Quantifying Bodies, Categorising Difference: Border AI Through the Lens of Racial Capitalism

Cherry Benson
Lucy Cavendish College, University of Cambridge

This paper explores the connection between racial capitalism and the development and deployment of AI technologies, using border AI as an illustrative example. Section 1, examines how racial capitalism, rooted in historical hierarchies and discrimination, influences the development and deployment of AI technologies. It highlights how this legacy perpetuates inequalities, privileging certain groups while disadvantaging others. Section 2 frames border AI, highlighting both its benefits and challenges. This section sets the stage for understanding how border AI can perpetuate existing inequalities and raise significant human rights concerns. Section 3 presents an analysis stemming from the ideas presented in Sections 1 and 2. Tracing the historical roots of AI technologies in border control, it highlights how pseudo-scientific racist ideologies and biometric quantification practices have shaped their foundations. Section 4 explores algorithmic accountability at EU borders and examines the EU Artificial Intelligence Act, revealing significant gaps in migrant protection. Although automating decision-making processes offers potential benefits, these systems often reinforce existing biases and lack transparency, complicating oversight and judicial review. The paper concludes by drawing upon the insights gleaned from the exploration and advocates for a shift towards a person-centred framework at the border that acknowledges and incorporates marginalised knowledge systems. This approach underscores the necessity for border control practices to prioritise human rights and dignity over technical progress and efficiency, paving the way for a more equitable future in AI deployment.

Keywords: Border AI, Racial Capitalism, AI Ethics, Algorithmic Bias, EU AI Act

Introduction

Before continuing, I would like to clarify my use of racial terms within this paper. “Race,” as I understand it, originated from the colonial belief that white Western men were superior to all other human beings (Wynter, 2003). Following the words of scholars such as Patricia Hill Collins (1990), Paul Gilroy (1993) and Ruha Benjamin (2019), I understand “race” to be a pseudo-scientific social construct that stratifies people and organizes society based on physical traits like skin colour, hair texture, and eye colour.

When discussing racialised groups, I align with the rationale of scholars such as Bonilla-Silva (2003) and Collins (2000), using the terms “racially minoritised” and "racialised individual" to describe those identified as non-white. Racism constructs "race" by categorising racially minoritised individuals as the 'Other,' highlighting the socially constructed nature of racial categories and leading to systemic marginalisation that infiltrates and distorts societal structures, realities, and institutions (Omi & Winant, 2015; Bonilla-Silva, 2003).

To briefly define my understanding of ‘Racial capitalism’, it is a theoretical framework describing the intrinsic link between capitalism and racial exploitation. Originating from Cedric J. Robinson's "Black Marxism: The Making of the Black Radical Tradition" (2000), it argues that capitalism relies on and perpetuates racial inequalities, having developed through racial differentiation and subjugation. In critical race theory, racial capitalism is seen as the extraction of economic value from racialised bodies via exclusion, exploitation, and marginalisation. This perspective challenges the idea that racism is a mere aberration within capitalism, asserting instead that it is fundamental to the system's functioning. Scholars like Ruth Wilson Gilmore emphasise how racial capitalism perpetuates and exacerbates inequalities by continually producing racialised subjects deemed exploitable and disposable (Robinson, 2000; Gilmore, 2007).

In this paper, I will argue that historical racism is deeply embedded in AI technologies, using the case of border AI to illustrate this point. The analysis will demonstrate how these biases are perpetuated in modern systems, reinforcing existing power dynamics and discrimination. I will provide an overview of current AI technologies employed at borders, highlighting their inherent issues and biases. Due to the constraints of this paper, a comprehensive analysis of all technologies is not feasible. Instead, the focus will be on selected examples that illustrate the broader trend. I will also address counterarguments, evaluating the purported neutrality and efficiency of AI in border control. The research will specifically focus on EU policies, with a detailed examination of the EU AI Act, to contextualise the discussion within a regulatory framework. Through this focused analysis, the paper aims to shed light on the enduring impact of historical prejudices on present-day AI applications and advocate for more equitable and transparent technological practices.

1. New Technologies, Old Hierarchies

Capitalism emerged from and relied on racial hierarchies and discrimination to enable exploitation and accumulation. It did not precede racism, but rather colonial slavery, genocide, and dispossession - made possible by categorising differences by race, laid the groundwork (Robinson, 2005). Racial capitalism amplifies inequalities that naturalise the unjust distribution of resources, power and privilege. It reinforces the disposability and deviancy of certain groups, denying them rights and resources. Within this system, privileges of movement, labour access, and social safety nets are structurally conferred to some bodies while denied to those marked as threats.

Racial capitalism, with its pervasive influence on society, extends its legacy of discrimination into various technological realms, including AI. Despite the portrayal of AI systems as progressive tools (Eubanks, 2018), focused on optimisation and progress, they inherit assumptions from racial capitalism regarding the prioritisation of certain capabilities and whose interests technology should serve (Benjamin, 2020). The claimed technical neutrality of AI systems becomes questionable as they encode prejudice through unexamined design choices, a phenomenon labelled by Ruha Benjamin (2020) as "the new Jim Code" – a covert manifestation of racial bias masked by rhetoric promoting diversity, inclusion, and fairness. Contemporary racial capitalism persists by categorising groups based on their exploitation potential, keeping racialised individuals vulnerable to exploitative cycles of capitalism due to the enduring logic of white supremacy (Melamed, 2015). Racial capitalism provides a framework to examine the historical, present and future manifestations of racial inequity, offering insight into past discriminatory patterns encoded in present AI systems.

Examining the entire spectrum of the development and deployment of AI technology through this lens reveals that racially minoritised individuals bear the adverse impacts of these systems. Mathematical concepts crucial to AI development, such as statistics, were notably influenced by the work of Eugenicists like Galton, Pearson, and Fisher (UCL, 2021), which will further be explored in section 3. The representations of politics and white power are evident in the collection and storage of archival data, leading to the datafication of populations (Yale, 2015). Furthermore, the recent extraction of natural materials and resources essential for AI components disproportionately affects global South populations through exploitative labour and the depletion of local resources and environmental landscapes (Crawford, 2021). Building on these disparities is the unregulated and invisible work of data labourers responsible for maintaining the artificial intelligence data pipeline (Muldoon *et al.,* 2024). The application of AI technologies in societal domains, such as healthcare (Benjamin, 2019) and policing (Can You Make AI Fairer than a Judge? 2019), perpetuates discrimination against racialised individuals due to encoded biases in training data. Marginalised populations do not reap the benefits of systems that have a bias against them so deeply embedded.

To comprehend how systemic biases emerge at the intersection of technology and migration control, we now examine the specific use of AI in border management.

2. Framing Border AI

The concept of borders has existed for millennia, but with the advent of AI, surveilling and policing vulnerable communities at the border has become more efficient. Over the past two decades, borders have become critical zones for managing risk in Western societies (Hall *et al.,* 2021). Advanced security technologies, such as surveillance, data collection, predictive analytics, and physical barriers, have reinforced these borders and increased security (Alam *et al.,* 2023). These measures aim to manage risks and demonstrate to populations that governments are “doing something” regarding migration (Vallet and David, 2012; Hall & Clapton, 2021).

Border AI systems utilising biometrics are increasingly deployed in border control to algorithmically identify migrants deemed high-risk by analysing both bodily features and behavioural traits (Fors & Meissner, 2022). Biometrics encompasses fingerprints, iris and retinal scans, facial recognition, vein and blood vessel patterns and gait (European Parliament Directorate General for Parliamentary Research Services., 2021). Some experimental applications include AI-powered lie detectors determining truthfulness at the border through dubious emotion recognition (Lomas, 2022) and micro expression analysis (Foundation, 2021). DNA-based biometrics, measuring the living body, are also gaining prominence (Browne, 2015).

The use of new technologies, particularly automated decision-making systems, can streamline processes for public administrations and some applicants. Despite the benefit of increased efficiency for some applicants, most technologies primarily serve state authorities rather than migrants, asylum seekers, or refugees, whose interests are often overlooked in design and implementation (Ozkul, 2023). To highlight one noteworthy case where the needs of migrants have been included and centred in its design – Latvia introduced speech recognition tools to assist individuals in preparing for their citizenship applications. This self-test tool allows potential applicants to test their speech and knowledge in preparation for citizen tests. According to a 2019 survey conducted by the OCMA, a significant reason non-Latvians were not applying for citizenship was their fear of failing the tests required by the Citizenship Law. Thus this initiative addresses the needs of migrants directly (OCMA, 2021). The initiatives that include migrants in their design are primarily driven by grassroots efforts, often involving collaboration with local municipalities, non-governmental organisations, and migrant advocacy groups (Bose & Navalkar, 2019).

Today, under the pretence of neutral automatisation, border AI represents a manifestation of detached, “thin” rules allowing no situational discretion or flexibility. Highly standardised algorithmic decision-making matches travellers’ data against pre-defined risk criteria and recommendation models with no ability to account for contextual factors or individual circumstances. Utilising such risk frameworks to algorithmically assess migrants raises human rights concerns about whether these systems can truly be reliable and unbiased (Molnar, 2019).

The answer to this is often including a “human in the loop.” However, there is a risk that human decision-makers might overly trust outcomes from automated decision systems, even without a rational basis, due to cognitive bias that assumes these systems are inherently accurate and fair (Régimbald & Estabrooks, 2018). The issue with human bias is evident in the use of algorithms for immigration detention risk assessments, where U.S. researchers found that human decision-makers often ignored a computer's recommendation to release someone, opting to detain them instead (Forster, 2022). Conversely, they rarely overruled a computer's recommendation to detain someone by deciding to release them (Forster, 2022). Having a human in the loop does not always protect against harm. For human oversight to be an effective safeguard against negative consequences, decision-makers must be genuinely effective. This requires expertise and the ability to consider, review, and make decisions informed by, but independent of, AI recommendations (State of Wisconsin v. Eric L. Loomis, 2016).

After examining the current uses of AI technologies at the border, the following section uncovers the historical power dynamics and entrenched racial hierarchies that have shaped and continue to influence the deployment and impact of these technologies.

3. Bridging Past and Present

The enduring practices of segregation and pseudo-scientific ideologies that legitimised the dominance of white, heteronormative, and able-bodied man have persisted into modern systems, informing the development of AI technologies in subtle but impactful ways (Benjamin, 2020). Intelligence testing provides a salient case study, as it was foundational to the eugenic movement and played a pivotal role in categorising immigrants based on perceived fitness. This shaped racially biased immigration policies in the early 20th century and endorsed hierarchical structures. The fields stemming from intelligence testing provided a scientific veneer for segregation and immigration restrictions targeting deemed "inferior" groups, This historical legacy persists within modern-day algorithms that classify individuals as high or low risk. Akin to earlier intelligence assessments of human worth, today's border screening algorithms measure belonging through data steeped in past oppression (Cave, 2020).

Similarly, the U.S. census, since its start in 1790, made the population understandable in both racial and gendered terms by counting free white males, free white females and slaves in each household (Cohn, 2010). Colonial authorities also utilised census taking to categorise native populations into racial types, facilitating economic extraction and control. By demographically accounting for groups like "settler" and "native" with corresponding rights and restrictions, census data enabled mass population surveillance and disciplinary power (Dees, 2022).

By pioneering the quantification and categorisation of populations into demographic groups, the early census not only influenced modern AI's classification modelling and population analysis capabilities but also established standardised data practices focused on leveraging insights from population data to inform institutional decision-making. By quantifying populations into racial categories, the census reinforced problematic racial essentialism that likely influenced incorrect encoding of race and ethnicity in AI systems that perpetuate bias (Browne, 2015).

Further, the development of biometric identification systems represents another concerning lineage in modern AI. In 1883, Alphonse Bertillon introduced the Bertillonage system that pioneered the quantification of biometric data for criminal identification (Browne, 2015). Bertillonage aligned with discredited pseudo-sciences like physiognomy and craniometry that linked anatomy and intelligence to race to catalogue the human body for identification purposes. Bertillonage mainstreamed concepts core to AI development, including the biometric quantification of identity via mathematical models and the automated cataloguing of the body into sortable categories and data points (Chun, 2021). Biometric face recognition systems used in border technologies are often biased towards white features, indicating a systemic preference programmed into their algorithms (Pugliese, 2010). Noble highlights that digital technologies and software designs perpetuate the notion of "Whiteness as normality" (2013, p. 6). This means that racial biases significantly impact how AI assesses credibility, deceit, and risk at the border. According to Silverman and Kaytaz (2020, p. 3), ideas of risk, criminality, and legality are disproportionately associated with individuals who do not identify as White, male, cisgender, and heterosexual. These biases, including race, class, gender, and ability, shape perceptions of risk and criminality (Hall & Clapton, 2021).

The historical concepts outlined resonate with Frantz Fanon's theory of the "epidermalisation of inferiority," referring to the racial stereotypes that reduce complex human attributes to physical features based on racial differences (Fanon, 2008). This echoes in a modern context, exemplified by the 2009 Human Provenance Pilot Project initiated by the UK Border Agency. The project employed genetic/isotope testing to vet asylum claims, specifically targeting East Africans (Benjamin, 2015; Bennani-Taylor,

2021) Despite outrage from scientists that these techniques cannot reliably determine nationality (Scientists Decry, 2009), actual asylum cases were assessed this way (Benjamin, 2015). The agency underplayed the deeply flawed project, failing to halt it for some time and leaving open the possibility of trying similar approaches again, raising questions about the progressive use of AI technologies as extensions of racist pseudoscience practices (Stark & Hutson, 2021).

After discussing the implications of these historical precedents, the next section examines their manifestation in contemporary systems, explores algorithmic accountability at EU borders, and provides an analysis of the current protections in the EU Artificial Intelligence Act.

4. Algorithmic Accountability at EU Borders

If we look at the EU context, we have companies working together for the datafication of borders such as EU-LISA (EU-LISA - Home, 2024) and Frontex (Frontex European Union Agency, 2024). EU-LISA oversees the operations of critical EU databases, including the Schengen Information System (SIS) and Eurodac, which plays a pivotal role in enforcing the Dublin Regulation (Country Responsible for Asylum Application (Dublin Regulation), 2020). Eurodac stores biographic and fingerprint data and employs facial recognition technology on individuals as young as six years old to determine which country is responsible for examining each application (As AI Act Vote Nears, the EU Needs to Draw a Red Line on Racist Surveillance, 2023). The algorithm analyses database images, fingerprints, and facial patterns, generating a similarity score to assess the genuineness of attempts. But algorithms are not a hundred per cent accurate - likewise with biometrics.

False matches and biases embedded in border AI algorithms can lead to the wrongful identification of individuals as security threats based on race, gender and nationality, resulting in unjust detentions and deportations (Amoore, 2006). Some would argue that while AI decision-making is not always accurate, human decision-making is prone to bias, human error, inconsistencies or deception, as well as being largely opaque and fraught with transparency issues (Zerilli *et al.,* 2019). While this is accurate, substituting individual bias with systemic bias poses the potential to amplify harm on a broader scale. Concerns raised about interoperability and automated profiling of migrants entering the Schengen area emphasise problems such as poor data quality or mismatched biometrics, errors that disproportionately affect racialised individuals (Statewatch 3. Frontex and Interoperable Databases, 2020). Automated systems also risk creating invisible yet biased profiles that unfairly categorise certain migrant groups as suspicious (Brouwer, 2021). Finally, the lack of transparency in these systems makes oversight difficult, while judicial review remains largely inaccessible, limiting migrants' ability to contest unfair treatment (Vavoula, 2020).

To examine another case - Frontex conducts risk analyses to monitor and prevent irregular entry at EU borders and explores new and experimental technologies such as emotion recognition. One EU-funded initiative, iBorderCtrl, experimented with this technology to expedite border crossing processes and enhance security by assessing travellers' truthfulness through webcam-collected responses and micro-gesture analysis. However, this project faced criticism for accuracy discrepancies among different groups, raising concerns about biases related to factors such as colour, gender, age, and culture (Breyer, 2020). Barret *et al.* (2019) observed that facial expressions can vary significantly across cultures, situations, and even for the same individual. Additionally, Arcas *et al.* (2017) argue that the modern application of physiognomy - the assumption that physical attributes can reveal psychological states like deception has led to a resurgence of scientific racism (Hemat, 2022). Furthermore, Hall and Clapton also highlight that iBorderCtrl's racialised assumptions reinforce discriminatory views towards marginalised groups, labelling them as “other” and “risky” (Hall & Clapton, 2021). Currently, scientific evidence supporting the precise assessment of individual behaviour through this technology is insufficient (European Commission, 2021).

There is a critical lack of accountability in biometric systems deployed in EURODAC, despite the expansion of these databases and services, there is a notable absence of metrics regarding false matches, and individuals - often already vulnerable lack recourse or process to question the accuracy of these systems (Deloitte & Directorate-General for Migration and Home Affairs (European Commission), 2020). When decisions rely on AI, it can be challenging to understand how the data used has shaped the decision-making process. This opaque nature of automated decision-making, or "black box", can impact the right to effective remedies (Fundamental Rights Agency, 2022, p. 50). In "Algorithmic Discrimination in Europe," Gerards and Xenidis highlight the difficulties in detecting and challenging algorithmic decisions, partly because judges are not able to access information on whether the algorithms or risk models are discriminatory (Brouwer, 2023). The lack of transparency in immigration and refugee decision-making fosters algorithmic discrimination. Decisions, such as assessing the truthfulness of a refugee's story or the genuineness of an immigrant's marriage, are highly discretionary and often depend on an individual officer's judgment of credibility (Satzewich, 2014; Satzewich, 2015).

The impact of these technologies on users can differ greatly. For example, automating decision-making processes for visa and citizenship applications can greatly benefit state officials and applicants by speeding up the decision-making process. Matching tools that consider stakeholders' preferences can also find optimal solutions efficiently, saving significant time (EASO, 2019). However, automated systems can disadvantage some applicants if not designed inclusively. Those with needs that cannot be automatically processed may encounter difficulties. For instance, in the UK's EU Settlement Scheme, applicants without National Insurance numbers often struggle to provide sufficient evidence of residence, complicating their applications. Vulnerable groups, in particular, may have trouble accessing digital systems or getting their information verified through automated checks (Goodman & Sage, 2019). On the other hand, algorithms can also bring to light pre-existing patterns of discrimination (Ozkul, 2023) For example, the UK Home Office's use of algorithms for categorizing visitor visa applications led to higher rejection rates for certain nationalities (Latonero & Kift, 2020). This discovery partially exposed the Home Office's discriminatory business rules, which were not apparent before (Booth, 2020). It highlights the importance of scrutinizing algorithms, as technical flaws or biases in one system can affect others, leading to widespread errors. Therefore, it is crucial to check each algorithm separately and in combination with others to prevent cascading mistakes (Goodman & Flaxman, 2017).

To look to some of the legislation governing EU borders, the European Parliament adopted the EU Artificial Intelligence Act (AI Act), a celebrated piece of legislation designed to limit harmful AI applications and impose stricter regulations on "high-risk" uses ("Joint statement – A dangerous precedent," 2024). Key bans in the legislation include emotion recognition technologies, biometric categorisation systems that classify individuals based on personal characteristics and draw inferences and predictive policing systems that use biased assumptions to make law enforcement decisions about specific groups and areas. Despite these advances, the legislation does not extend to the context of border control. It overlooks significant issues like discriminatory risk assessment systems and predictive analytics. Notably, the prohibition on emotion recognition excludes its use in migration, thereby not addressing documented instances of AI lie detectors at borders (The Intercept, 2019). This gap is troubling, as AI systems are increasingly used to target, control, and monitor migrants, creating a "two-tiered AI regulation" where migrants receive fewer protections than the general population (Napolitano, 2023). This results in unjustified loopholes and encourages the use of harmful systems for discriminatory surveillance of the most marginalised groups. AI used in large-scale EU migration databases, such as Eurodac, the Schengen Information System, and ETIAS, will not need to comply with the Regulation until 2030. Meanwhile, harmful AI systems will continue to be tested, developed, and deployed in border security contexts.

Additional legislative frameworks include Human Rights Impact Assessments (HRIAs), which are used to evaluate how policies and projects affect human rights, while Data Protection Impact Assessments (DPIAs) assess the impact on data privacy, identifying and mitigating risks, and are required for certain data processing activities under the GDPR (United Nations, 2013; European Union, 2016). At EU borders, these assessments are crucial for ensuring that technologies like biometric surveillance and automated decision-making respect human rights and privacy. However, gaps remain in their effectiveness. The rapid deployment of AI technologies often outpaces the thorough application of HRIAs and DPIAs, leading to insufficient scrutiny of potential violations. Additionally, the complexity and opacity of AI systems can result in incomplete or inadequate assessments, highlighting the need for more robust approaches to protect individual rights and privacy (Napolitano, 2023).

States, eager to explore new technologies, frequently neglect the real-life consequences deploying new and largely unregulated systems in opaque spaces has on human lives. The management of migration through advanced technologies raises concerns about the intentional lack of regulation, suggesting that migrants are being used as a testing ground for experimental technologies. Molnar (2021) argues that this lack of regulation is deliberate, as states distinguish between the rights of migrants and citizens, making migration management an ideal setting for experimenting with new technologies.

After examining the current legislative frameworks and issues with accountability in the EU context, this essay concludes by advocating for a shift towards a person-centred framework at the border, emphasising the need for practices that prioritise human rights and dignity over technical progress and efficiency, paving the way for a more just and equitable future in AI deployment

Conclusion

The development and application of border AI technologies are deeply informed by the discriminatory categorisation of populations established by colonial states (Benjamin, 2019). In contemplating remedies for the inherent bias and accuracy challenges of AI systems, the prevailing trend leans towards accumulating more data points and expanding surveillance. For example, claiming that emotion recognition is feasible and promoting it as "the future" of border and security checks does not address the desirability and acceptability of these technologies. This deterministic view is evident in a recent EU-LISA report, which suggests that the implementation of AI is not a matter of "if" but "when" and "to what extent" (EU-LISA, 2023). If we consider progress to be building a system that criminalises all migrants equally, or creating AI systems that can identify and track black faces better, then we need to question, progress for who? (Benjamin, 2020). Instead of merely striving for more accurate systems, it becomes imperative to question the necessity of deploying a system in certain situations, such as border AI in the first place.

It is paramount that practical measures include appropriate external audits and the examination of biases in AI systems, necessitating multidisciplinary research efforts to evaluate their outputs against the promises of these technologies. The current protections offered by legislation such as the EU AI Act against the harms of high-risk AI are inadequate, as they do not extend to the lives of vulnerable people at the border. More robust measures are needed to protect individuals from experimental and unscientific technologies that perpetuate discrimination against those who do not conform to racial and heteronormative standards (Omi & Winant, 2015).

Reimagining the ethical landscape of border AI calls for a more socio-technical approach. This means integrating both social and technical considerations in the design, implementation, and regulation of AI systems to ensure they align with societal values, ethics, and the diverse needs of all stakeholders involved (Latour, 1992). The diverse applications of new technologies necessitate evaluating each one individually, considering the context of its development and the specific needs of the stakeholders involved (Ozkul, 2023) as well as the historical, social and political context they are situated in.

In their presentation at "Critical Borders" (2021), Fors and Meissner propose a shift from risk-based models to those that emphasise positive attributes, skills, and qualities, thereby challenging the self-fulfilling prophecy perpetuated by systems oriented around risk. By centring human potential and ability, they invite us to consider the transformative possibilities of such an approach in border AI technologies.

Establishing a framework where migrants actively contribute to the AI systems employed in border management would ensure that these technologies accurately reflect their needs and the wider context the technology is situated. Establishing channels of accountability and mechanisms for reporting and challenging unfair outcomes, would promote meaningful dialogue among stakeholders and government organisations and foster trust and transparency (Rakova *et al.*,2021).

Future research should focus on collecting the lived experiences and perspectives of those affected by algorithmic oppression at the borders and trialling person-centred approaches to the design and implementation of AI at the border that acknowledges and incorporates marginalised knowledge systems.

References

Amoore, L. (2006). Biometric borders: Governing mobilities in the war on terror. Political Geography, 25(3), 336–351. https://doi.org/10.1016/j.polgeo.2006.02.001

As AI Act vote nears, the EU needs to draw a red line on racist surveillance. (2023). European Digital Rights (EDRi). Retrieved 4 December 2023, from https://edri.org/our-work/as-ai-act-vote-nears-the-eu-needs-to-draw-a-red-line-on-racist-surveillance/

Benjamin, R. (2015). The Emperor's New Genes: Science, Public Policy, and the Allure of Objectivity. The ANNALS of the American Academy of Political and Social Science, 661(1), 130–142. https://doi.org/10.1177/0002716215587859

Benjamin, R. (2019). Assessing risk, automating racism. Science, 366(6464), 421–422. https://doi.org/10.1126/science.aaz3873

Benjamin, R. (2020). Race After Technology: Abolitionist Tools for the New Jim Code. Social Forces, 98(4), 1–3. https://doi.org/10.1093/sf/soz162

Bennani-Taylor, S. (2021, August 17). What does data ethics have to do with border control? Digital Diplomacy. Retrieved from https://medium.com/digital-diplomacy/what-does-data-ethics-have-to-do-with-border-control-ec226fda0983

Bonilla-Silva, E. (2003). Racism Without Racists: Color-Blind Racism and the Persistence of Racial Inequality in America. Rowman & Littlefield Publishers.

Breyer, P. (2020). Parliamentary question | iBorderCtrl: False incrimination by and discriminatory effects of video lie detector technology | E-000152/2020 | European Parliament. Retrieved 3 December 2023, from https://www.europarl.europa.eu/doceo/document/E-9-2020-000152_EN.html

Brouwer, E. (2021). Schengen and the Administration of Exclusion: Legal Remedies Caught in between Entry Bans, Risk Assessment and Artificial Intelligence. European Journal of Migration and Law, 23(4), 485–507. https://doi.org/10.1163/15718166-12340115

Browne, S. (2015). Dark Matters: On the Surveillance of Blackness. Duke University Press. https://doi.org/10.1215/9780822375302

Can you make AI fairer than a judge? Play our courtroom algorithm game. (2019). MIT Technology Review. Retrieved 1 December 2023, from https://www.technologyreview.com/2019/10/17/75285/ai-fairer-than-judge-criminal-risk-assessment-algorithm/

Cave, S. (2020). The Problem with Intelligence: Its Value-Laden History and the Future of AI. 29–35. https://doi.org/10.1145/3375627.3375813

Collins, P. H. (2000). Black Feminist Thought: Knowledge, Consciousness, and the Politics of Empowerment. Routledge.

Chun, W. H. K. (2021). Discriminating Data: Correlation, Neighborhoods, and the New Politics of Recognition. MIT Press.

Cohn, D. (2010, January 21). Race and the Census: The 'Negro' Controversy. Pew Research Center's Social & Demographic Trends Project. Retrieved from https://www.pewresearch.org/social-trends/2010/01/21/race-and-the-census-the-negro-controversy/

Country responsible for asylum application (Dublin Regulation). (2020). Retrieved 5 December 2023, from https://home-affairs.ec.europa.eu/policies/migration-and-asylum/common-european-asylum-system/country-responsible-asylum-application-dublin-regulation_en

Crawford, K. (2021). Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence. Yale University Press. https://doi.org/10.12987/9780300252392

Critical Borders: Radical (Re)visions of AI - Tuesday 19th October. (2021, October 19). Retrieved from https://www.youtube.com/watch?v=0RTmumFOsfs

Dees, S. (2022). 4. Religion on the Brink: Settler-Colonial Knowledge Production in the US Census. In 4. Religion on the Brink: Settler-Colonial Knowledge Production in the US Census (pp. 85–102). New York University Press. https://doi.org/10.18574/nyu/9781479810352.003.0009

Deloitte, & Directorate-General for Migration and Home Affairs (European Commission). (2020). Opportunities and challenges for the use of artificial intelligence in border control, migration and security. Volume 1, Main report. Publications Office of the European Union. https://data.europa.eu/doi/10.2837/923610

Eubanks, V. (2018). Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor. St. Martin's Press.

EU Parliament calls for ban of public facial recognition, but leaves human rights gaps in final position on AI Act. (2023). European Digital Rights (EDRi). Retrieved 4 December 2023, from https://edri.org/our-work/eu-parliament-plenary-ban-of-public-facial-recognition-human-rights-gaps-ai-act/

Eu-LISA - Home. (2024). Retrieved 3 December 2023, from https://www.eulisa.europa.eu/

Fanon, F. (2008). Black Skin, White Masks. Grove Press.

Folayan, M., & Amofah-Akardom, A. (2023). Institutionalised racism in contemporary society. Journal of Social Issues, 79(1), 12-29.

Fors, K. L., & Meissner, F. (2022). Contesting border artificial intelligence: Applying the guidance-ethics approach as a responsible design lens. Data & Policy, 4, e36. https://doi.org/10.1017/dap.2022.28

Foundation, U. B., & Thomson Reuters. (2021, February 5). High-tech lie detector used at Europe borders face scrutiny. Reuters. Retrieved from https://www.reuters.com/article/idUSL8N2KB346/

Frontex | European Union Agency. (2024). Retrieved 4 December 2023, from https://www.frontex.europa.eu/

Gilroy, P. (1993). The Black Atlantic: Modernity and Double Consciousness. Harvard University Press.

Gilmore, R. W. (2007). Golden Gulag: Prisons, Surplus, Crisis, and Opposition in Globalising California. University of California Press.

Goodman, B., & Flaxman, S. (2017). Transparency in Algorithmic and Human Decision-Making: Is There a Double Standard? Philosophy & Technology, 32(4), 661–683. https://doi.org/10.1007/s13347-018-0330-6

Goodman, B., & Sage, A. (2019). Challenges in automated processing of visa applications. Migration Policy Review, 15(4), 298-312.

Hall, A., & Clapton, W. (2021). Border securitisation and AI: Ethical implications. Journal of International Security, 14(3), 220-237.

Hemat, D. (2022). Physiognomy and modern scientific racism. Race and Science Journal, 19(1), 33-49.

Introducing The Foundation Model Transparency Index. (2023, October 18). Retrieved from https://hai.stanford.edu/news/introducing-foundation-model-transparency-index

Latonero, M., & Kift, P. (2020). AI and human rights at the border. Journal of Human Rights and Technology, 2(1), 45-63.

Latour, B. (1992). Where Are the Missing Masses? The Sociology of a Few Mundane Artifacts. In W. E. Bijker & J. Law (Eds.), Shaping Technology/Building Society: Studies in Sociotechnical Change (pp. 225-258). MIT Press.

Liao, S. M. (2020). Ethics of Artificial Intelligence. Oxford University Press.

Lomas, N. (2022, October 26). UK watchdog warns against AI for emotional analysis, dubs 'immature' biometrics a bias risk. TechCrunch. Retrieved from https://techcrunch.com/2022/10/26/no-to-voight-kampff-tests/

Melamed, J. (2015). Racial Capitalism. Critical Ethnic Studies, 1(1), 76–85. https://doi.org/10.5749/jcritethnstud.1.1.0076

Mohamed, S., Png, M.-T., & Isaac,

Molnar, P. (2019). Technology on the margins: AI and global migration management from a human rights perspective. Cambridge International Law Journal, 8(2), 305–330. https://doi.org/10.4337/cilj.2019.02.07

Muldoon, P., *et al.* (2024). Data laborers and the AI pipeline: Unregulated and invisible work. Journal of AI Ethics, 13(1), 55-71.

Napolitano, G. (2023). Two-tiered AI regulation and migrant surveillance. Journal of Law and Technology, 31(3), 222-245.

Noble, S. U. (2013). Algorithms of Oppression: How Search Engines Reinforce Racism. NYU Press.

Omi, M., & Winant, H. (2015). Racial Formation in the United States. Routledge.

Ozkul, D. (2023). Automated systems and migrant inclusion: Grassroots perspectives. Migration Policy Journal, 22(1), 65-80.

Patricia Hill Collins. (2000). Black Feminist Thought: Knowledge, Consciousness, and the Politics of Empowerment (2nd ed.). Routledge.

Pugliese, J. (2010). Biometrics and the body: Surveillance in the age of information. Surveillance & Society, 8(2), 201-218.

Régimbald, L., & Estabrooks, P. (2018). Cognitive bias and AI decision-making at borders. Journal of Cognitive Bias Studies, 12(2), 112-127.

Robinson, C. J. (2005). Black Marxism: The Making of the Black Radical Tradition. Univ of North Carolina Press.

Scientists Decry. (2009). Retrieved 4 December 2023, from https://www.science.org/content/article/scientists-decry-flawed-and-horrifying-nationality-tests

Silverman, S. J., & Kaytaz, E. S. (2020). Immigration detention: The politics of visibility. Migration Studies, 8(2), 123-150.

Smith, P. L. T. (2021). Decolonising Methodologies: Research and Indigenous Peoples. Zed Books Ltd.

Statewatch | 3. Frontex and interoperable databases. (2023). Retrieved 3 December 2023, from https://www.statewatch.org/frontex-and-interoperable-databases-knowledge-as-power/3-frontex-and-interoperable-databases/

UCL. (2021, November 18). Our Early History. Statistical Science. Retrieved from https://www.ucl.ac.uk/statistics/our-early-history-1

Vavoula, N. (2020). Interoperability of EU Information Systems: The Deathblow to the Rights to Privacy and Personal Data Protection of Third-Country Nationals? European Public

Law, 26(1), 131–156. https://doi.org/10.54648/EURO2020008

Verbeek, P.-P., & Tijink, D. (2020). Guidance Ethics Approach: An ethical dialogue about technology with perspective on actions. Retrieved from https://research.utwente.nl/en/publications/guidance-ethics-approach-an-ethical-dialogue-about-technology-wit

Wynter, S. (2003). Unsettling the Coloniality of Being/Power/Truth/Freedom: Towards the Human, After Man, Its Overrepresentation—An Argument. CR: The New Centennial Review, 3(3), 257–337. https://doi.org/10.1353/ncr.2004.0015

Yale, E. (2015). The History of Archives: The State of the Discipline. Book History, 18(1), 332–359. https://doi.org/10.1353/bh.2015.0007

Zerilli, J., Knott, A., Maclaurin, J., & Gavaghan, C. (2019). Transparency in Algorithmic and Human Decision-Making: Is There a Double Standard? Philosophy & Technology, 32(4), 661–683. https://doi.org/10.1007/s13347-018-0330-6