BIAS IN ARTIFICIAL INTELLIGENCE (AI)

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Biases in Healthcare

Research Representation

Sexual Identity	Geographic Location	Socioeconomic Status
Obesity	Age	Ableism
Education	Sex and Gender	Racial bias

Inequality In Healthcare

Maternal deaths for various ethnic groups in comparison to White mothers (BMA, 2021)

Black		5x more likely
Asian		2x more likely
Likelihood of medication receipt for Non-White patients (Dehon et al., 2016)		
Analgesic Medicine		22-30% less likely
Narcotic Analgesics		17% to 30% less likely

Waiting times are usually longer for Non-White Patients. Similarly, they usually have less likelihood of admission (Shah et al., 2015)

Hospitalisation was the highest for South Asian communities, with the highest being men and women of Pakistani origin.

Some medical professionals were more likely to dismiss chronic pain in women than in men (Samulowitz et al, 2018)

LGBTQIA+ Medical Experiences (Samulowitz et al., 2018)				
Percentage of medical students with implicit bias to LGBTQIA+ peoples	>80% of medical students			
Common ailments for LGBTQIA+ patients due to avoidance of medical assistance	 Anal Cancer Cardiovascular Disease Asthma 	 Substance Misuse Obesity Suicide 		

Use Of Artificial Intelligence In Healthcare

Rapid diagnosis of cancer - MALIMAR (Machine Learning in Myeloma Response)

Study using machine learning¹ to read whole-body MRI scans in myeloma patients to find evidence of cancer.

Intelligent symptom checker using chatbots

https://www.buoyhealth.com/

Radiology reporting and analysis

https://www.nanox.vision/

Oculus Muscular Degeneration Prediction

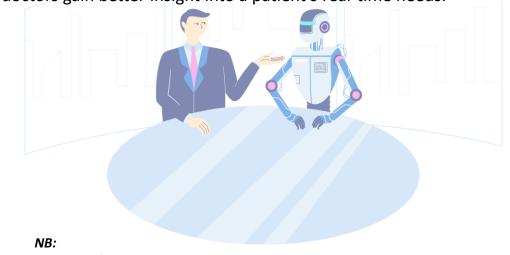
Predicts whether people with age-related macular degeneration will develop the more serious form of the condition in their 'good eye'. **(Digitalhealth.net, 2020)**

Unstructured Medical Data Analysis with AI

Deep learning platforms like <u>Enlitic</u> can be used to analyse large, unstructured medical data. This includes:

- □ Radiology Images.
- Blood Tests.
- EKGs.
- Genomics.
- Patient medical history.

These enable doctors gain better insight into a patient's real-time needs.



Types Of Biases In Al

Implicit Bias

Unconscious prejudice formed against person(s) that is not easily noticed by the owner of such prejudice.

Sampling Bias

A statistical problem where the sample data may be **skewed towards specific sections** of the data.

Temporal Bias

We can build a machine-learning model that eventually becomes obsolete due to **future events not factored into the model**. .

Over-fitting to training data

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When AI models accurately predict values from the training dataset but **cannot predict new data accurately**, thus unrepresentative of general population.

Edge Cases & Outliers

Outliers are **data points not within the data's normal distribution**. Edge cases are errors (missing/incorrect datasets) or noise (additional, irrelevant datasets that could impact the machine learning process negatively).

Examples Of Bias In Artificial Intelligence



Amazon

In 2014, a team of software engineers at Amazon were building a program to review the resumes of job applicants. Unfortunately, in 2015 they realized that the system discriminated against women for technical roles (Dastin, 2018)



One university considered using AI to direct case management resources to patients for early discharge, until leaders recognized that doing so would preferentially benefit wealthy white patients and disadvantage poorer African-Americans (Rajkomar et al, 2018)



Health Insurance

A commercial algorithm to guide resource allocation in healthcare was found to be profoundly biased against black patients (Obermeyer et al, 2019)

Facial Recognition

In 2019, San Francisco legislators voted against the use of facial recognition, believing they were prone to errors when used on people with dark skin or women (BBC, 2019)



Examples of Bias in Artificial Intelligence

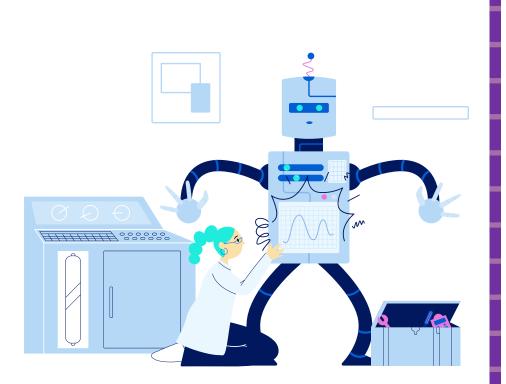
Pre-existing bias in datasets results in training biased models; under sampling of marginalized populations results in worse predictive accuracy in comparison to more privileged, represented populations. (*Forde et al,2021*)

This skin cancer prediction model showed that in striving to achieve overall accuracy, male accuracy was considerably greater

Table 1: Algorithms resulting in different model accuracy–fairness trade-offs for skin cancer risk prediction as presented in Srivastava et al. (2019). The authors asked test subjects to choose between the presented models and found that subjects preferred A_1 (which has highest overall accuracy).

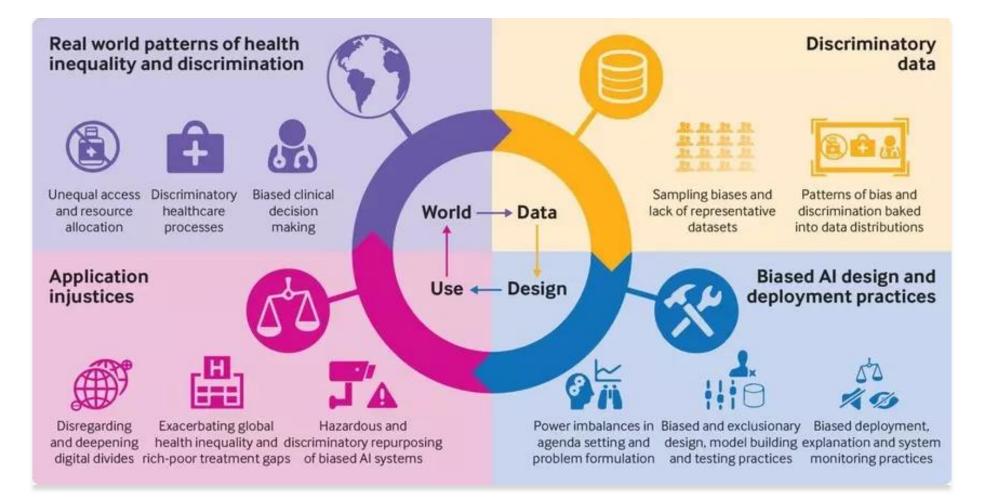
Algorithm	Overall Accuracy	
A_1	94%	
A_2	91%	
A_3	86%	

Bias In Choosing Models



- During model selection for solving a particular task, the model developer compares differences in the performance of several learned models trained under various conditions, such as different optimizers or hyperparameters.
- This procedure is not a strictly computational; rather, the metrics used to distinguish between models are subject to human interpretation and judgement (Adebayo et al., 2018; Jacobs & Wallach, 2019).
- Human preferences, often geared toward the particular application domain, ultimately play an important role in choosing the model to deploy.
- A Columbia University study found that "the more homogenous the [engineering] team is, the more likely it is that a given prediction error will appear." This can create a lack of empathy for the people who face problems of discrimination, leading to an unconscious introduction of bias in these algorithmic-savvy AI systems. (Wiggers, 2020)

Designing For Equality



Best Practice To Eliminate Bias

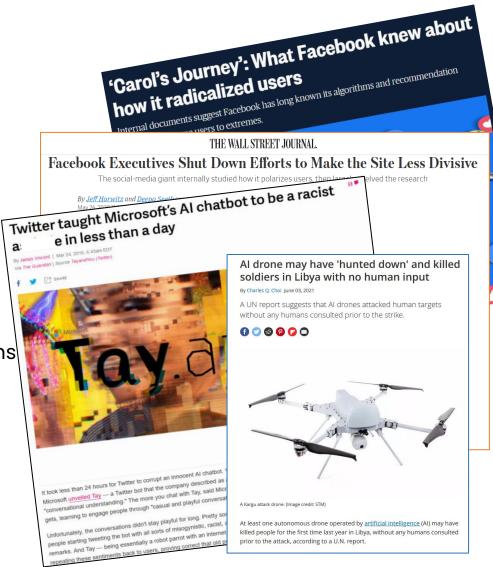
In October 2021, the US Food and Drug administration published a set of guidelines to advise on best practice when developing AI algorithms (US Food and Drug Administration, 2021).

• Key aspects include:

- Clinical Study Participants and Data Sets Are Representative of the Intended Patient Population.
- Training Data Sets Are Independent of Test Sets.
- Testing Demonstrates Device Performance During Clinically Relevant Conditions. Considerations include the intended patient population, important subgroups, clinical environment and use by the Human-AI team, measurement inputs, and potential confounding factors.
- Deployed Models Are Monitored for Performance and Re-training risks are managed.
- □ Inclusive design emphasizes inclusion in the design process (*Omowole, 2021*).
- The AI product should be designed with consideration for diverse groups such as gender, race, class, and culture.
- Foreseeability is about predicting the impact the AI system will have right now and over time.

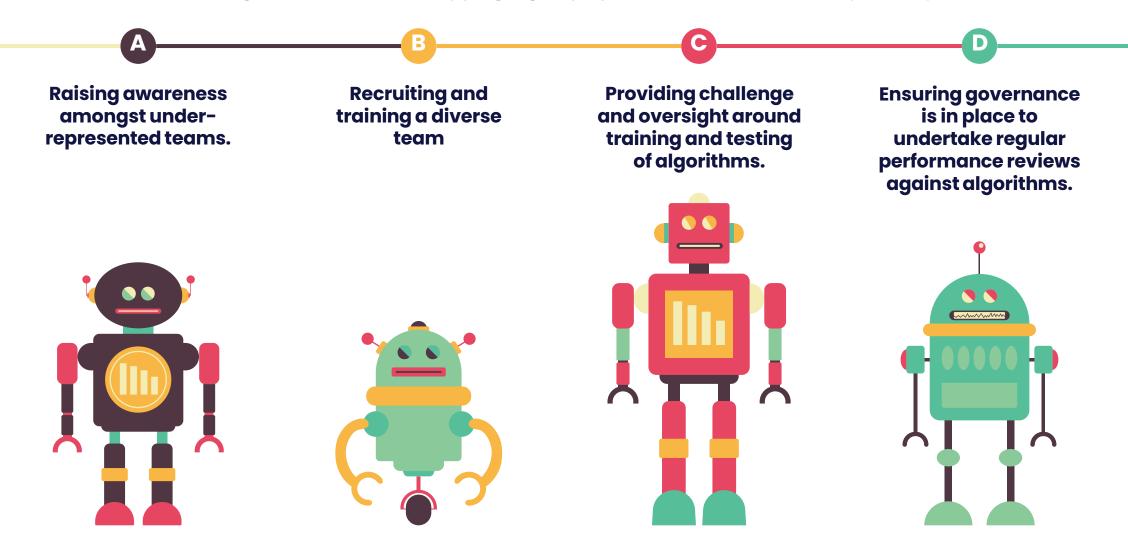
Being An Ally In The Digital World

- □ AI poses a threat to societal harmony, & equality
 - Facebook
 - Twitter
 - Alexa/Siri
- AI will increasing be used to augment & then replace humans processes
- There is an urgent need to address this issue now before algorithms become pervasive.



Being An Ally In The Digital World

To be an ally in the digital world is not just about designing for inclusive UX, but ensuring diversity in the design and use of AI algorithms. Its about stopping digital prejudice before it becomes by actively:



Digital Ethics Charter

https://www.ethicscharter.co.uk



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