# Cognitive Violence: The Neurological and Elevated Cancer Consequences of Environmental Racism in Communities of Color and Its Implications in Artificial Intelligence

Authored by: Anvi J., Bhargavi N., Sarah K.
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## Objective

How does environmental racism contribute to neurological harm and an increase in cancer risk in communities of color, and how can AI either help uncover or unintentionally obscure these inequities?

**Useful Definitions**

- **Generative AI**: AI that generates new content based on patterns learned from existing data. (NCI, 2024)
- **Predictive AI**: AI that makes predictions about new data based on patterns learned from existing data. (NCI, 2024)
- **Large language model:** AI that understands and generates human-like text by analyzing vast amounts of written-language data. (NCI, 2024)
- **Explainable AI:** AI that allows humans to understand and trust how the model makes its predictions or decisions. (NCI, 2024)
- **Machine Learning:** A field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalise to unseen data, and thus perform tasks without explicit instructions.
- **Neural Network:** A computer system modeled on the human brain and nervous system.
- **Gray Matter:** One of the main components of the Central Nervous System that processes information, controls movement, memory, and emotions
- **PM2.5:** Tiny airborne particles emitted from traffic and industrial sources
- **Benzene:** A colorless flammable liquid that evaporates easily and is used to make or dissolve other chemicals or as a motor fuel
- **Formaldehyde:** A colorless pungent gas in solution made by oxidizing methanol

# Abstract

In neighborhoods bordering factories, highways, landfills, or in areas where police sirens are more frequent than birdsong, a saddening reality exists: environmental racism has not only damaged the body but the mind as well. Across the United States and beyond, communities of color are disproportionately exposed to neurotoxic pollutants in the environment around them, such as lead, mercury, and fine particulate matter, often a result of discriminatory zoning. The agents infiltrate not only the lungs and bloodstreams but also the delicate brain, impairing focus, cognitive development, and long-term neurological health. This form of harm, what some scholars call environmental violence, is a slow, systematic assault on the human mind. Yet in the age of technological advancements, artificial intelligence (AI) emerges as both a potential remedy and risk. This paper explores the current situation of environmental racism through various techniques to assist in solving the effects of environmental racism for the General Public.


## A. Environmental Racism and its increase in cancer and other degenerative diseases.

Systematic environmental racism significantly increases cancer risk for communities of color in the United States, as landmark studies continue to demonstrate. Decades of discriminatory housing policies, such as redlining, have forced marginalized populations into neighborhoods adjacent to highways, factories, and carcinogenic waste sites, where exposure to pollutants like benzene, arsenic, formaldehyde, and polycyclic aromatic hydrocarbons is much higher than in predominantly Caucasian communities. (Kyrematen,2025; Puckrein,2024)

A recent report found that 56% of people living within 3 kilometers of carcinogenic-producing sites in the U.S. are people of color, with cities like Houston, Flint, and the infamous “Cancer Alley” in Louisiana serving as prime examples of these disparities.( Kyrematen,2025) People of color face disproportionately higher risk of cancer from environmental toxins, new study finds)

Airborne carcinogens and toxic chemicals in drinking water, such as lead, asbestos, and hazardous vehicular emissions, pervade these environments, damaging cellular structures and triggering mutations that can cause cancers of the lung, bladder, liver, and skin. The Environmental Protection Agency’s ( EPA) assessments have found that areas with dense concentrations of Black and Hispanic residents experience estimated cancer risks far exceeding those in mostly White communities. For example, in St. John the Baptist Parish within Cancer Alley, the risk of cancer was 5.5 times higher for black residents than elsewhere in Louisiana (EPA).

Carcinogens, when inhaled, ingested, or absorbed through the skin, initiate a cascade of molecular events that ultimately disrupt normal cellular function and division. Many environmental carcinogens seen in disproportionately financially disadvantaged communities, such as benzene, polycyclic aromatic hydrocarbons and arsenic, are metabolized by the liver, where they are often converted into even more reactive intermediates. These metabolites can form DNA adducts, directly binding to genetic material and causing base-pair mutations during cell replication. If key genes regulating cell growth and apoptosis, such as TP53 or BRCA1, are mutated, it can lead to uncontrolled proliferation - a hallmark of cancer ( Lacayo, 2025). Persistent oxidative stress, incited by exposures to fine particulate matter and heavy metals, generates reactive oxygen species (ROS) that further damage DNA, proteins, and cell membranes, enhancing mutagenesis (Hurbain, 2024).

Additionally, chronic inflammation from recurrent pollutant exposure creates a microenvironment conducive to tumor development: cytokines and growth factors are released, promoting angiogenesis-the formation of new blood vessels- which further contribute to malignancy. The immune system, once responsible for eliminating abnormal cells, can become suppressed or dysregulated due to ongoing toxin intake, permitting mutated cells to evade detection and persist (Morello-Frosch et al., 2006).

In the finale, these exposures are aggravated by socioeconomic barriers, including minimal access to quality healthcare and preventive cancer screenings. Cancer chances are dominant in disproportionately disadvantaged communities due to the environment.

# B. Environmental Racism and Neurological Harm: A Legacy of Toxins in Marginalized Communities

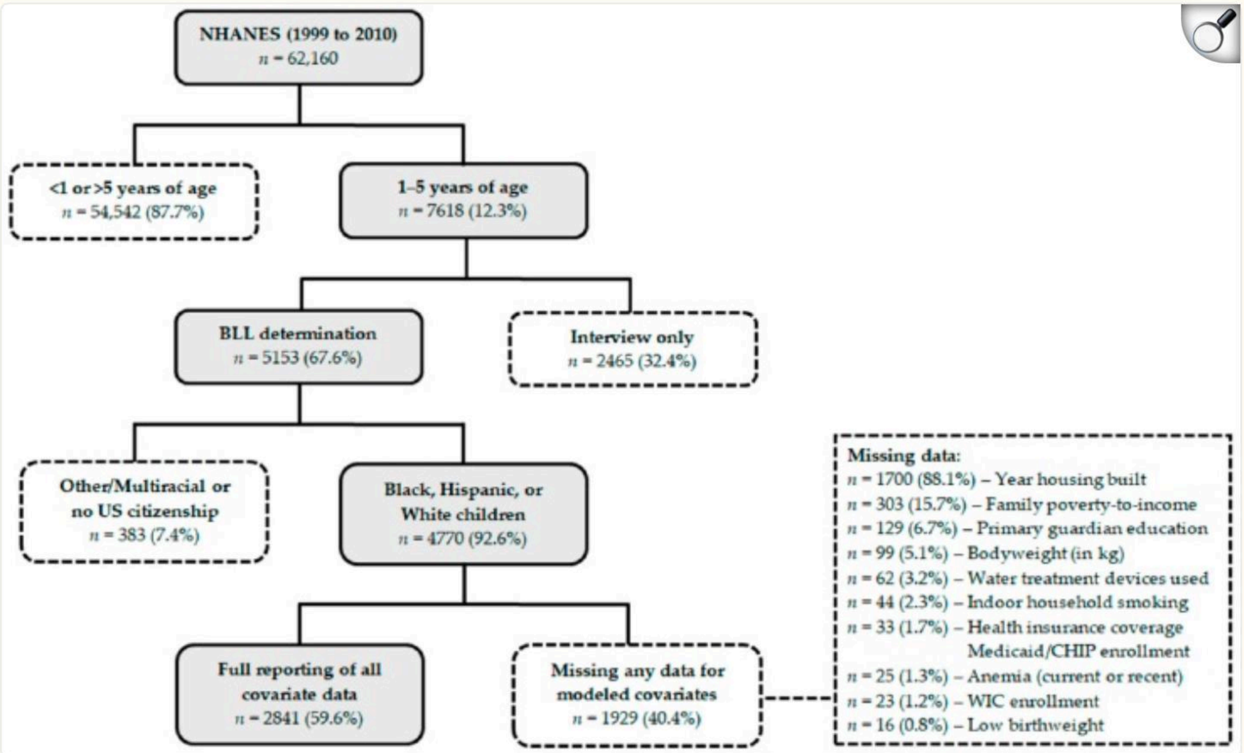
## Background

Environmental racism isn't just a historical neglect; it's an ongoing issue that significantly impacts the neurological health of communities of color. Marginalized communities tend to suffer through disproportionate exposure to environmental hazards due to discriminatory policies, zoning laws, environmental racism, and more. This results in a higher exposure to neurotoxic pollutants such as lead, mercury, arsenic, carcinogenic chemicals, and any other hazardous materials. These toxins don't just break down by themselves and disappear; they enter the human body and brain leading to long-term results in cognitive and neurological damage. Organizations such as The Lancet Commission on Pollution and Health and the U.S. EPA found that environmental pollution kills around nine million people through increased neurological disorder rates and mental health challenges worldwide annually which causes significant threats in human societies. In addition, the situation becomes worse as climate change accelerates, since we'll witness more extreme weather patterns, frequent and intense disasters, and consequent environmental justice and health issues, which are even more burdened as industrial toxicants and hazards are released. In other words, environmental racism contributes to neurological harm through exposure to heavy carcinogens and hazardous materials, the developmental impact on marginalized communities, and the broader implications for public health and racial equity.

## Current Environmental Conditions and Neurotoxic Exposure

Across the United States children in low-income, mostly Black or colored neighborhoods, are more likely to live near highways, power plants, waste incinerators, or factories, all unaware that they emit dangerous neurotoxic substances. For example, lead, once widely used in paint and plumbing, continues to remain a major threat in older housing stock, especially in communities that were denied investment and repairs. The National Health and Nutrition Examination Survey (NHANES) conducted a secondary analysis of blood Pb determinations for 2841 US children at ages 1-5 years and experimented that black children in risk factors such as polluted areas had an adjusted +0.73 to 1.41 blood Pb and a 1.8 to 5.6 times higher odds of having an EBLL. They ended up concluding that Black children are more likely than white children to have elevated blood lead levels, which is known to reduce IQ, hinder memory, and increase neurological disorders such as ADHD. In addition, PM2.5, known as a harmful airborne particle, penetrates deep into the lungs and brain, leading to inflammation, impaired cognitive development, and reduced gray matter. Furthermore, researchers through PubMed found that long-term exposure to PM2.5 was associated with higher risks of Alzheimer's and Parkinson's disease, both of which affect people of color in polluted areas.

Figure 1.

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Case selection schematic for exclusion or inclusion in the studied sample.

Meanwhile, carcinogens such as benzene and formaldehyde are released from petroleum refineries, plastic plants, and landfills, which poses a serious threat to the brain. Not only do they increase cancer risk, but they also disrupt the blood-brain barrier and impair brain function. Benzene, for example, has been linked to decreased white matter volume, mood disorders, and long-term neurological degeneration. Children living near industrial areas suffer the most since their developing brains are way more vulnerable to toxins. In addition, the increasing effect of environmental pollutants is linked with delayed speech, poor academic performance, and even increased need for special education services. These harms are all due to the consequences of environmental racism which includes the lack of access to quality healthcare, clean air, and safe housing.

## Where the System Fails

Despite decades of environmental regulations, enforcement is often weaker in communities of color. Studies have shown that polluting facilities are more likely to be sited near Black and colored neighborhoods, which raises concerns about the health effects of disproportionate exposure to environmental burdens. Moreover, scientific studies documenting these harms often exclude race as a key component of the issues of rising neurological problems, contributing to a huge burden on marginalized populations. While many environmental and health monitoring systems rely on aggregated data, they often fail to capture the specific ways that exposure accumulates across the lifespan. Additionally, the classification of certain substances as "carcinogenic" but not "neurotoxic" can obscure the cognitive damage they inflict, making it way more difficult for affected discriminated communities to demand justice, equality, or intervention. Without targeted race-conscious research and policy implementation, the neurological consequences of environmental racism will persist and continue to grow along with the cycle of disinvestment, illness, and inequality.

## Future Notes

Moving forward, addressing environmental racism consequences as a public health crisis requires a multi-disciplinary approach that includes stronger environmental regulations, equitable urban planning, and racially disaggregated data in health and pollution research. Community-driven random data collection and citizen science initiatives can help illuminate the hidden harms in under-resourced neighborhoods. Moreover, public investment in lead remediation, air filtration, strong infrastructure, and access to neurological healthcare is essential to breaking the link between geography, race, and brain health. Recognizing environmental racism not just as a civil rights issue, but as a neurological health risk factor, is a necessary step toward justice and collective well-being.

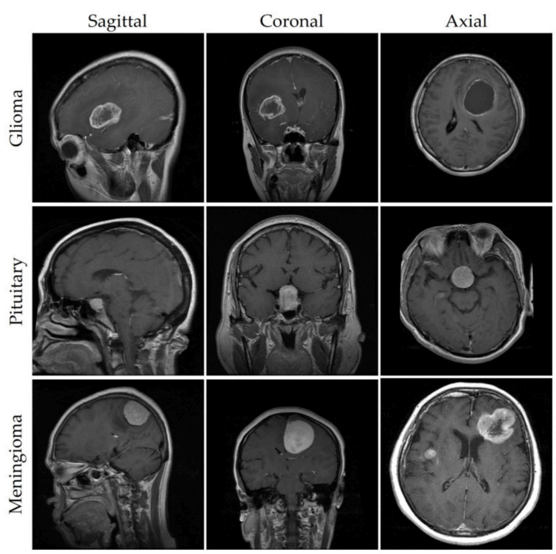
# C. AI in Medicine: The Power and Perils of Data-Driven Diagnosis

## Background

Artificial Intelligence (AI) is not merely a trend in today's society but a tool and necessity. AI refers to the simulation of human intelligence in machines that are trained to learn and reason like humans, including the ability to analyze data, recognize patterns, and more.

This tool has proved to be instrumental in spotting disparities in environmental health and its intersection with neurology. To provide a more concrete definition: “AI... is defined as the broad science of mimicking human abilities, while machine learning (ML) is defined as a set of algorithms that is fed with structured data in order to complete a task without being programmed how to do so (Haenlein and Kaplan, 2019)” (Aschner and others, 2022). This technology can be instrumental or detrimental in efforts to mitigate neurological inequalities in society. In the field of medicine, AI has the potential to either abate or exacerbate existing inequalities, depending on how it is trained and deployed.

Environmental racism - a key implication of this paper - describes situations where communities of color are exposed to greater environmental risks than others as a result of specific policies, regulations, and laws that place more environmental burdens on marginalized groups. This section aims to provide an overview of the impact AI (specifically, AI predictive modeling, Large Language Models, and AI imaging algorithms) has had on modern medicine/research, its racial concerns, limitations, and prospects.




*A sample of MRI images from a brain tumor dataset*

## Current Applications in Medicine

Today, AI is rapidly accelerating drug discovery, predicting how immune cells (T cells) respond to tumors, and improving immunotherapy. AI finds patterns in large biological datasets to map drug response pathways and is also increasingly successful in facilitating precision treatment (NCI, 2024). It essentially expedites genetic subtyping of brain tumor tissue during surgery, speeding up decisions and predicting survival outcomes for patients with breast cancer using digital pathology images. For instance, in one study, researchers successfully detected brain tumors in MRI scans using a large collection of brain tumor images by demonstrating that fine-tuning a YOLOv7 model through transfer learning significantly improved its performance in detecting gliomas, meningioma, and pituitary brain tumors, reaching up to a staggering 99.5% accuracy (Abdusalomov, 2023). AI is now being trained in neuroscience and cancer care to detect tumors from MRI scans, assisting in treatment planning, and predicting cognitive functions. And yet, studies show that such models perform worse on patients of color because of data that underrepresents such marginalized populations - medical gaps that deepen the existing health disparities.

## Where AI Falls Short

Despite these advances in new technology, biases still exist. Because AI models in medicine depend heavily on large, diverse, and well-annotated datasets, if the data used to train these models is not appropriately diverse and representative of the population, these models can pose a dangerous medical bias: even the most advanced models risk bias, misdiagnosis, and reduced generalizability, ultimately providing inaccurate information for minorities and women. An AI model trained mostly on data representing white males may not effectively detect early signs of certain cancers in women of color, for instance. According to Anne Trafton at MIT News, MIT researchers have found that artificial intelligence models that are most accurate at predicting race and gender from X-ray images also show the biggest "fairness gaps," ie, discrepancies in their ability to accurately diagnose images of people of different races or genders (Trafton, 2024). Alarmingly, these findings suggest that models may be using demographic shortcuts when making their diagnostic evaluations, which ultimately lead to incorrect results for women, African Americans, and other groups, the researchers say (Trafton, 2024).

This, thus, is a highly unfair route AI models are taking.

However, no model is perfect and all come with their unique challenges: "Large and granular datasets are needed to develop ML models and get accurate predictions. Little data results in a poor approximation and may cause over-fitting. High-throughput "omics" technologies which are increasingly used to measure thousands of variables (e.g. metabolite levels, gene expression, or image acquisitions) are thus very suitable to develop ML algorithms. They can be used to identify harmful substances." These models are incredibly good at predicting diseases, MIT scientists say, but during training learn to predict other aspects that may not be desirable.

A consequence of AI models, as MIT researchers note, is that when models trained on patients from one hospital are found to be biased, researchers attempt to retrain them to improve fairness. However, debiasing works best when the test and training patients are similar, i.e., from the same hospital. The fairness gaps reappear when models are applied to patients at different hospitals, so in that sense, medical AI models are still limited. This is worrisome because in many cases, hospitals use models that have been developed on data from other hospitals, especially in cases where an off-the-shelf model is purchased, the researchers say (MIT 2024). Researchers would always need to evaluate external models on their data, knowing that fairness guarantees may not transfer between populations, and if enough data is available, training models on their own data would fetch better results.

MIT researchers further explored the *why and how* behind machine learning models worsening existing inequities in medical diagnosis and treatment. Led by Professor Marzyeh Ghassemi, these researchers identified four types of subpopulation shifts - differences in the way machine learning models perform for one subgroup as compared to another - that cause these disparities (Nadis, 2023). These biases stem from either "class", "attribute," or both.

<u>They identified 4 main types of this shift (examples) :</u>

A. **Spurious Correlations:** There is a bias in both the class and the attribute.

   The "Camels and Cows" example: Take an ML model that sorts images of animals into two classes: cows and camels. Attributes are descriptors not specific to the class, like the animal's background. If all training images show cows on grass and camels on sand, the model might erroneously assume that cows are only found on grass and camels are only on sand.

B. **Attribute Imbalance**: If the dataset used for training has a significant attribute imbalance. For instance, if 100 males are diagnosed with pneumonia for every one female, the model would likely perform better at detecting pneumonia in men than in women.
C. **Class Imbalance**: If there are significantly more healthy subjects than sick ones, the model would be biased toward healthy cases.
D. **Attribute Generalization**: If a sample contained 100 male patients with pneumonia but zero female subjects with the illness, the model should ideally still be able to generalize and make predictions for female subjects despite the lack of training data for that specific subgroup.

While improving the classifier (the final layer of the neural network) can reduce spurious correlations and class imbalance, and improving the "encoder" (an uppermost layer) can mitigate attribute imbalance, attribute generalization remains an unresolved issue that researchers are unsure how to fix (Nadis, 2023). Furthermore, the commonly used metric for evaluating fairness, "worst-group accuracy" (WGA), has a surprising drawback. WGA measures the accuracy of a model on a subgroup that performs the worst compared to the others. Ideally it is to ensure that no one group is disproportionately disadvantaged as WGA is based on the assumption that if you improve the accuracy, you improve the model as a whole (Nadis,2023). However, researchers note that boosting WGA can lead to a decrease in "worst-case precision", the scenario where precision is at its lowest possible point. This isn't desirable because both accuracy (validity of findings) and precision (reliability of methodology) are crucial in medical diagnostics and ideally should not be traded for one another, researchers say (Nadis, 2023).

## Future Notes

Though researchers today acknowledge that achieving fairness in healthcare among all populations is the goal, achieving this requires a more nuanced understanding of the sources of fairness and how they affect our current systems. This understanding must be established before fully implementing these models. Furthermore, there is also a growing need for randomized clinical trials to validate AI's practice in clinical practice (NCI, 2024). Without broadly accepted and adopted standards for the development of AI and machine learning, it will be difficult to ensure reproducibility and medical fairness for marginalized communities overall.

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