Spring 5-22-2023

Algorithmic Bias: Causes and Effects on Marginalized Communities

Katrina M. Baha
University of San Diego

Algorithmic Bias: Causes and Effects on Marginalized Communities

A Thesis

Presented to

The Faculty and the Honors Program

Of the University of San Diego

By

Katrina Michelle Baha

Computer Science & Philosophy

2023

Abstract

Individuals from marginalized backgrounds face different healthcare outcomes due to algorithmic bias in the technological healthcare industry. Algorithmic biases, which are the biases that arise from the set of steps used to solve or analyze a problem, are evident when people from marginalized communities use healthcare technology. For example, many pulse oximeters, which are the medical devices used to measure oxygen saturation in the blood, are not able to accurately read people who have darker skin tones. Thus, people with darker skin tones are not able to receive proper health care due to their pulse oximetry data being inaccurate. This research aims to highlight the ethical implications of marginalized communities facing different healthcare outcomes and provide suggestions on how to prevent algorithmic bias from appearing in healthcare. In order to do this, this paper will first give examples of algorithmic bias, then discuss the ethical implications of those biases, and lastly provide solutions that may help prevent algorithmic bias. It is unethical that marginalized communities are being misread, misdiagnosed, and mistreated due to algorithmic biases. Additionally, the technological healthcare industry must be diversified in order to prevent algorithmic biases from arising in their medical technologies.

Examples of Algorithms and Algorithmic Bias

An algorithm is the set of steps used to solve or analyze a problem in computer science and mathematics. Algorithms are often used for data processing, calculations, and sorting (Hill, 2016). Additionally, algorithms generally take an input, follow a set of steps using the input, and produce an output. One example of an algorithm would be the one that is used to recommend videos to users on TikTok. TikTok is a social media platform that contains video content created by TikTok account holders and can be watched by other TikTok users. While TikTok has not released their entire algorithm, some of the general steps the TikTok algorithm takes is known. First, the algorithm takes into account how the user is interacting with TikTok, such as what videos they are liking and what accounts they are following. Second, the algorithm analyzes the video information of what the user is watching on TikTok, such as reading the hashtags and captions. Lastly, the algorithm takes note of the user's device and account settings, such as their language preference and location (Newberry, 2023). After all these steps are followed, TikTok's algorithm can then make its video recommendations for a user by finding videos and accounts that share similarities to the data collected from these steps. So, if a TikTok user were to follow Nicki Minaj, only like and watch videos about Nicki Minaj, and have their language preference set to English, there is a very high chance that TikTok's algorithm will mostly recommend videos and accounts about Nicki Minaj in English to this user.

Algorithmic bias then is the bias that arises from algorithms. Algorithmic bias is problematic because it ends up negatively impacting people, especially people from marginalized communities. Some algorithmic biases are more indirect, such as Google Maps referring to Malcolm X Boulevard as "Malcolm Ten Boulevard" (Benjamin, 2019). Here, it can be seen how the Google Maps voice navigation algorithm misread the X in the name Malcolm X as the roman numeral for the number ten. This is disrespectful and a clear oversight from the developers who work on Google Maps because Malcolm X was a famous Black historical figure known for his role in the civil rights movement. The developers must have focused on improving the Google

Maps voice navigation algorithm to recognize roman numerals without realizing the cases where letters are meant to be read as letters.

Others are more obvious, such as how an algorithm used to calculate the likelihood of a defendant committing a crime again in Broward County, Florida incorrectly flags Black defendants as twice as more likely to commit a crime again compared to white defendants (Benjamin, 2019). Black people in the United States already face many systemic issues in the legal justice system, but it is extremely problematic that the judicial predictive technology that is supposedly neutral is also biased against Black people. This algorithmic bias may have been caused by the biases of the developers, bad data that is unrepresentative of Black people, or bad testing where Black people were not present.

Ruha Benjamin, the author of *Race After Technology*, refers to these algorithmic biases as "the new Jim Code" due to the similar damage done to Black people as Jim Crow laws from the 19th and 20th centuries in the United States. Benjamin also powerfully says that "anti-Blackness is no glitch. The system is accurately rigged, we might say, because, unlike in natural weather forecasts, the weathermen are also the ones who make it rain" (Benjamin, 2019). She is suggesting that algorithmic biases happen because the people who create algorithms are either not Black themselves or they are not being considerate towards the Black people that will be using their technologies. Additionally, algorithmic biases can also reflect the implicit biases that developers of algorithms have. Implicit bias in this case would happen when the developers create algorithms that cause discrimination, but the developers did not intentionally choose to harm marginalized communities. These are just some of the broad, harmful examples of algorithmic biases. However, the purpose of this paper is to show specifically how algorithmic bias in healthcare technology affects people from marginalized communities.

Moral Implications

The moral problem that needs to be addressed in terms of how algorithmic bias affects marginalized communities is an issue of personal motivation and autonomy, which German philosopher Immanuel Kant does a great job of covering from his deontological perspective in his work titled *Groundwork for the Metaphysics of Morals*. A basic philosophical principle developed by Kant is the categorical imperative. Essentially, Kant believes that there are universalized moral laws all rational beings follow and expect from others (Kant, 2002). Also, he believes that rational beings should follow the categorical imperative for the sake of it. Furthermore, the ability to universalize moral laws stems from the reason of a human being. What this means is that human beings should not act on inclinations or emotions when making moral decisions. For example, Kant considers not lying to be a universalized moral law because you should not like lying and you should not like when others lie to you.

It is important to make a distinction between the categorical imperative and the hypothetical imperative because the categorical imperative is what Kant considers the basis of morality. The categorical imperative is when things are done for their own sake of being good whereas the hypothetical imperative is when things are done as means for some other end (Kant, 2002). Additionally, Kant discusses how in order for rational beings to display morality and follow the categorical imperative, they must be able to self-legislate morality, as in being willing themselves to be moral (Kant, 2002). One's morality cannot come from happiness or desires, it should come from one's own reason. Kant refers to this concept as volition, and believes that not only is it important for one's morality, but it is also important for one's autonomy since if people are able to undermine your reasons for action, then you cannot be said to be acting autonomously.

One interesting take away from Kantian ethics is the humanity formulation, which is derived from the categorical imperative. Kant argues that every rational being is an end in themselves, which is why rational beings should not be treated as means to some other subjective end. He also goes on to further explain how we should view humanity together as a whole and harmonize with humanity. Thus, humanity itself should be treated as an end in itself (Kant, 2002). It is important to note that Kant believes that sometimes it is possible to use human beings as means for some ends, but the means must be morally permissible and consensual. For example, a student uses a professor as a means to their end of graduating and a professor uses a student as a means to their end of making money, but at least both the student and the professor are aware of this exchange.

So, Kant believes that human beings are ends in themselves, which means that their lives should be respected and not used as means for other ends. Additionally, one's morality must come from one's reason in order to actually be autonomous and moral. Kant gives the shopkeeper example to show this concept. In the shopkeeper scenario, Kant imagines how a shopkeeper would be motivated to action, with an emphasis on identifying the morally permissible type of motivation. This ties in with Kant's emphasis on the role of volition. In the shopkeeper example, a shopkeeper states that they decided to not pocket some change from a customer because if the customer realized they did not get enough change back and told other customers, the shopkeeper's business would be ruined (Kant, 2002). Here, we can see that the shopkeeper did not give the customer their full change back in a way that Kant would view as morally permissible because the shopkeeper gave the full change back out of fear of a ruined reputation. Additionally, Kant would argue that the shopkeeper example also illustrates how there needs to be a motivation for morality through reason, not superficial things such as reputation. This is an important concept from Kantian philosophy to understand because being able to have motivation for morality through reason means that you can act autonomously and respect the autonomy of others.

So, in order to treat all of humanity as ends in themselves, moral actions must come from reason. As identified by Kant, there are some scenarios where individuals are not treated as ends in themselves that are morally permissible, but there are also scenarios where it is immoral. I have identified violations of these Kantian moral principles in technological uses of algorithms in healthcare. I will intervene and make recommendations pertaining to violations of autonomy found in the technological healthcare industry due to developers not treating patients from marginalized communities as ends in themselves, not having the appropriate basis for moral action, and not respecting the autonomy of patients from marginalized communities. Using patients as mere means instead of end in themselves and not respecting patient autonomy is never morally permissible.

Algorithmic Bias in Healthcare

One example of where algorithmic bias shows up in technological healthcare is in pulse oximeters. A pulse oximeter is a noninvasive healthcare technology that measures the oxygen saturation in a patient’s blood as well as their heart rate (Yale Medicine, 2023). It is considered noninvasive since a pulse oximeter is simply a small device that is generally clamped around a patient’s fingertip, although there are other possible places the device can clamp onto as well.

Pulse oximeters are important because they are used to check whether or not the lungs are working properly, which especially became a concern during the rise of the COVID-19 pandemic in the United States. One symptom of COVID-19 is difficulty breathing, which can be severe enough as to require patients with COVID-19 to use ventilators (CDC, 2022). Ventilators are healthcare technologies used to move air in and out of the airways of patients who are not properly breathing well enough (NHLBI NIH, 2022).

Pulse oximeters work by sending different wavelengths of light through the patient's skin in order to see how much of the light gets absorbed by the oxygenated and deoxygenated blood cells called hemoglobin. The light wavelengths generally used for pulse oximeters are red and infrared. Then, the amount of light that did not get absorbed by the hemoglobin is measured and used to calculate the blood oxygen level of the patient (University of Iowa Health Care, 2017).

The problem with this version of pulse oximetry is that red and infrared wavelengths do not necessarily pass though darker skin tones well compared to lighter skin tones because skin pigment called melanin blocks some wavelengths from completely passing through the skin (Wickerson, 2022). Additionally, the algorithms designed to calculate blood oxygen levels generally do not account for the variance of accuracy between different skin tones. Together, these two issues in pulse oximetry would be considered an algorithmic bias because they stem from computational and technological flaws. This algorithmic bias can lead to misleading pulse oximetry data due to the algorithms not being designed to read data from people with darker skin tones, which causes marginalized individuals to receive incorrect or absent medical treatment (Wickerson, 2022). For example, during the COVID-19 pandemic, Black patients were 29% less likely to receive supplemental oxygen in a timely manner and approximately three times more likely to have occult hypoxemia compared to white patients due to algorithmic bias present in the software engineering behind pulse oximeters (Sjoding et al., 2020). Occult hypoxemia is the term used by medical professionals when the blood oxygen level measured from a pulse oximeter is showing normal oxygen levels while the blood oxygen level measured from the artery is showing low oxygen levels. This startling statistic shows how algorithmic bias can not only be an issue of racism, but also colorism, both which affect marginalized communities.

Through Kantian philosophy, we are able to clearly see the moral implications of algorithmic bias against marginalized communities in healthcare. When healthcare technology developers create algorithmic biases, they are violating the categorical imperative, violating the humanity formulation, their morality is not coming from the right place, and they are not respecting the autonomy of others.

First, they are violating the categorical imperative because they are not treating patients as ends in themselves, specifically patients from marginalized communities. In the pulse oximetry example, we can see how the developers in this case did not treat Black patients as ends in themselves, meaning that they did not respect their lives. Additionally, if Black patients had been properly informed about their health and physicians had been properly informed about the patients' health through the healthcare technology, then potentially better healthcare solutions and plans could have been made. Further, if the developers purposefully ranked Black patients lower in their algorithm or used inferior technology when checking their health, that would mean that the developers used Black patients as mere means to the end of instead focusing on accurately checking the health of white patients.

Second, developers that create algorithmic biases violate the humanity formulation because they are not designing their algorithms to work on everyone, which means they are not treating all of humanity as an end in itself. Revisiting the pulse oximetry example, it is evident that pulse oximeters only work on certain groups of people, which happen to be people with lighter skin tones. Healthcare technology developers are not being inclusive of all of humanity by not making algorithmic and technological considerations towards people with darker skin tones when creating pulse oximeters, which means that they are leaving behind marginalized communities from having equal healthcare access.

Further, the morality of the healthcare technology developers is not coming from their reason because they might only be motivated by making money and protecting their reputation. Most healthcare professionals use pulse oximeters in order to check their patients' blood oxygen levels, so developers should be concerned that their healthcare technology does not work on everyone, but they are instead motivated by working in a lucrative career and having a good professional reputation instead of their reason when creating products. This is similar to Kant's shopkeeper scenario where Kant argues that being motivated by greed, money, or emotions undermines one's morality. Emotions in particular are unreliable due to how easily one's emotions can be manipulated, and Kant argues that morality should not be easily undermined or manipulated.

Lastly, healthcare technology developers are not respecting the autonomy of the marginalized patients who will be using the products that they create, which means that the patients face even more barriers in terms of deciding their own healthcare outcomes and living their lives how they wish to. For example, since the pulse oximetry data of Black patients claimed that their blood oxygen levels were normal, they were denied proper healthcare access despite the Black patients coming to hospitals for the obvious reason of them seeking healthcare. Through all of these moral implications of algorithmic bias and through the example of algorithmic bias in pulse oximeters, it is clear that algorithmic bias is an issue that must be addressed.

Solution

One way to mitigate algorithmic biases from arising in healthcare technology is by diversifying the people involved at every step of product development. The original data used to create healthcare technology should be inclusive of people from diverse backgrounds, the developers creating the healthcare technology should be people from diverse backgrounds, and the people who test the healthcare technology should be people from diverse backgrounds.

Another solution to consider is educating all the people involved with the creation of healthcare technology on biases and how harmful algorithmic biases can be to marginalized communities if not caught and corrected. Part of this education can be based around Kantian philosophy since it stresses the importance of treating people as ends in themselves, treating humanity as an end in itself, having morality come from a place of reason, and respecting the autonomy of others.

While there is a lot of work to be done, there do exist people who are advocating and making change against algorithmic bias. Dr. Joy Buolamwini is a computer scientist from the Massachusetts Institute of Technology Media Lab and founder of the Algorithmic Justice League (Benjamin, 2019). The Algorithmic Justice League strives to combine technology and art in order to illustrate the harms of algorithm misuse or miscreation to researchers, policymakers, and industry workers (Algorithmic Justice League, 2022). Additionally, I have made my own educational examples of good and bad healthcare algorithms in order to help visualize and understand what code without algorithmic biases looks like. For my example of the good healthcare algorithm, I tried one solution that digital activists have suggested where marginalized people in data are weighted higher than usual in order to compensate for generally being overseen and underrepresented in data.

Code

I have created two healthcare algorithms as educational examples of what good and bad algorithms may look like. I developed these two algorithms using the programming language Python in the GitHub Codepsaces integrated development environment (IDE). GitHub is a website where programmers can publish their code either publicly or privately. You are able to view my project using this link: https://github.com/katrinamb/honorsthesis. For my project, called ‘honorsthesis’, you will see three files: README.md, honorsthesis.py, and patients.txt. honorsthesis.py is the actual code where you will be able to see how I created and implemented the two different algorithms, patients.txt is a data file with sample data of patients I created, and README.md is a file that contains my abstract.

I designed a program that takes in patient data such as their sex, age, and symptom in order to make healthcare recommendations. If the symptom does not seem too serious, the program will reassure that the patient is most likely fine and offer a possible solution to their health concern. If a symptom does seem serious, the program will recommend further healthcare inspections.

One noticeable difference between the good algorithm and the bad algorithm is that the good algorithm prompts patient input in order to foster a more patient-centered healthcare experience. Whenever a patient has a symptom they are concerned about, the algorithm will first ask the patient what level of intensity they are feeling the symptom before making a healthcare recommendation. The bad algorithm is not patient-centered and does not prompt patient input when creating a healthcare recommendation.

A less noticeable difference between the two algorithms is how I factored in the consideration of a patient's sex when making a healthcare recommendation. For the bad algorithm, I purposefully wrote it in a way where it would often dismiss the concerns of a female patient even if it was the exact same concern as someone of a different sex. I chose to do this because female patients often do not receive the same level of evidence-based healthcare as male patients do, leading women to having a harder time accessing equal healthcare outcomes as men (Duke Health Referring Physicians, 2020). Meanwhile, in the good algorithm, I intentionally wrote it in a way where female patients would get extra attention, even if they did not report a high level of intensity for their symptom. This would be an example of explicit bias because I intentionally prioritized female patients, which is one specific group of individuals out of the entire dataset.

If I were to develop my project further in order to have it reflect more types of algorithmic bias and the solutions to preventing the bias, I would expand it to include people with disabilities and people of color since these two groups also face extreme healthcare disparities due to algorithmic bias. Developers often include their own implicit bias against these marginalized groups when creating technological healthcare algorithms, so I would want to assist developers in identifying implicit bias and removing it from the code. However, for the purpose of having a basic framework of what good and bad healthcare algorithms look like, I chose to only examine a patient's sex.

Below is all my code from the honorsthesis.py file:

```
def bad_algorithm(filename):
        '''This is an example of a bad healthcare algorithm
        filename = the file name that contains patient information'''
        file = open(filename, 'r')
        for line in file:
            info = line.split()
            if (info[3] == "Headache"):
                if (info[1] == "Female"):
                    # female with a headache --> women are often dismissed of their
pains so I reflected that bluntly here
                    print(f"Patient {info[0]} is considered healthy. Please suggest
that they take ibuprofen.\n")
                else:
                    # everyone else with a headache gets further checks from physician
                    print(f"Patient {info[0]} may have health concerns. Consider
further healthcare inspections.\n")
            elif (info[3] == "Stomachache"):
                if (info[1] == "Female"):
                    # female with a stomachache --> women are often dismissed of their
pains so I reflected that bluntly here
                    print(f"Patient {info[0]} is considered healthy. Please suggest
that they take bismuth subsalicylate.\n")
                else:
                    # everyone else with a headache gets further checks from physician
                    print(f"Patient {info[0]} may have health concerns. Consider
further healthcare inspections.\n")
            elif (info[3] == "Chestpain"):
                if (info[1] == "Female"):
                    if (int(info[2]) >= 50):
                        # only concerned with women having chestpain if 50 or older
                        print(f"Patient {info[0]} may have health concerns. Consider
further healthcare inspections.\n")
                    else:
                        # female with a chestpain and younger than 50 --> women are
often dismissed of their pains so I reflected that bluntly here
                        print(f"Patient {info[0]} is considered healthy. Please suggest
that they get rest.\n")
```

```
                else:
                    # everyone else with a headache gets further checks from physician
                    print(f"Patient {info[0]} may have health concerns. Consider
further healthcare inspections.\n")
        file.close()

def good_algorithm(filename):
    '''This is an example of a good healthcare algorithm
    filename = the file name that contains patient information'''
    file = open(filename, 'r')
    for line in file:
        info = line.split()
        if (info[3] == "Headache"):
            if (info[1] == "Female"):
                ask = input("On a scale of 1-10, rate your headache: ")
                if (int(ask) > 3):
                    # weighed it since the pain women have tends to be dismissed
                    print(f"Patient {info[0]} has a bad headache. Consider further
healthcare inspections.\n")
                else:
                    print(f"Patient {info[0]} has a moderate headache. Please suggest
that they take ibuprofen.\n")
            else:
                ask = input("On a scale of 1-10, rate your headache: ")
                if (int(ask) > 5):
                    print(f"Patient {info[0]} has a bad headache. Consider further
healthcare inspections.\n")
                else:
                    print(f"Patient {info[0]} has a moderate headache. Please suggest
that they take ibuprofen.\n")
        elif (info[3] == "Stomachache"):
            if (info[1] == "Female"):
                ask = input("On a scale of 1-10, rate your stomachache: ")
                if (int(ask) > 3):
                    # weighed it since the pain women have tends to be dismissed
                    print(f"Patient {info[0]} has a bad stomachache. Consider further
healthcare inspections.\n")
                else:
                    print(f"Patient {info[0]} has a moderate stomachache. Please
suggest that they take bismuth subsalicylate.\n")
            else:
                ask = input("On a scale of 1-10, rate your stomachache: ")
```

```
                if (int(ask) > 5):
                    print(f"Patient {info[0]} has a bad stomachache. Consider further healthcare inspections.\n")
                else:
                    print(f"Patient {info[0]} has a moderate stomachache. Please suggest that they take bismuth subsalicylate.\n")
        elif (info[3] == "Chestpain"):
            if (info[1] == "Female"):
                ask = input("On a scale of 1-10, rate your chestpain: ")
                if (int(ask) > 3):
                    # weighed it since the pain women have tends to be dismissed
                    print(f"Patient {info[0]} has bad chestpain. Consider further healthcare inspections.\n")
                else:
                    print(f"Patient {info[0]} has moderate chestpain. Please suggest that they get rest.\n")
            else:
                ask = input("On a scale of 1-10, rate your headache: ")
                if (int(ask) > 5):
                    print(f"Patient {info[0]} has bad chestpain. Consider further healthcare inspections.\n")
                else:
                    print(f"Patient {info[0]} has moderate chestpain. Please suggest that they get rest.\n")
    file.close()

if __name__ == "__main__":
    print("---Bad Algorithm---\n")
    bad_algorithm("patients.txt")
    print("---Good Algorithm---\n")
    good_algorithm("patients.txt")
```

Conclusion

Through the moral framework of Kantianism, it is clear that algorithmic bias in healthcare technology is problematic, especially affecting patients from marginalized communities. Marginalized communities are not being treated as ends in themselves and are not having their autonomy respected. Additionally, healthcare technology developers are not treating humanity as a whole as an end in itself and their morality for making healthcare technologies is not coming from a place of reason. For example, pulse oximeters are unable to accurately read the blood oxygen levels of people with more melanated skin because the light wavelengths used in most pulse oximeters do not pass well through lots of melanin and the developers did not account for that in their code. This oversight from the developers creates an algorithmic bias that leads to forming even more harmful barriers for many marginalized communities in terms of being able to equally access their healthcare as other communities can. Until algorithmic biases are addressed and fixed, marginalized communities will continue to be misread, misdiagnosed, and mistreated in healthcare.

Works Cited

Algorithmic Justice League - Unmasking AI Harms and Biases. (2022). https://www.ajl.org/

Benjamin, R. (2019). *Race After Technology: Abolitionist Tools for the New Jim Code*. Polity.

Campbell, L. V. (2017). Kant, autonomy and bioethics. *Ethics, Medicine and Public Health*, *3*(3), 381–392. https://doi.org/10.1016/j.jemep.2017.05.008

COVID-19 and Your Health. (2020, February 11). Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/symptoms.html

Hill, R. *(2016). What an Algorithm Is. Philosophy & Technology, 29(1), 35–59. https://doi.org/10.1007/s13347-014-0184-5*

Johnson, Robert and Adam Cureton, "Kant's Moral Philosophy", *The Stanford Encyclopedia of Philosophy* (Fall 2022 Edition), Edward N. Zalta & Uri Nodelman (eds.), URL = <https://plato.stanford.edu/archives/fall2022/entries/kant-moral/>.

Kant, I., Schneewind, J. B., Baron, M., & Kagan, S. (2002). Second Section: Transition from popular moral philosophy to the metaphysics of morals. In A. W. Wood (Ed.), Groundwork for the Metaphysics of Morals (pp. 22–62). Yale University Press. http://www.jstor.org/stable/j.ctt1njjwt.8

Newberry, C. (2023). 2023 TikTok Algorithm Explained + Tips to Go Viral. *Social Media Marketing & Management Dashboard*. https://blog.hootsuite.com/tiktok-algorithm/#:~:text=Much%20like%20the%20Instagram%20algorithm,%2C%20or%20doesn't%20like.

Pulse Oximetry. (2023, January 3). Yale Medicine. https://www.yalemedicine.org/conditions/pulse-oximetry#:~:text=Basically%2C%20pulse%20oximetry%20is%20a,well%20the%20lungs%20are%20working.

Pulse Oximetry Basic Principles and Interpretation | Iowa Head and Neck Protocols. (2017, November 3). University of Iowa Health Care https://medicine.uiowa.edu/iowaprotocols/pulse-oximetry-basic-principles-and-interpretation

Recognizing, Addressing Unintended Gender Bias in Patient Care. (2020, January 14). Duke Health Referring Physicians. https://physicians.dukehealth.org/articles/recognizing-addressing-unintended-gender-bias-patient-care.

Sjoding, M. W., Smits, H. H., Iwashyna, T. J., Gay, S. L., & Valley, T. S. (2020). Racial Bias in Pulse Oximetry Measurement. *The New England Journal of Medicine*, *383*(25), 2477–2478. https://doi.org/10.1056/nejmc2029240

What Is a Ventilator?. (2022, March 24). NHLBI NIH. https://www.nhlbi.nih.gov/health/ventilator#:~:text=Mechanical%20ventilators%20are%20machines%20that,the%20ventilator%20into%20your%20lungs

Wickerson, G. (2022, November 1). *An Overdue Fix: Racial Bias and Pulse Oximeters*. Federation of American Scientists. https://fas.org/blogs/sciencepolicy/an-overdue-fix-racial-bias-and-pulse-oximeters/