



**Before the
FEDERAL TRADE COMMISSION
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**Re: Trade Regulation Rule on Commercial Surveillance and Data Security
ANPR R111004**

Comments of AARP

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Introduction

AARP respectfully submits these Comments for the Commission’s consideration and thanks the Commission for the opportunity to participate in this important proceeding regarding commercial surveillance practices.¹ Information technology now permeates the economic and social lives of Americans, and the growing reliance on technology platforms to mediate nearly all aspects of the lives of individuals has resulted in fundamental shifts in the control and application of personal information. As the Advanced Notice of Proposed Rulemaking (ANPR) notes, this personal information has become the foundation for a new surveillance economy,² which is largely invisible to consumers as their data is captured and monetized by third parties.³ Especially troubling is the application of algorithmic decision-making technologies that may be biased against protected groups, including older Americans.

AARP is Deeply Concerned by the Potential for Algorithmic Bias, Discrimination, and Error⁴

Algorithmically based commercial surveillance practices may contain bias, enable algorithmic discrimination, or make errors, to the detriment of consumers. Those who design algorithms, or the artificial intelligence that creates algorithms, may not be aware of the bias that is embedded in this technology. The roots of bias may run deep, ranging from historical, societal, and institutional factors that generate systemic bias, to human bias that may be associated with

¹ The ANPR employs the term “commercial surveillance.” These comments will refer to those entities that employ commercial surveillance technologies as “commercial surveillance companies.”

² ANPR, p. 3.

³ ANPR, p. 3, see also, for example, Zuboff, Shoshana. *The Age of Surveillance Capitalism*, Public Affairs Press, 2019, p. 70.

⁴ ANPR questions 53, 56, 65, 66, 67, 68, 69, 83, 84, 85, 86, 90, and 91.

individuals or groups, as well as statistical and computational bias.⁵ For example, technology firms are less likely to employ African Americans,⁶ women,⁷ and older adults.⁸ Thus, the lack of diversity among those who initially develop the algorithms may contribute to algorithmic bias. In addition, the data sets that are used to train artificial intelligence may have racial bias,⁹ may be biased against women,¹⁰ or may be biased against older adults.¹¹ As a result, for example, data sets associated with hiring decisions may reflect age and gender bias in hiring, and AI hiring decisions may themselves reflect bias against protected groups.

As noted by the philosopher Nick Bostrom, assurances that emerging AI systems are “safe and effective” may be difficult to accept given current and future applications of machine-based decision-making:

Imagine an engineer having to say, “Well, I have no idea how this airplane I built will fly safely—indeed I have no idea how it will fly at all, whether it will flap its wings or inflate

⁵ *Towards a Standard for Identifying and Managing Bias in Artificial Intelligence*, NIST Special Publication 1270, March 2022, pp. 6-9, <https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1270.pdf>.

⁶ “The Need for More Black Workers in Tech,” *SHRM*, March 4, 2022, <https://www.shrm.org/resourcesandtools/hr-topics/behavioral-competencies/global-and-cultural-effectiveness/pages/the-need-for-more-black-workers-in-tech.aspx>; “Black and Hispanic underrepresentation in tech: It’s time to change the equation,” *Brookings*, March 28, 2018, <https://www.brookings.edu/research/black-and-hispanic-underrepresentation-in-tech-its-time-to-change-the-equation/>.

⁷ “Women in tech statistics: The hard truths of an uphill battle,” *CIO*, March 8, 2021, <https://www.cio.com/article/201905/women-in-tech-statistics-the-hard-truths-of-an-uphill-battle.html>; “Women Are Still Underrepresented In Tech Leadership: Here’s How To Change That,” *Forbes*, February 3, 2022, <https://www.forbes.com/sites/benjaminlaker/2022/02/03/women-are-still-underrepresented-in-tech-leadership-heres-how-to-change-that/?sh=475043b26832>.

⁸ “Tech Job Posting ‘We Hire Old People’ Went Viral For Highlighting Ageism,” *Forbes*, August 26, 2021, <https://www.forbes.com/sites/jackkelly/2021/08/26/tech-job-posting-we-hire-old-people-went-viral-for-highlighting-ageism/?sh=4d598083272a>; “Age discrimination: An overlooked diversity issue in tech,” *ComputerWeekly.com*, September 3, 2021, <https://www.computerweekly.com/feature/Age-discrimination-an-overlooked-diversity-issue-in-tech>.

⁹ Kostick-Quenet, K., *et al.* “Mitigating Racial Bias in Machine Learning,” *Journal of Law, Medicine, and Ethics*, Vol. 50 (2022), <https://doi.org/10.1017/jme.2022.13>

¹⁰ “The Use of Artificial Intelligence in Business Codifies Gendered Ageism. How Do We Fix It?” *Forbes*, October 25, 2021, <https://www.forbes.com/sites/bonniemarcus/2021/10/25/the-use-of-artificial-intelligence-in-business-codifies-gendered-ageism-how-do-we-fix-it/>

¹¹ *Id.* See also, “Ageism in Artificial Intelligence for Health,” WHO Policy Brief, 2022, p. 6, <https://www.who.int/publications/i/item/9789240040793>.

itself with helium or something else I haven't even imagined—but I assure you, the design is very, very safe.” This may seem like an unenviable position from the perspective of public relations, but it's hard to see what other guarantee of ethical behavior would be possible for a general intelligence operating on unforeseen problems, across domains, with preferences over distant consequences.¹²

Algorithmic errors or biases are particularly insidious as these problems are not always visible to the victims of the errors or biases, leading to the potential for systematic but unrecognized discrimination. Furthermore, algorithmic bias can often be overlooked because of the illusion that data-based algorithmic decision can be more objective than decisions made by humans. As the ANPR notes, algorithmic discrimination can impact a variety of protected groups,¹³ thus AARP believes that it is important for the Commission to focus on harms that impact protected classes.

Older Americans May Be Harmed by Algorithmic Bias and Discrimination

Algorithms are trained as they learn from data sets. That training process presents many opportunities for bias to be embedded in algorithms:

Most AI systems and algorithms are data driven and require data upon which to be trained. Thus, data is tightly coupled to the functionality of these algorithms and systems. In the cases where the underlying training data contains biases, the algorithms trained on them will learn these biases and reflect them into their predictions. *As a result, existing biases in data can affect the algorithms using the data, producing biased outcomes. Algorithms can even amplify and perpetuate existing biases in the data. In addition, algorithms themselves can display biased behavior due to certain design choices, even if the data itself is not biased.* The outcomes of these biased algorithms can then be fed into real-world systems and affect users' decisions, which will result in more biased data for training future algorithms.¹⁴

¹² Bostrom, Nick. “The Ethics of Artificial Intelligence,” Cambridge Handbook of Artificial Intelligence, eds. William Ramsey and Keith Frankish (Cambridge University Press, 2011).

¹³ ANPR, p. 36.

¹⁴ Mehrabi, N. *et al.* “A Survey on Bias and Fairness in Machine Learning,” *ACM Computing Surveys*, July 2022, emphasis added. Available at: <https://arxiv.org/pdf/1908.09635.pdf>

As noted above, algorithmic bias may result from cultural bias embedded in data. However, bias may also result from the underrepresentation of protected classes in the data. For example, the World Health Organization has identified bias in medical AI systems based on age arising from the exclusion of older individuals from data sets.

[D]ata sets used to train AI models often exclude older people, who are frequently within a “minority” data set for AI technologies that are not explicitly classified as gerontechnology. They are excluded despite the fact that they are likely to be the single largest group that uses health-care services in many countries. Exclusion of older people from data sets could introduce biases, especially in AI technologies for health intended for use in many age groups.¹⁵

There is also evidence of algorithmic bias affecting medical decisions because the underlying data upon which the algorithm is based embeds racial bias.¹⁶

Alternatively, older Americans may experience employment discrimination due to biased algorithmic systems that reflect long-standing cultural bias, which can easily be absorbed by algorithms through machine learning practices.¹⁷ For example, as noted in a 2017 study conducted by the National Bureau of Economic Research, there is “robust evidence of age

¹⁵ “Ageism in Artificial Intelligence for Health,” WHO Policy Brief, 2022, p. 6, <https://www.who.int/publications/i/item/9789240040793>.

¹⁶ “Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations,” *Nature Medicine*, Vol. 27, 2021, <https://www.nature.com/articles/s41591-021-01595-0>; “Algorithms Are Making Decisions About Health Care, Which May Only Worsen Medical Racism,” *ACLU News and Commentary*, October 3, 2022; “Algorithmic Bias in Health Care Exacerbates Social Inequities — How to Prevent It,” *Harvard School of Public Health*, March 12, 2021, <https://www.hsph.harvard.edu/ecpe/how-to-prevent-algorithmic-bias-in-health-care/>; “Medical Algorithms Are Failing Communities Of Color,” *Health Affairs*, September 9, 2021, <https://www.healthaffairs.org/doi/10.1377/forefront.20210903.976632/full/>.

¹⁷ See, for example, “Can machine-learning models overcome biased datasets?” *MIT News*, February 21, 2022, <https://news.mit.edu/2022/machine-learning-biased-data-0221>; van Giffen, B. et al. “Overcoming the pitfalls and perils of algorithms: A classification of machine learning biases and mitigation methods,” *Journal of Business Research*, Vol. 144, May 2022, <https://www.sciencedirect.com/science/article/pii/S0148296322000881>; Jones, T. “Machine Learning and Bias,” IBM Developer Blog, August 27, 2019, <https://developer.ibm.com/articles/machine-learning-and-bias/>; Osoba, Osonde A. and William Welser IV, “An Intelligence in Our Image: The Risks of Bias and Errors in Artificial Intelligence.” Santa Monica, CA: RAND Corporation, 2017. https://www.rand.org/pubs/research_reports/RR1744.html

discrimination in hiring against older women, especially those near retirement age.”¹⁸ Because hiring algorithms are trained using data sets that reflect the preexisting age and gender bias, it is likely that algorithms will reproduce existing age and gender bias:

Most of the AI-based HR tools, especially in the context of HR processes use some form of Machine Learning, an approach that identifies patterns in training data which includes many past examples of tasks and past outcomes. It assumes these patterns will hold when applied to new cases. For example, a machine learning algorithm designed to predict high potential job candidates might look at historical records of previous hires and look for patterns in the types of hires and their characteristics that correlate better with performance. . . . If you consider the differences in the lifecycle patterns of women, especially later in the career, the likelihood of someone who is over 45 years old, with multiple career gaps (to take care of children or aging parents) and multiple career pivots to gain necessary flexibility or support a partner’s career will rarely end up in the training data correlated with high performance.¹⁹

Biased outcomes in AI can be especially harmful to older adults who are from groups that have been discriminated against. For example, older adults are more likely to have a disability than younger people, and there is a growing literature associated with algorithmic bias affecting individuals with disabilities.

Disabled people have been subject to historical and present-day marginalization. . . . Such patterns of marginalization are imprinted in the data that shapes AI systems, and embed these histories in the logics of AI. . . .

...Those who have borne discrimination in the past are most at risk of harm from biased and exclusionary AI in the present. And when these discriminatory logics are reproduced and amplified by AI systems, they are likely to be read as authoritative, the product of sophisticated technology. Beyond biased data, additional risks are presented by the significant power asymmetries between those with the resources to design and deploy AI systems, and those who are classified, ranked, and assessed by these systems. . . .²⁰

¹⁸ Neumark, D. et al. “Is it Harder for Older Workers to Find Jobs? New and Improved Evidence from a Field Experiment,” NEBR Working Paper Series, November 2017. <http://www.nber.org/papers/w21669>

¹⁹ “The Use of Artificial Intelligence in Business Codifies Gendered Ageism. How Do We Fix It?” *Forbes*, October 25, 2021, <https://www.forbes.com/sites/bonniemarcus/2021/10/25/the-use-of-artificial-intelligence-in-business-codifies-gendered-ageism-how-do-we-fix-it/>

²⁰ Whittaker, M., et al. “Disability, Bias, and AI,” *AI Now*, November 2019, <https://ainowinstitute.org/disabilitybiasai-2019.pdf>. See also, Tilmes, N. “Disability, fairness, and algorithmic bias

Given the expanding application of AI decision-making systems, the problems of algorithmic bias are likely to encompass more elements of the lives of older Americans.

Regarding the potential for algorithmic bias, AARP believes that solutions must be developed by the Commission with industry cooperation and input from affected stakeholders. The Commission should emphasize addressing the need for the correction of algorithmic bias that affects protected classes. As it develops the necessary framework to establish fair and transparent algorithmic decision making, the Commission should encourage best practices, including the right for consumers to know when algorithmic decision-making is being used and to consent to its use, as well as the right to opt-out and seek human intervention. The Commission should incentivize providers of commercially deployed algorithms to provide evidence, based on pre-deployment testing, that common areas of bias, including but not limited to, age, race, ethnicity, gender and gender identity, disability, political beliefs, or religious affiliation, are not present.²¹

in AI recruitment,” *Ethics and Information Technology*, Vol. 2024, 2022, <https://link.springer.com/article/10.1007/s10676-022-09633-2>; Venkit, P.N., *et al.* “A student of Implicit Language Model Bias Against People With Disabilities,” *Proceedings of the 29th International Conference on Computational Linguistics*, October 2022, <https://aclanthology.org/2022.coling-1.pdf> ; Trewin, S. “Considerations for AI fairness for people with disabilities,” *AI Matters*, Vol. 5, Issue 3, September 2019, <https://dl.acm.org/doi/abs/10.1145/3362077.3362086> ; “How Algorithmic Bias Hurts People With Disabilities,” *Slate*, February 6, 2020, <https://slate.com/technology/2020/02/algorithmic-bias-people-with-disabilities.html> ; “Disability Bias Should Be Addressed in AI Rules, Advocates Say,” *Bloomberg Law*, May 6, 2022, <https://news.bloomberglaw.com/daily-labor-report/disability-bias-should-be-addressed-in-ai-rules-advocates-say> .

²¹ “Algorithmic bias detection and mitigation: Best practices and policies to reduce consumer harms,” *Brookings*, May 22, 2019, <https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/> ; “Closing the AI accountability gap: defining an end-to-end framework for internal algorithmic auditing,” Google, January 27, 2020, <https://dl.acm.org/doi/abs/10.1145/3351095.3372873> .

The Commission should also encourage companies that create and apply algorithms to develop fair and transparent algorithms by design.²² Building from a foundation that strives to weed out bias will contribute to future generations of algorithms that are less likely to do harm. To the extent that fair and transparent algorithms undermine the ability of commercial surveillance companies or others to achieve their objectives, the Commission could expect those entities to revert to previous methods of addressing product access, product features, product quality, pricing, or price discrimination.²³ To the extent that those practices harm consumers, the Commission may have existing rules that address those unfair practices.

Where consent is required for the use of algorithmic decision making, AARP believes that the Commission should ensure that consent notifications are based on plain language that a reasonable person will understand. For individuals who may be cognitively impaired, consent should be given in consultation with a competent adult.

Older Americans May Be Harmed by Algorithmic Error

The existence of algorithmic error may be difficult for consumers to identify; thus, it is likely that algorithmic error will be misunderstood by consumers. Consumers face a variety of application processes that present the consumer with a “black box”—for housing, employment, education, healthcare, parole, or otherwise. Consumers learn the results of their application (acceptance or rejection) but may not be able to determine why they were rejected.²⁴ The Fair

²² See, for example, “Ethics By Design and Ethics of Use Approaches for Artificial Intelligence,” European Commission, Version 1.0, November 25, 2021, https://ec.europa.eu/info/funding-tenders/opportunities/docs/2021-2027/horizon/guidance/ethics-by-design-and-ethics-of-use-approaches-for-artificial-intelligence_he_en.pdf.

²³ ANPR, question 61.

²⁴ “What happened when a ‘wildly irrational’ algorithm made crucial healthcare decisions,” *The Guardian*, July 2, 2021, <https://www.theguardian.com/us-news/2021/jul/02/algorithm-crucial-healthcare-decisions>; “The Higher Education Industry Is Embracing Predatory and Discriminatory Student Data Practices,” *Slate*, January 13, 2021, <https://slate.com/technology/2021/01/higher-education-algorithms-student-data-discrimination.html>; “An Algorithm

Credit Reporting Act and Equal Credit Opportunity Act provide consumers with rights regarding the disclosure of information surrounding their credit applications.²⁵ Consumers need similar rights regarding algorithmic decision making in all areas where this technology is applied. The Commission should determine whether the existing disclosure rules are sufficient for credit-related decisions that rely on automated decision making. However, for algorithmic decisions made in areas outside of existing laws, additional protection is needed. The Commission should develop appropriate trade regulation or work with Congress to craft legislation, in the spirit of the Fair Credit Reporting Acts' and Equal Credit Opportunity Acts' disclosure requirements, that will apply to all algorithmic decision making.

Conclusion

AARP commends the Commission for undertaking this important work. The integration of commercial surveillance technology into the lives of consumers has generated benefits but has also caused harms and expanded risks.

Like any new technology, there must be a reconciliation between social values, legal rights, and the capabilities and design of technologies. Consumers deserve to use technology products and services that are not harmful, manipulative, or biased. Consumers deserve to have their data used for their benefit, rather than for others to discriminate against them. As a result, the

That Grants Freedom, or Takes It Away,” *New York Times*, February 6, 2020, <https://www.nytimes.com/2020/02/06/technology/predictive-algorithms-crime.html> ; “Algorithms were supposed to make Virginia judges fairer. What happened was far more complicated,” *The Washington Post*, November 19, 2019, <https://www.washingtonpost.com/business/2019/11/19/algorithms-were-supposed-make-virginia-judges-more-fair-what-actually-happened-was-far-more-complicated/> ; “AI Black Box Horror Stories — When Transparency was Needed More Than Ever,” *Medium*, October 28, 2019, <https://odsc.medium.com/ai-black-box-horror-stories-when-transparency-was-needed-more-than-ever-3d6ac0439242>; “Fleeing from Frankenstein’s monster and meeting Kafka on the way: Algorithmic decision-making in higher education,” *E-Learning and Digital Media*, Vol. 14(3), 2017, <https://journals.sagepub.com/doi/pdf/10.1177/2042753017731355> .

²⁵ 15 U.S.C. Chapter 41, Subchapter III, § 1681g; 15 U.S.C. Chapter 41, Subchapter IV, § 1691.

Commission must address issues associated with algorithmic discrimination and bias. If the Commission is not certain that it can achieve these objectives using its existing authority, the Commission should work with Congress to seek the needed authority to fully protect consumers from algorithmic bias and discrimination.