Infrastructural Perspectives on Artificial Intelligence—on the Implications of AI Infrastructures for Global (In)Justice

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Abstract

The paper explores the impact of Artificial Intelligence (AI) on global orders by asking to what extent current practices of AI development, production, and use can be considered globally just. It adopts an infrastructural perspective, addressing both the infrastructures on which AI is built, and AI as a (particularly powerful) infrastructure, capable of transforming almost every sphere of life, as well as traditional infrastructures that used to function without AI. Drawing on insights from decolonial theory, Global South Studies, and Critical Technology Studies, as well as current examples, the article reveals how AI and related infrastructures create and reinforce colonial and patriarchal orders and transform social structures to the detriment of minorities and vulnerable groups. By demonstrating that those who benefit most from AI are not the same as those who are most affected by risk and harm, the paper argues that AI and related infrastructures in their current form cannot be considered globally just, and thus contribute to structural inequality with ordering effects on a global scale.

Keywords

Artificial Intelligence · Infrastructures · Global Justice · Global South · Decolonial Theory · Algorithmic Discrimination · Extraction · Exploitation · Diversity-Aware Design · AI Ethics

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H.-J. Bieling et al. (eds.), *Transnational Infrastructures and the Transformation of Global Orders*, RaumFragen: Stadt – Region – Landschaft,
https://doi.org/10.1007/978-3-031-74846-2_6

1 Toward an Infrastructural View on AI and Global Justice

Scholars and activists concerned with issues of social justice have drawn attention to the exacerbation of structural power asymmetries associated with the development, production, and use of Artificial Intelligence (AI). Contributions from decolonial theory and activism have particularly highlighted the colonial nature of the AI industry's practices that establish colonial hierarchies, new forms of labour exploitation, and extractionism, mostly in countries of the Global South (Amrute, 2019; Arun, 2019). The decolonial perspective reveals that AI not only deepens social inequalities but also reproduces and reinforces colonial orders, thus posing a problem of global injustice (Burkhardt, 2023, pp. 3–5). But how can we approach the phenomenon of AI from a global justice perspective?

For Kate Crawford, *Artificial Intelligence* is more than just *Machine Learning* which she describes as "a range of technical approaches" (Crawford, 2021, p. 9) within computer science. She proposes to move beyond the technical notion of AI to understand its serious social implications. To this end, Crawford drafts an "Atlas of AI" by describing and analysing selected microcosms of the AI sector and involved practices and operations. Using an ethnographic approach, she identifies the material and human-made underpinnings of the power structures at work in and around AI. She concludes that AI is "fundamentally political" (Crawford, 2021, p. 9), as it follows the specific interests of its creators, primarily private BigTech companies based in the Global North. In addition, by understanding AI as a "massive industrial formation that includes politics, labour, culture, and capital", Crawford (2021, p. 9) points to the multiple societal dimensions involved in AI—and to the economic, political, and ideological interests that drive its development. Considering the extractive practices of BigTech corporations and the impact of (especially generative) AI on public discourse and knowledge production, AI can be conceptualized as a set of "physical infrastructures that are reshaping the Earth, while simultaneously shifting how the world is seen and understood" (Crawford, 2021, p. 19). With this definition, Crawford acknowledges that AI has a major impact on the structuring of global orders, both at the physical and the epistemic levels: AI can be considered a "registry of power" (Crawford, 2021, p. 8), a system based on infrastructures that both reflects and reinforces unequal global power relations.

Crawford's approach seems promising for further reflection from an infrastructural perspective, that is, from a perspective that focuses both on *the infrastructures on which AI is built* and on *AI as an infrastructure* that profoundly transforms social and epistemic orders on a global scale. Drawing on the definition by Brian Larkin who describes infrastructures as "built networks that facilitate the flow of goods, people, or ideas and allow for their exchange over space" (Larkin, 2013, p. 328), I will elaborate on why a differentiated infrastructural view holds promise for thinking about AI and global justice:

First, the key infrastructures on which AI is built—such as digital communications infrastructure, IT hardware and software, skilled and unskilled labour, private and public research institutions—are deeply transnational. Although AI development is often carried

out at the national or even local level (think of the Silicon Valley or the Tübingen Cyber Valley), the big players such as Alphabet (Google), Meta (Facebook) or Amazon think and act transnationally. Likewise, the huge data sets that form the core of AI technologies are usually collected across borders. Moreover, the material basis for high-performance computers, servers, digital hardware, and communication infrastructures (such as metals, plastics, fiber optics), as well as the human workforce involved in the production of AI and its components, are spread across the globe. As noted above, these transnational infrastructures have been criticized for reproducing and reinforcing colonial hierarchies. However, the coloniality of AI infrastructures has often been projected onto AI itself, conflating different spheres without further consideration. An infrastructural perspective provides a more nuanced view, assessing the infrastructures that support AI and AI technologies separately.

Second, AI itself can be regarded a particularly powerful transnational infrastructure with the potential to transform not only information and communication technology (ICT) but almost every sphere of life: (industrial) production; governance, administration, security, and defence; housing, transportation, and health; entertainment and arts; and even knowledge production and creation. However, as contributions from gender studies, *Black* feminism, or decolonial theory show, the AI-driven transformation of life is often accompanied by discriminatory and harmful effects on minorities and vulnerable groups. Here, the infrastructural perspective serves to identify which groups are most advantaged or disadvantaged by AI as infrastructure.

Third, AI is transforming traditional infrastructures, taking over functions that were previously reserved for humans. For example, AI is widely used to conduct, moderate, and filter online communication and information, taking on tasks that touch on fundamental civil rights (namely freedom of speech and non-discrimination) and require moral consideration. In addition, AI is increasingly being used for public surveillance and security purposes, such as smart policing, airport security, or even warfare, exacerbating existing ethical and moral dilemmas. Here, an infrastructural perspective helps to reflect on the shift in human–machine interaction and its implications for social and global orders.

With respect to global justice, the infrastructural perspective on AI raises the following questions: How do AI-supporting transnational infrastructures impact global power relations? For whose benefit and at whose expense do they operate? How does AI as infrastructure, or as part of traditional infrastructures, affect social and epistemic orders, including the human–machine hierarchy? Do these transformations have a global dimension, and to what extent are they just?—The present article outlines a first approach to answer these questions. Drawing on insights from AI-related research in the social sciences and humanities, including decolonial theory and Critical Technology Studies, the article reflects on AI and global justice from an infrastructural perspective. It follows Crawford's approach of focusing on the (infra)structures upon which AI is built, to which I add the consideration of the transformation of life and traditional infrastructures *through* AI.

2 AI Infrastructures and Their Implications for Global Justice

To identify how AI and related infrastructures affect global justice, it is crucial to clarify what is meant by 'global justice' and what criteria are used to assess it.

In decolonial theory, the key to understanding global injustice is what Aníbal Quijano (2014) has called the "coloniality of power". Coloniality has been described by decolonial scholars concerned with AI as "the long-term global asymmetries in economic, cultural and knowledge production" (Couldry & Mejias, 2021, p. 789), or as "what survives colonialism" (Mohamed et al., 2020, p. 663). Consequently, from a decolonial perspective, it is the colonial world order and the resulting power asymmetries that divide the world into those who dominate and those who are being dominated. Global justice from a decolonial perspective thus means decolonization. With respect to AI, decolonization is understood as "an invocation to make intelligible, to critique, and to seek to undo the logics and politics of race and coloniality that continue to operate in technologies and imaginaries associated with AI" (Adams, 2021, p. 190).

Another approach to describing what decolonial scholars have called the "colonial matrix of power" (Mignolo, 2009, p. 163) has been the classification of the world into the "Global North" and the "Global South". The North/South terminology derives from foreign development aid, replacing the former and more discriminatory "first world"/ "third world" terminology. It has been criticized for reproducing colonial and capitalist worldviews (Arun, 2019, p. 4) and for misleadingly suggesting that the categories of "North" and "South" were purely geographical and homogeneous (Milan & Treré, 2019, pp. 325–326). However, as Stefania Milan and Emiliano Treré point out, in most contexts the term refers to structural power inequalities that need to be made terminologically transparent. They propose "the Souths" (in the plural, and as opposed to "the *Global* South") as an alternative term that subsumes all individuals or groups that "suffer discrimination, and/or enact resistance to injustice and oppression" (Milan & Treré, 2019, p. 325). Besides coloniality, the term includes gender, race, class, and intersectional discrimination. Global justice from a Norths/Souths perspective thus means the elimination of structural inequalities, including those (re)produced by AI and related infrastructures.

In this article, I combine the decolonial perspective on global justice with the more comprehensive Norths/Souths concept by Milan and Treré. Given the strong impact of historical colonialism on global orders and related (trade) infrastructures and the historical link between colonialism and capitalism as a main driver of AI development (Couldry & Mejias, 2021, p. 787), the decolonial perspective is essential for any consideration of global justice. The concept of the "Souths" adds to it the consideration of structural inequalities beyond the category of colonial power. Moreover, the concept is helpful in distinguishing between issues of *social* justice (within and beyond societies) and *global* justice (understood as social justice from a global perspective). But what exactly does 'global justice' mean when it comes to AI technology?

Regina Ammicht Quinn et al. (2014, p. 257) point out that shaping technology means, first and foremost, shaping society. Ethical values are inscribed in technologies,

affecting their design, accessibility, and potential uses. Therefore, the key question behind any technology development must be: "What kind of society do we want to live in?" (Ammicht Quinn, 2014, p. 28; my translation) Consequently, from an ethical perspective, we must further ask how a technology should be designed to contribute to an ideal society. To assess whether a technology can be considered just, Ammicht Quinn suggests a simple and effective rule: "A […] technology is just if those who enjoy its benefits are the same ones who bear its (not only monetary) costs […] and if these costs are distributed approximately equally." (Ammicht Quinn, 2014, p. 37; my translation) In the following, this rule serves as a rough guideline for assessing the level of justice of AI and its infrastructures. Thus, my exploratory reflections will focus on the question of who is benefited and who is harmed by these infrastructures, and whether the negative and positive consequences between these groups are balanced.

2.1 Infrastructures that Sustain AI: Reinforcement of Colonial World Orders

The interactive "Map of Internet Territories" (Coding Rights, 2024) provides an overview of the main infrastructures sustaining the Internet. It shows a dense concentration of servers, connectivity infrastructure such as satellites and cables, and IT-producing companies in the (geographic) Global North. In the Global South, it reveals a high incidence of natural resource extraction, exploitative labour, and the dumping of e-waste and related hazardous substances. Aluminium, potassium, copper, lithium, and gold are among the most needed materials for digital hardware components. In some cases, they are illegally extracted from indigenous lands to supply BigTech companies. China is the world's leading producer of electronics—and the largest importer of e-waste. Meanwhile, the US, globally the second largest producer of digital hardware, exports its toxic e-waste to countries in the Global South, such as Malaysia, India, Nigeria, or Ghana. In terms of connectivity infrastructure, both the US and China are on the winning side: the more than 420 undersea cables that allow data to flow around the world mainly connect the Global North (US-Europe-North Asia-Japan-US). The submarine cables—cynically—follow the former routes of colonial navigation (Coding Rights, 2024). The only example of Global North countries paying a proportionate share of the (non-monetary) infrastructural costs is the high energy and water consumption of their servers, which notably affect local ecosystems: The world's largest data centre, located in Oregon, USA, consumes a quarter of the city's water supply—with a rapid upward trend (Coding Rights, 2024). However, the AI-driven increase in water and energy consumption and CO2 emissions (Li et al., 2023; Luccioni et al., 2022) also has a *global* dimension, as climate change hits hardest those countries that do not have the resources to effectively adapt. The map draws a picture of global injustice: While the Global North largely benefits from good connectivity and BigTech's production, nature and people in the Global South are being exploited and endangered by hazardous substances. In this sense, people

in the Global South bear a high proportion of the harms associated with these infrastructures, while not being their main beneficiaries.

The impact of AI infrastructures on global ordering has been (implicitly) described in contributions focusing on the coloniality of practices of the AI industry. To structure the main findings in light of an infrastructural perspective, it is worth referring to Sareeta Amrute (2019) and her characterization of colonial relationships as "hierarchical, extractive, and exploitative". *Hierarchical* global power relations emerge from the monopoly position of BigTech, giving way to a one-way export of IT from the Global North (including China) to the South, intensifying the digital divide in terms of access and design (Schopp et al., 2019, pp. 13–14). In addition, there are epistemological hierarchies reflected in a pronounced male, *white* mainstream in AI research and even AI ethics (Adams, 2021; Roche et al., 2021). As Walter Mignolo (2009, p. 159) notes, Latin and Native Americans have historically been denied the ability to do science: "As we know: the first world has knowledge, the third world has culture; Native Americans have wisdom, Anglo Americans have science." In AI research, the gap between the Global North and South is particularly pronounced: only 1.3% of the journal publications come from Latin America, only 0.3% from Sub-Saharan Africa (Hakopian, 2024, p. 31). Colonial hierarchies are further reproduced in *extractivism*. In addition to the extractive mining of natural resources in Global South countries, which reinforces colonial dependencies and causes massive environmental damage (Warnecke-Berger et al., 2022, pp. 5–7), Couldry and Mejias (2019, p. 337) point to BigTech's practice of data extractivism in the Global South, which they refer to as "data colonialism". *Beta testing* is a form of data extractivism that particularly affects the Global South: BigTech companies offer free use of their products in Global South countries, circumventing stricter data protection policies in their home countries (Mohamed et al., 2020, pp. 668–669). A well-known example is Facebook's "Free Basics" program that has been implemented mostly in African countries. It provides access to limited and predefined online services while collecting users' data. In India, the program was banned, due to massive protests by activists fighting for freedom of information and data protection (Nothias, 2020, p. 330). People in the Global South are furthermore affected by the *exploitation* of low-wage human labour all along the AI supply chain (Crawford, 2021; Gray & Suri, 2019). The stressful work in hardware manufacturing, data labelling, or content moderation is mostly performed by workers from Africa, Latin America, or South-East-Asia. BigTech companies and their subcontractors have actively recruited workers from countries in crisis, such as Venezuela or Syria, taking advantage of their precariousness (Gruber, 2024; Hao & Hernández, 2022). As revealed by the Time Magazine (Perrigo, 2023), during the training of ChatGPT, underpaid Kenyan workers had to clean the chatbot's beta version of toxic language and images, causing severe psychological harm to the workers. In some cases, the IT industry even relies on forced labour (Verité, 2014), making its labour infrastructure, including that of AI, an arena for new forms of slavery.

In light of these findings, I conclude that the infrastructures on which AI is built are deeply unjust, as they contribute to the maintenance and reinforcement of colonial power

relations, and as those who benefit the most are not the same as those who are most harmed.

2.2 AI as Infrastructure: Unjust Transformations of Social Structures

Mohamed et al. (2020, p. 663) have defined coloniality as a result from "territorial appropriation, exploitation of the natural environment and of human labour, and direct control of social structures". In the previous section, I have shown that the first two aspects apply to extractive and exploitative practices in the AI industry. The third aspect, the control of social structures, comes into focus when considering AI *as* infrastructure.

There are (at least) three levels of consideration that indicate that AI is unjustly transforming social and epistemic orders: First, AI is often associated with being objective, neutral, and therefore "just", while being loaded with social biases that lead to discrimination against underrepresented groups, such as women or *People of Color* (Buolamwini & Gebru, 2018). When biased AI systems are applied to public infrastructure, there is a serious risk of intensifying structural violence against those groups that Milan and Treré (2019, p. 325) refer to as "the Souths". Second, AI tends to reproduce dominant patterns of knowledge in written language and images. This is especially true for generative AI tools that rely on deep learning algorithms. Large Language Models (LLMs) such as ChatGPT as well as image and video generation tools like DALL.E, Stable Diffusion, or Runway, are built on massive datasets with notable gender and racial biases which are reproduced in the (re)creative outputs of the tools (Gondwe, 2023; Sun et al., 2023). These outputs often end up back on the web and become part of future datasets, further replicating the biases they contain (Ananya, 2024, p. 723). In this sense, generative AI deepens unjust hierarchies of information and knowledge, intensifying epistemic injustice (Fricker, 2010) and contributing to the "epistemicide" (Santos, 2014) of Southern knowledge. Third, as noted in the introduction, AI is being incorporated in all kinds of technical, social, and public infrastructures, carrying the attribution of being 'just' while being discriminative, and promoting the reinforcement of dominant knowledge, with severe implications for social and global justice.

2.2.1 Discrimination

Whiteness is a dominant norm in datasets. As a result, facial recognition tools built on these data struggle to correctly recognize *People of Color* (Buolamwini & Gebru, 2018). This leads to discriminatory results, as in the case of an early version of the facial recognition feature in Google Photos that misclassified two *Black* persons as "gorillas" (Spiegel Netzwelt, 2015). Similarly, a *Black* woman in the U.S. was arrested for a crime she had not committed after a false facial recognition match (Hill, 2023). While it could be argued that errors in facial recognition systems are less common than racial discrimination by human police officers, it must be countered that the use of AI in smart policing

and other sensitive areas is deeply problematic, given our tendency to assume AI's judgments to be fact-based and objective.

Also, women have frequently become victims of algorithmic discrimination, with training datasets showing biases against them. For example, an AI-driven Amazon recruiting tool trained to select top candidates by scanning summaries of job applications actively downgraded women because it looked for patterns in the profiles of successful candidates over the past 10 years that had been predominantly male (Dastin, 2018). Amazon didn't notice the problem until years later, and the developers failed in their efforts to eradicate the bias. In fact, the gender gap among BigTech's employees in technical roles is immense (Huang, 2017), which resonates in a lack of diversity-awareness in tech design (Schelenz, 2023). Another example of AI-driven discrimination against women is the chatbot "Berufsinfomat" that was developed by the Austrian Public Employment Service (AMS) to help high school graduates choose a career (Proschofsky, 2024). Shortly after its launch, it became apparent that the GPT-based chatbot was advising young men to pursue careers in IT, while young women with the same interests were advised to study gender studies or work in the restaurant industry. The chatbot was reproducing the social biases contained in the training data of ChatGPT, which cover large swaths of the Internet.

The examples show that the impact of AI-driven classification is not limited to the technical realm: the use of AI in public services has real-life consequences for the affected groups. Given the multiple harms faced by *People of Color*, women, and other underrepresented groups, algorithmic discrimination can be considered "infrastructural violence". Rodgers and O'Neill (2012, p. 404) have defined infrastructures as both "a material embodiment of violence (structural or otherwise)" and the "instrumental medium" of violence. In this sense, infrastructures not only reflect but also reinforce social orders. In light of the given examples, this is clearly the case with AI as infrastructure, which therefore cannot be considered "just".

Finally, the infrastructural violence of AI has a symbolic dimension that is reflected in visual designs and representations. As Stephen Cave and Kanta Dihal (2020) show, *whiteness* is also a dominant norm in the visual design of robots, smart home assistants, and other AI tools (Cave & Dihal, 2020, pp. 688–693). The authors argue that *whiteness* has historically been associated with intelligence to legitimize *white* supremacy (Cave, 2020, pp. 29–32). They further reason that the white design of intelligent machines implicitly elevates *white* people (as particularly intelligent) and devalues *Black* people (as less intelligent) (Cave, 2020, pp. 698–699). Since smart devices are frequently used in the field of domestic labour—a traditional work domain of the *Black* U.S. population since the colonial era—Cave and Dihal (2020, p. 699) argue that the predominantly *white* design of smart home assistants is an implicit attempt to exclude *People of Color* from *white* utopia, marking the *whiteness* of machines an extreme form of discrimination by design—and *People of Color* its main victims.

2.2.2 Knowledge

"Artificial Intelligence is the development of computer systems that can perform tasks requiring human-like intelligence, such as learning, reasoning, problem-solving, and perception." (ChatGPT, personal communication, 19.01.2024) This definition of AI by ChatGPT is the condensation of countless texts that were scraped from the Internet and used to train the chatbot's underlying program GPT3.5. However, ChatGPT's (self-)definition is not based on comprehensive reasoning, but on the statistical probability that a particular word will be followed by another. As a result, it reproduces and, if widely used, reinforces dominant patterns of knowledge that, in the given example, tend to emphasize AI's technical domain rather than its political or social dimensions. Underrepresented knowledge, such as that found in indigenous languages, worldviews, and wisdom, is rarely integrated into AI datasets and thus has little impact on the outcomes of generative AI—despite evidence that indigenous AI is feasible and that users would benefit from a greater diversity of perspectives (Abdilla et al., 2020; Maitra, 2020; Williams & Shipley, 2021).

In addition to increasing epistemic injustices, generative AI spreads misleading or false information. This has serious implications for democracy if, for example, electorally relevant information is misrepresented. This was the case with Microsoft's Bing Chat, which was asked by a team of researchers working at the German NGO AlgorithmWatch (2023) about the candidates of the Bavarian and Hessian state elections. Since the chatbot provided incorrect information about the representatives, their party affiliations, poll ratings, and political goals, it is certainly not advisable to rely on generative AI models when making voting decisions (algorithmwatch.org 2023). Even scientific work seems to be at risk if ChatGPT is used as a research tool. When being asked about the state of research in a particular field, the chatbot provided a list of scientific papers that did not exist (Amaro et al., 2023, p. 31). A major shortcoming of ChatGPT is its inability to mark its 'invented' answers as such. However, the user is inclined to trust the chatbot due to its consistently competent language style—and our tendency to believe in the 'objectivity' of AI systems.

In addition, generative AI reinforces gender and racial stereotypes. Popular text-to-image generators such as Stable Diffusion or Dall.E are "overwhelmingly resorted to common stereotypes, such as associating the word 'Africa' with poverty, or 'poor' with dark skin tones." (Ananya, 2024, p. 723) Similarly, Dall.E reproduces gendered occupational stereotypes as it "systematically underrepresents women in male-dominated occupations and overrepresents them in female-dominated jobs" (Sun et al., 2023, p. 13). Furthermore, generated images of women in different occupations tend to show them smiling and looking up, making them appear more submissive than men in similar created images (Sun et al., 2023, p. 13). These biases do not disappear even if users try to actively avoid stereotypes by prompting for the desired genders or skin tones (Ananya, 2024, p. 725).

There are several reasons why image generators are particularly susceptible to stereotyping: Images depicting people are hardly neutral since they visually express gender and skin tone. Furthermore, colours are not always taken into account when labelling

image data (e.g., a banana is labelled as "banana", not as "yellow banana") (Ananya, 2024, p. 723). When the desired colour is specified by a prompt, the meanings associated with that colour are inevitably incorporated into the image, which leads to stereotyping (Ananya, 2024, pp. 723–724). *Prompt engineering* (that is, learning how to prompt efficiently) is often cited as a solution, shifting the responsibility to the user. AI companies are also making efforts to eliminate the bias in image generators—so far with moderate success (Ananya, 2024, p. 724).

2.2.3 Traditional Infrastructures

A striking example of how AI is transforming traditional infrastructures and thereby affecting social orders is the impact of AI-driven algorithms on online information and communication. As scholars studying the impact of social media on democracy have demonstrated, algorithms create *echo chambers*, in which the content we are shown reveals a limited range of perspectives, reinforcing our attitudes and opinions (Cinelli et al., 2021). *Echo chambers* are suspected of fostering radicalization and extremism, often directed against minorities (Cinelli et al., 2021, p. 1). In addition, the content that receives the most interactions tends to be the content that ranks highest on users' profiles. Yet a key factor in getting high interactions is negativity, which is created in part by using provocative or even offensive language (Fine & Hunt, 2023). Hate speech and other forms of defamation are not exclusively, but disproportionately, directed at minorities and vulnerable groups, such as the LGBTQ+community (Gorenc, 2022, p. 420). Automated content moderation has also been found to discriminate against minorities on social media: According to Oliver Haimson et al. (2021), social media posts containing typical expressions and slang words associated with the transgender or *Black* communities, as well as those using their respective hashtags, are most likely to be censored. In line with this, a report by the Brennan Center for Justice (Díaz & Hecht-Felella, 2021, p. 3) criticizes that "all too often, the viewpoints of communities of colour, women, LGBTQ+communities, and religious minorities are at risk of over-enforcement, while harms targeting them often remain unaddressed."

These examples illustrate how the use of AI in online communication infrastructure contributes to the limitation and radicalization of public discourse and aggravates the situation of minorities. It is evident that the delegation of the traditional gatekeeper function of journalists to automated systems is accompanied by social risks that, once again, affect the most vulnerable groups in society the most.

AI has furthermore fundamentally changed the infrastructures of industrial production and logistics. One example that particularly affects the Global South is the phenomenon of *reshoring*. The term refers to the relocation of production facilities from emerging markets back to the established industrialized countries where the companies are based. *Reshoring* has become profitable thanks to automation and intelligent systems that make automated production in the Global North cheaper than human labour in the Global South. Workers in emerging economies, where thousands of jobs are at stake, are most affected by *reshoring* (Ripani et al., 2020, p. 18). The transformation of the logistics

industry through automation and *coboting* as well as AI-driven surveillance has been described by Crawford (2021, pp. 53–57) with reference to Amazon's warehouses. There, unskilled, low-wage workers work alongside robots against which their performance and error rates are measured. Amazon warehouse workers are even automatically fired if they fall below a minimum workload. This example illustrates how AI is not only transforming workflows and related infrastructure, but also challenging the human–machine hierarchy: Instead of using intelligent systems to help human workers solve logistical challenges, machines are being used *against* humans, competing with them, monitoring them, and even punishing them (Burkhardt forthcoming). In the logic of Amazon's semi-automated workflows, intelligent systems paradoxically stand above the low-wage workers in the social order, threatening not only labour rights but human dignity in general.

A final and particularly startling example is the increasing role of AI in warfare. According to an investigation by +972 Magazine and Local Call (Abraham, 2024), the Israeli army has used an AI system called Lavender to identify potential Hamas operatives in Gaza in the 2024 conflict. The system relies on facial recognition, public space surveillance, and other types of data the nature and origin of which are not made transparent to the public. By analysing this data, Lavender assesses how likely it is that an individual is involved in terrorist activities. These calculations become decisive for targeting and killing individuals—and those who happen to be close to them. As the investigative report reveals, the soldiers carrying out the Israeli army's operations were instructed to accept unusually high numbers (up to 20) of civilian casualties, even for low-ranking potential Hamas members. The AI-driven system proved to have a high error rate of 10%, which officials deemed acceptable (McKernan, 2024). Lavender created a list of tens of thousands of potential terrorists to be monitored and targeted with 'dumb bombs', a particularly cheap and highly destructive type of weapon, while they were in their homes: "We were not interested in killing [Hamas] operatives only when they were in a military building or engaged in a military activity. […] It's much easier to bomb a family's home. The system is built to look for them in these situations", explains one of the military officials interviewed (Abraham, 2024). The targeting of civilians based on error-prone AI-based assessments marks a new level in the history of warfare. Since it seems more likely that highly developed industrialized nations will be able to develop and deploy such systems, this example raises questions not only about infrastructural violence but also about global justice.

3 Conclusion

This exploratory study has demonstrated that both the infrastructures on which AI is built and AI as infrastructure tend to create or reinforce structural injustices. In this sense, AI has an ordering effect that can be considered global in several respects: first, because unequal (e.g. colonial or patriarchal) world orders are recreated by AI infrastructures; second, because social structures and epistemic orders are influenced to the detriment of

vulnerable or marginalized groups (that is, the "Souths")—all over the world, but particularly in the Global South where some of the most disadvantaged groups are strongly represented. By employing an infrastructural perspective, I have shown that corporations and societies in the Global North, and particularly the male, *white* mainstream, tend to benefit the most from AI, while people in the Global South, minorities, marginalized groups, and women are most affected by the risks and harms associated with it. AI in its current form and related practices thus cannot be considered just.

There still seems to be a long way to go to achieve a form of AI that promotes global justice and reduces coloniality and structural inequalities. Decolonial scholars and activists have emphasized the need for a globally inclusive and equal exchange of knowledge and experience between the Norths and the Souths, and for the willingness of corporations and governments in the Global North to respond to the needs of people in the Global South (Cruz, 2021, pp. 1850–1851; Mohamed et al., 2020, p. 659). A fundamental problem is certainly that the big players in the AI industry are private companies that primarily pursue economic interests and whose regulation, especially at the global level, is challenging. According to Couldry and Mejias (2021, pp. 797–798), users and governments should put pressure on companies by boycotting their extractive products and switching to alternatives that pursue resource ecology, fair labour, and non-discrimination. Much could also be done by researchers, programmers and designers, e.g., with regard to a diversity-aware design of AI technologies that addresses the needs of users outside the Western norm. The question of whether the use of AI should be avoided altogether in certain areas should also not be taboo. After all, "the solution to a problem should not create worse problems than originally existed." (Ammicht Quinn, 2014, p. 43; my translation).

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