (Q78, mean = 6.41), and increasing diversity in the tech industry itself (Q79, mean = 6.76), were both identified as key strategies for developing inclusive tools. Where applicable, government regulations should aim to protect people with disabilities from potential harm while balancing access to these technologies with individual privacy protections. Experts agreed that federal privacy laws should be shaped with input from the disabled community (Q75, mean = 6.50), and that balancing privacy standards with accessibility needs is critical in AI development (Q72, mean = 6.47). Many also emphasized the risks of waiting until harm occurs before regulating, what one participant referred to as "death by a million small cuts" (Q83, mean = 5.56).

Although this research identifies areas of expert agreement, further studies are needed to explore unresolved questions. The lack of consensus on the benefits of autonomous vehicles could stem from differing opinions about the capabilities of automated driving systems or differing views on the likelihood of their adoption for use. This research reflects the current understanding of experts in academia, industry, and disability organizations regarding the effect of AI on people with disabilities but does not comprehensively capture the lived experiences of AI users with disabilities across various domains. Future research should explore how individuals with disabilities use AI to enhance accessibility, as well as the direct or indirect harms they may face—especially given the identified gap between technology development and user experience (Q74b, mean = 6.19), and the lack of meaningful involvement of people with disabilities in research (Q74a, mean = 6.12).

Implications for Practitioners

There are several clear implications for practitioners that have been revealed by this research. Many of the statements that experts agreed with speak to the benefits and opportunities AI presents for people who are blind or have low vision. Practitioners should be on the lookout for opportunities to incorporate the skills required for AI use into their work with clients and students. Professionals can directly promote AI tools and user skills for on-the-fly image description, wayfinding and navigation, or job-enhancing AI products that improve the efficiency of learners or employees. Professionals also play a role in the indirect way of ensuring interested blind or low vision people have opportunities to pursue careers in science, technology, engineering, and mathematics that will equip them to provide necessary representation in AI development and management. Where AI training materials and courses are made available by companies who are developing such tools, it may often require the intervention of vision professionals to make that content fully accessible to people who are blind or have low vision.

The cautionary statements that relate to possible harms that AI may cause to disabled communities also affect practitioners. Blind rehabilitation and education professionals should advocate alongside people with disabilities in regards to the importance of agencies only purchasing and distributing tools that are accessible to people who are blind or have low vision. Professionals may also find opportunities to advocate for effective regulation that protects people with disabilities from algorithms that are biased.

The importance of human oversight in high-stakes AI decisions affects every aspect of the professional life cycle. As identified in Q43, keeping a human in the loop on algorithm-supported decisions is essential. Practitioners may see a range of opportunities to advocate for this human interaction within the agencies for which they work. Professionals may see AI being used to promote the efficiency of internal decision-making. First, professionals should advocate to keep a human involved in important decisions. Then, as people with expertise in disability, vision professionals may need to serve in the role of identifying whether an algorithm is making decisions that harm people with disabilities. The risk of algorithmic bias for people with disabilities is identified in Q7. Similarly, practitioners may be preparing people who are blind or low vision for roles in which they may serve as the human oversight for another system; as such, they would have an important role in making sure their clients have the skills to understand and fully access digital interfaces. Vision professionals should prepare clients to recognize when they are missing information because of a lack of accessibility, as well as to be aware of their own ingrained automation bias (Q79). Clients need to be able to ask for reasonable accommodations to have enough information and time to review the computer-generated recommendations they are meant to oversee. The findings in this paper provide an important foundation for professionals as they seek to stay abreast of developing technology so that they may be aware of what developments to be most attuned to at the intersection of AI and disability.

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