PART 2

How Is AI Development Viewed by the Global Majority?

CHAPTER TWENTY FIVE

The Making and Management of Computational Agency

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A Introduction

In early 2021, I launched a collaborative research project (Singh 2021) aimed at mapping the emergent concerns and ethical principles guiding artificial intelligence (AI) governance from the perspective of the global south,[1] which is increasingly being framed as the "global majority" (Oxfam 2023). This project was anchored in two key orienting principles: (a) developments in the global south are significant in their own right and should not be treated as derivative of global north trajectories (Comaroff and Comaroff 2012); and (b) South is a critical lens to analyze and shape developmental, postcolonial, and decolonial computing practices (Amrute and Murillo 2020). Global south is a rich empirical site to think through the diffraction in ethics and politics of data-driven technologies broadly and AI particularly. My hope was also that insights emerging from this project would contribute meaningfully to allied computational justice efforts in the north.

In this chapter, I offer methodological reflections grounded in the project's central outcome: *Parables of AI in/from the Majority World*, an anthology documenting stories of everyday interactions with computational systems from around the world (Singh et al. 2022). These reflections engage three interconnected debates on impact, storytelling, and attention that have come to shape contemporary approaches to study the consequences of AI development and deployment.

At the core of these debates is the shared recognition that the risks of algorithmic harm are routinely underestimated before deployment. A primary driver of this neglect is the uneven distribution of AI harms: *people most likely to be harmed by an AI system are also those least likely to have decision-making power over it*. Taking the unevenly distributed consequences of AI as a

[1] The lower-case use of "global south" and "global north" in this chapter is meant to acknowledge the fluidity and complexity of global relationships.

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point of departure, my reflections are structured around three questions that drive these ongoing debates:

1. What constitutes "impact" and how should it be evaluated?
2. What role can storytelling play in making visible the lived impact of algorithmic systems on communities?
3. What strategies draw attention to the uneven consequences of algorithmic deployments?

These questions open a deeper, more consequential inquiry: *how does the global majority view AI development*? Beyond the literal implications of majority through numbers and scale, "global majority" serves as a conceptual frame to describe how the majority of people often find themselves at the receiving end of computational systems – as subjects to processes of datafication and building AI-based infrastructures. Yet, this does not imply that they do not have agency.

A standpoint grounded in the global majority is oriented towards building communities in terms of what they have, rather than what they lack (Tuck 2009). It is a relational framework, a unifying metaphor, and a space for gathering, exchanging, and analyzing diverse stories – stories of becoming subject to AI and of resisting, adapting, and reclaiming agency within its systems (Singh and Guzmán 2022; see also Alam 2008). While this framing offers a critical standpoint, it is also equally important to recognize the heterogeneity within the global majority: not all contexts in the global south converge on the same conditions or perspectives, and experiences of algorithmic systems remain deeply shaped by contingencies of local histories, infrastructures, and politics (Singh 2023b).

Understanding how the global majority experiences AI requires not only recognizing their heterogeneity of but also clarifying the meaning of "AI" itself. Throughout this chapter, I use the terms *data-driven systems, algorithmic systems,* and *AI* to refer to a set of computational systems that are increasingly being used to organize everyday life. This focus on everydayness opens space to examine how AI is conceptualized by different communities of practice.

For computer science practitioners, AI is a set of techniques for engineering systems that exhibit a form of intelligence – typically benchmarked against human performance, though not necessarily modeled on human intelligence itself. For business practitioners, AI is a tool to enhance productivity by automating discrete tasks in the short term – with a longer-term aim of fully outsourcing entire job roles, particularly where those roles are composed of automatable routines. For social science practitioners, AI is a means to explore how computational systems mutually shape human experience. These different approaches to thinking through AI reflect different commitments to understanding what is at stake in ongoing investments in building and deploying AI systems – from pattern recognition to productivity to experiences of living with AI. Given these divergences, there are valid reasons to be cautious with the term "AI." It often obscures more than it reveals (Tucker 2022).

However, for the purposes of this chapter, AI is useful precisely because of how frequently agency is attributed to computational systems in everyday life. In my own fieldwork on India's biometrics-based national identification infrastructure (Singh and Jackson 2021), I often encountered variations of the same argument: street-level bureaucrats want to help citizens, but their computers will not let them (Singh 2023a). Sometimes, this reflected genuine helplessness; other times, it served as a way to deflect accountability onto machines. Folk explanations of computational agency are a recurring motif in how people describe their interactions with data-driven systems.

In some cases, what is called *AI* takes the explicit form of a recommendation system or an automated decision-making system or a large language model. In others, it emerges in more subtle ways, embedded in the struggles of people contending with the agency of computational systems – often described in terms of how the *intelligence* of these systems manifests in ordinary, everyday life. This attribution of agency to computational systems, whether rhetorical or experiential, invites a closer examination of the term "agency" itself. I am using "agency" here to refer to the power algorithmic systems exert in shaping decisions, structuring choices, and organizing everyday life. Not because they are autonomous, but because people increasingly encounter their outputs, and even judgments, in the course of ordinary routines, especially as practices and institutions form around how these systems are operationalized.

In the following sections – each introduced with a story from the *Parables* anthology (Singh et al. 2022) – I explore the three questions I laid out, beginning with an examination of *impact*: how it is conceptualized, evaluated, and used as an analytical frame to understand the consequences of algorithmic systems. I then turn to *stories* as a methodological resource for capturing the lived experiences of AI, arguing that narratives of everyday interactions with computational systems provide critical insights into how the global majority views AI development. Finally, I reflect on strategies for drawing *attention* around AI's uneven consequences, considering how communities engage, resist, and reshape these systems in response to their deployment. In the process, I illustrate how the global majority not only navigates but actively negotiates the ways in which AI manifests in their everyday lives – contending with computational agency, while asserting their own.

B Impact

For many living in the majority world, the impacts of AI systems are felt not through abstract metrics but through everyday struggles of living with them. In *The Body, Spread Out into a Database* Kimberly Fernandes (2022) narrates the story of a family, documenting their struggle to enroll their child, Praveen, who lives with multiple sclerosis, as the Indian bureaucracy transitioned from paper-based disability identification to a centralized database for Unique Disability IDs.

Praveen's life unfolds in subtle acts of resistance, carving out possibilities in a data-driven world that is quick to constrain him. Yet, his story becomes entangled in a Kafkaesque bureaucracy – certificates that expire, simplified forms detached from messy reality, and digital databases incapable of accounting for the complexities of everyday life with multiple sclerosis.

Fernandes narrates a moment both ordinary and profound: Praveen sits with his father, eyes fixed on the official form intended to document his disabilities. Each line his father reads aloud feels incomplete. "Where is multiple sclerosis?" he asks quietly looking down a list of options to describe his disability, as his father can only respond with silence.[2] The form demands a precise percentage of Praveen's disability and data fields without room for multiple disabilities – leaving father and son suspended in a quiet confusion. In that pause, Fernandes reveals a deeper problem: Praveen's lived experience of disability surpasses the narrow data categories through which it is documented. Yet the bureaucratic data-driven system demands that he fragment himself, distill his experiences into tidy boxes. Together, father and son hover

[2] At the time of Praveen's enrollment, multiple sclerosis had been recognized by law but was not yet reflected in hospital-level practice, revealing a lag in institutional alignment.

anxiously between what is known and unknown, tangible and invisible, certain only that paperwork might never fully grasp the fullness of a life like his. With every uncertain promise of eventual resolution of Praveen's problems with enrollment, his story becomes an aching reminder that sometimes life's most daunting hurdles aren't our bodies, but the fragile computational systems that surround them.[3]

B.1 What Is Impact?

At its core, impact is an evaluative framework used to assess and understand the potential consequences of AI systems, enabling their regulation and governance. Scholars of algorithmic accountability have consistently highlighted that impact is a sociotechnical construct (Metcalf et al. 2021), serving as a proxy for anticipated harms in efforts to organize accountability around the development and deployment of algorithmic systems (Groves 2022; Moss et al. 2021; Selbst 2021). Here, harm is not a fixed or readily available category of analysis, but an articulation of a setback to interests that are contextually defined and often made legible through everyday encounters with systems that misrecognize, exclude, or constrain people's ability to act. What is harmful is not always obvious in advance, it emerges through the processes of impact assessment – alongside negotiations among stakeholders over what counts as harm, how it should be measured, and who bears responsibility for addressing or mitigating it.

These negotiations are also the site of public debates over power dynamics, differing valuations of expertise, and institutional interests that shape how impact is framed and operationalized in governance. Critical to these debates is distinguishing clearly between (a) impacts as evaluative constructs designed primarily to anticipate and measure algorithmic systems' unintended consequences, and (b) the tangible harms and lived consequences actually experienced by affected individuals and communities (Metcalf et al. 2021).

Praveen's story provides a window into the complex facets of these debates, specifically surrounding the impacts of digital IDs and biometric-based identification systems deployed by the state. These anticipated impacts revolve around three potential outcomes: (a) *recognition* – a state must identify citizens clearly to mitigate fraud and provide essential services; (b) *surveillance* – the act of identifying citizens inevitably enables tracking their behaviors and entitlements; and (c) *exclusion* – changes to identification processes may exclude vulnerable populations from accessing state services (Singh and Jackson 2021; Weitzberg et al. 2021).

At first glance, Praveen's experiences appear primarily as a case of exclusion, illustrating how transitions to digital identification systems can introduce new forms of friction and inaccessibility. Although Praveen's disability was officially recognized on paper, the shift to a centralized digital process required his family to meet additional eligibility conditions and navigate institutional misalignments. Upon deeper reflection, however, Praveen's story encapsulates all three anticipated impacts. His disability gains a new form of institutional recognition through digital registration; yet, because the system is designed to categorize individuals in order to determine eligibility, it also facilitates surveillance by tracking Praveen's entitlement to services. Ultimately, the difficulties he faces during enrollment marginalize him further, ironically distancing him from a system explicitly meant to streamline and facilitate government service delivery to citizens like him.

[3] Praveen did eventually receive his Unique Disability ID, but only after considerable effort and delay.

What seems unintended in Praveen's enrollment experience is the system's inability to adequately represent multiple disabilities. Multiple sclerosis, for instance, was not explicitly recognized as a category of disability within the system, nor was there a way to indicate more than one disability in the enrollment form. These problems were ultimately resolved and he was able to secure a digital Unique Disability ID. However, during the process of navigating the challenges of enrollment, the representational complexity of Praveen's condition becomes lost within a bureaucratic infrastructure that seemed to be initially designed around singular and clearly defined disabilities. Praveen's particular difficulties exemplify the broader pattern of everyday struggles people experience in navigating data-driven systems – each comprising numerous mundane, yet cumulatively significant, challenges. His story illustrates how institutional reliance on computational systems can reconfigure the very meaning and boundaries of disability – not through the system's own agency, but through the rigid ways it is often operationalized and encoded.

Praveen's case is emblematic of how impact assessments, when narrowly framed, risk obscuring the lived realities of those they claim to serve. His struggle underscores a broader tension: designed to anticipate harm before deployment, impact assessments often fail to capture the complexity of harm as it unfolds in practice. This limitation is not a bug, but a feature. As software safety expert Nancy Leveson succinctly argues, "We are building systems today for which we cannot anticipate or guard against all unintended behavior" (Leveson 2023, p. 50). Since it is impossible to foresee every potential impact of a system in advance, the process of assessment can turn into a recursive self-referential exercise with no clear resolution, as illustrated here (Metcalf et al. 2021):

Q: How do we detect algorithmic harms?
A: We conduct an algorithmic impact assessment (AIA) to assess the likely impact of an algorithmic system to people who may experience these harms.
Q: How do we know if the AIA is [… adequate]?
A: We know that the assessment is adequate if the AIA detects possible harms caused by the algorithmic system.
Q: How do we detect these possible harms?
A: We conduct an AIA.
And so on…

This recursion highlights the difficulty of relying solely on predefined assessment protocols to capture the evolving, real-world harms of AI systems. The vocabulary of ethical concerns around AI is broadly oriented to contend with this difficulty. In the global north, ethical frameworks revolve around concerns such as bias and fairness (Mehrabi et al. 2021), accountability (Wieringa 2020), transparency (Ananny and Crawford 2018), explainability (Ehsan and Riedl 2020), and responsibility (Ghallab 2019) – which often prioritize designing better systems. AI is primarily seen as a tool that can be embedded with specific features to reflect a particular ethical vision.

In contrast, scholars engaging with the lived experiences of the global majority analyze the unevenly distributed consequences of AI through concepts such as dignity (Latonero 2018), labor (Casilli 2017), extraction (Ricaurte 2019), colonialism (Couldry and Mejias 2019), experimentation (Donovan 2018), sovereignty (Carroll et al. 2024), and solidarity (Mohanty 1988). AI is seen as an everyday experience that is shaped by ordinary ethical judgments people make as they navigate two key challenges: *how to represent oneself within computational systems and how to contend with their outputs and decisions* (Singh 2024). The differences between these conceptual vocabularies do not represent a binary but rather a spectrum of concerns – ranging from anticipating impacts to documenting actual harms – in understanding the consequences of AI. These concerns are often made tangible through storytelling.

C Stories

If assessing impacts helps us anticipate harm, storytelling brings us closer to how that harm is felt, interpreted, and lived. In *The Pavlovian Machine*, Henry Chavez and María Belén Albornoz (2022) portray Josiel, an undocumented delivery worker trapped in the mercurial world of an on-demand delivery app. Josiel's days unfold in a relentless cycle of waiting under harsh sunlit skies, checking his phone in desperate anticipation of orders that rarely arrive.

This cycle of searing heat and empty orders breaks when Josiel has a chance encounter with Leonel, a seasoned worker, who carefully explains the invisible rules of the app – its hidden rating systems and color-coded statuses, and the subtle art of coaxing it into compliance through persistent politeness and unwavering punctuality. Leonel speaks gently, yet with a weary resignation born from experience, teaching Josiel how to court the algorithm, to text customers politely even if unanswered, and to chase the diamond status that promises better work.

Despite his earnest attempts, Josiel finds the app capricious and unpredictable, behaving like a "jealous girlfriend" – at times rewarding his efforts, other times coldly withholding attention. Just as Josiel starts to master this algorithmic dance, a biometric checkpoint brands him an "unidentified citizen," thrusting his personal struggle as a gig worker into the vast machinery of data-driven control and state surveillance.

C.1 Why Storytelling?

A crucial part of the *Parables* project involved co-organizing a storytelling workshop in 2021 for practitioners in the field and early-career academics working at the intersection of science and technology studies and information science (Guzmán and Singh 2022; Singh and Guzmán 2021). When scheduling hour-long orienting conversations with each selected storyteller, we assumed that these would primarily focus on workshop logistics. Much to our surprise, however, participants often asked: "What do you mean by a story?" Embedded in this question was a deeper assumption – that academics write papers rather than tell stories. My collaborator, Rigoberto Lara Guzmán, and I spent much of each conversation convincing participants that we were, in fact, looking for a story: vignettes from field research, accounts of everyday experiences, or incidents that readers and listeners could recall and use to illustrate a shared understanding of their research topic.

Beyond the workshop, focusing on storytelling offers a way to articulate and understand ordinary struggles with the agency of computational systems. For the majority of people – including those who neither build nor directly critique these systems – algorithmic technologies often appear as opaque black boxes. They sit between the experience of providing inputs and the challenges of navigating outputs, with their inner workings frequently inaccessible even to experts. Stories provide a way to illuminate the presence and effects of these black boxes – not by revealing their inner workings, but by making visible how they are experienced in everyday life. They serve as a resource for building familiarity, surfacing patterns, and developing the capacity to contend with the difficulties computational systems often introduce. Storytelling, then, is more than a method; it is a craft, an intellectual practice, and a foundational principle for community building among the global majority as they grapple with the increasing role of computational agency in their everyday lives (Reilly and Morales 2023).

The use of "craft" is deliberate here, evoking both the art of shaping narratives and the idea of a vessel capable of transporting experiences across contexts. As a relational process involving both a storyteller and a listener, storytelling is one of the oldest forms of knowledge transmission and remains essential for democratizing power and participation in the discursive economies of AI. Grounding the project within the social sciences, our focus in organizing the storytelling workshop was on how data-driven systems mutually shape everyday life. AI, in this sense, is not merely a set of computational techniques; it functions as a narrative engine – actively generating, circulating, and embedding stories that shape social understandings of people, power, and possibilities. To put it more succinctly, ordinary experiences of AI can be understood at the intersection of two key questions (Singh 2024): (i) *Inputs:* What stories do we tell about ourselves to data-driven systems?; and (ii) *Outputs:* What stories do data-driven systems tell about us?

Parables of AI are narrative devices designed to explore these questions and to explore configurations (Suchman 2012) of human–machine agency that shape ordinary life. Just as proverbs shape common sense by distilling lived experience into shared wisdom, parables contribute to what we might call a proverbial economy (Shapin 2001; Singh and Lynch 2024) of AI. This proverbial economy does not simply reflect AI's presence in everyday life – it actively shapes how societies conceptualize, justify, and respond to algorithmic systems through shared cultural narratives (Gillespie 2024).

In representing such narratives, parables become more than anecdotes; they can shape judgment, inform action, and gain legitimacy within public and scholarly discourse – not because they inherently deserve such status, but because they resonate, circulate, and come to be valued within specific communities and contexts. Some of them are speculative, imagining AI's role in possible futures. Illustrative examples of speculative parables that currently influence public discourse about AI can be found in science-fiction films like *The Terminator* (Watts and Bode 2024) and *Her* (Roose 2024). Others are grounded in present realities of living with AI. We focused on these lived realities to make sense of AI's impacts in ways that are simultaneously rigorous and deeply human.

Storytelling grounds us as listeners within the storyteller's ordinary world. A story becomes a parable when it travels – valued by its listeners, adapted through retelling, and used as a resource for shared judgment and reflection, much like the citation magnets that animate the proverbial economies of academic fields.[4] This framing of "parables" intentionally departs from its classical framing as a story with an explicit moral lesson. Rather than offering moral instruction, the parables I describe function as shared reference points that highlight situated experiences of computational systems. They gain traction not by resolving ambiguity but by holding it open: illuminating dynamics of power, negotiation, and adaptation without prescribing clear ethical conclusions.

The power of such parables lies in several interconnected features (Joerges 1999). First, parables allow for multiplicity in interpretation while remaining anchored in concrete references to the storyteller's lived experiences. Second, they frequently capture shared experiences among listeners and resonate as expressions of common sense – especially around the push and pull of inputs and outputs that mutually shape the workings of algorithmic systems. Along these lines, while Praveen's story in the previous section illustrates how we tell stories to AI, Josiel's story reveals how AI tells stories about us.

[4] For a fuller articulation of the "proverbial economy" framework and how parables circulate as narrative infrastructure within academic disciplines, see Singh and Lynch (2024).

Josiel's story is not unusual; rather, it portrays conditions under which forms of solidarity (Qadri 2020) and mutual aid (Qadri and Raval 2021) have emerged among gig workers around the world. Although the app's allocation of orders appears capricious to Josiel, he gradually develops a folk understanding of how to navigate its algorithmic regime with Leonel's guidance. Particularly illustrative in this story is the intuitive metaphor of the app as a *"jealous girlfriend,"* which captures the emotional complexity and unpredictability of contending with algorithmic systems designed to manage the allocation of work. Such metaphors are a form of folk sensemaking; they offer ways to comprehend experiences and name things that are not yet fully understood.

These forms of sensemaking are central to the work of critical data studies scholars, who have increasingly come to recognize the role that people – as active subjects as well as participants in computational ways of organizing life – play in generating folk understandings of the workings of the black box of algorithmic systems (Kennedy 2018; Ziewitz and Singh 2021). While ordinary people might not articulate these black boxes through statistics or code, they nonetheless form meaningful insights into how these systems function and affect their lives. Early studies of such folk theories of algorithms focused primarily on everyday sensemaking about how social media algorithms curate users' newsfeeds (Bucher 2017; Burrell et al. 2019). Over time, these inquiries expanded into domains such as credit scoring (Kear 2017) and identification systems (Singh and Jackson 2021). At the heart of these studies is an exploration of the ordinary conditions that both trigger and sustain public sensemaking about algorithmic systems. This can range from discussing experiences on social media platforms, (see e.g. Bucher 2017; Burrell et al. 2019) to conducting informal, everyday audits (Shen et al. 2021) aimed at seeking remediation and redress.

When it comes to design and policy decisions, public discourse in the global north is often focused on speculative fiction and thought experiments that inspire developers to build new algorithmic systems or policy makers to anticipate potential consequences of AI deployment. Along these lines, there has been a surge in speculative storytelling workshops (Calo et al. 2020; Johnson 2019). They have also increasingly become part of researchers' methodological toolkits for imagining potential futures involving AI-based technologies. Speculation invites us to engage storytelling not only as a way to conduct research but also as a mode to (re)present it (Cahill and Newell 2021). In fiction, it is entirely acceptable – indeed, encouraged – to leave imaginative gaps for readers to fill, enabling multiple interpretations and possibilities within a storyline (Davison 2016).

However, it remains equally crucial to engage deeply with mundane, everyday stories of the majority of people contending with data-driven technologies. When these stories are valued, they become data. How we recognize, interpret, and employ this value is central to understanding how we are collectively implicated in shaping our present, material conditions of living with data and AI. Attention to speculation and lived experience shapes public perception and the material conditions of algorithmic governance in their own ways. As I show in the next section, this attention lays the groundwork for collective strategies to resist and reshape algorithmic systems and hold their deployments accountable.

D Attention

While storytelling helps make harm legible, attention is a resource to grapple with when and why certain stories rise to the surface, while others remain overlooked. In *The Digital Silk Road as Planetary Intelligence: A Story of China in Africa*, Andrea Pollio (2022) narrates his exploration of the intricate relationship between Chinese mobile technology and the bustling streets of Nairobi, especially along Luthuli Avenue, the vibrant heart of Kenya's electronics trade.

Wending his way through the tightly packed stalls of this street, Pollio discovers how each clerk, university recruit, and customer becomes a vital thread in the vast tapestry of China's Digital Silk Road (DSR) – an intricate data ecosystem pulsing through Nairobi's street-level commerce. Amid the daily negotiations over battered secondhand phones or flashy new handsets, he wrestles with the humbling realization that seemingly ordinary gestures – an idle chat, a snapped photograph – are cataloged and analyzed thousands of miles away in Shenzhen and Beijing.

In this busy corridor thronged with hawkers and bright store signs, he senses both exhilaration and unease of the shift toward a multipolar technological order where AI is not confined to individual devices or software but emerges from the complex interplay of humans, infrastructure, and global systems. In conceptualizing DSR as a form of planetary-scale geospatial intelligence, Pollio offers a poignant critique of modern connectivity, where human complexity resists being boxed into neat algorithmic systems yet remains enmeshed in their endless global reach.

D.1 When Is Attention?

The patterns in the growth of the data economy shows that attention – both as a resource and as a product of user data – has become a commodity (Davenport and Beck 2002). Although it has generated immense capital for Big Tech firms, public attention remains uneven and fleeting. Along these lines, the public itself, as John Dewey has argued, is a contingent formation of "amorphous and unarticulated" (Dewey 2016) collectives: groups of people who organize themselves in the face of problems that affect them to express their concerns. If impact asks what consequences AI systems produce and storytelling explores how those consequences are made legible, then attention determines when and why certain conversations about AI enter public discourse while others remain unnoticed, buried beneath layers of technical opacity and normalized inconvenience.

When an AI system fails spectacularly, such as an autonomous vehicle crash (Schmidt 2018) or service delivery failures that result in high-profile court cases (Haki na Sheria Initiative 2021; Metcalf et al. 2023), public attention surges. But more insidious, everyday harms – biased hiring algorithms, exploitative platform labor, or mundane forms of digital exclusion – rarely generate the same intensity or visibility. Even the dramatic failures struggle to sustain public engagement for long. In a fast-moving media environment, attention flares and fades quickly, making it difficult to build lasting momentum toward structural accountability.

Yet, harm is only one among many experiences that AI engenders, ranging from wonder and aspiration to convenience and dependency. Attention to AI spans not only its failures, but also our speculative projections, grand promises, and narratives of technological inevitability. In this interplay between expectation and lived reality, attention adds nuance to the challenges of achieving legibility by inviting deeper reflection on timing, framing, and resonance of certain experiences of AI that shape public consciousness. What conditions bring certain algorithmic issues to the forefront while others remain in the background? Whose voices are amplified in these moments of attention, and whose experiences are overlooked? Simply put, attention is not given, it is organized. Examining when and how public attention crystallizes around AI is crucial to understanding not just how harm is recognized, but how accountability is (or isn't) demanded.

In articulating AI as planetary-scale geospatial intelligence, Pollio shows the infrastructure that undergirds the DSR thrives on asymmetries of awareness – where data are collected seamlessly but often only noticed in moments of disruption and change: when a phone model becomes mysteriously unavailable, when a sales agent is asked to remodel the layout of their shop or reduce their prices, when online commentators more conspiratorially speculate that Chinese phones conceal spyware. By tracing these asymmetries, he (re)presents a global technological order that underpins the flows of hardware and capital that animate Nairobi's electronic trade. More crucially, however, his story is a reminder that attention is a matter of perspective; it is not only about *what* we see, but *when*, *how*, and *why* we see it.

A core tactic through which perspective is operationalized in building ethical frameworks around AI is to ground them in the voices of those who belong to systemically marginalized groups (Birhane, Ruane, Laurent et al. 2022; Lee et al. 2020). This approach is premised on the recognition that all knowledge is limited and partial. This limitation can also be a strength. It gives us a standpoint (Haraway 1988). Those excluded from social and political privilege often inhabit standpoints grounded in lived experiences of how AI systems fail to serve them. We see systems differently when they do not work for us. What we see is not just dysfunction; we also see the ordinary ways in which these systems become daily objects of concern. A parent negotiating their way through a child welfare bureaucracy may not know how deep learning works, but they do know where and how the system fails to account for their individual situation (Eubanks 2018).

The moral case for valuing the standpoint of the marginalized, then, lies not in treating these perspectives as universally authoritative, but in recognizing the critical insights they offer into how systems operate on the ground. Such knowledge is not comprehensive but situated – revealing possible outcomes and modalities of failure that may not be accessible to others. Its value lies in how it challenges dominant narratives and becomes part of a broader collective effort to understand and reimagine technological systems. Yet marginality also implies a lack of power. AI ethics is caught in a fundamental paradox: those with the most grounded understanding of harm often lack the institutional power to shape design and governance of AI, while those with such power frequently lack exposure to the lived realities of system failure. Put succinctly: those with knowledge lack power; those with power lack knowledge.

AI ethics practitioners have developed several strategies to draw public attention to the workings of AI systems with different theories of change to address this paradox (Hu and Singh 2024). Practitioners of *AI literacy* programs operate on the principle that knowledge is power, seeking to equip the public with the skills to use and understand AI technologies and prepare them for a future in which economic participation is presumed to require algorithmic fluency (Ng et al. 2021). Yet this approach tends to position the public as users rather than active agents, emphasizing adaptation to algorithmic systems and the competence to recognize their failures, rather than transformation of the systems themselves.

Those invested in *AI governance*, by contrast, work from a principle of collective responsibility, aiming to create spaces for the public to respond to the risks and harms of AI by participating in decision-making and policy processes (Wilson 2022). However, these spaces are often inaccessible or underdeveloped, raising critical questions about what forms of knowledge and capacity citizens need to govern meaningfully (Gilman 2023).

Finally, *participatory AI* initiatives center on the prerogative of shifting power to marginalized groups, advocating for their enrollment not just as observers or regulators, but as co-creators of AI systems (Delgado et al. 2023; Young et al. 2024). This approach invites people to draw on their lived experiences to shape how AI is developed and deployed. Yet even here, participation risks being instrumentalized – it can be used to legitimize predesigned systems or surface values that are later encoded into models without altering the underlying distribution of power (Birhane, Isaac, Prabhakaran et al. 2022; Sloane et al. 2022). Each of these strategies orients attention to AI systems by imagining people in the global majority as literate, responsible, and contributive actors in their development and deployment.

I conclude this section by noting that attention is not only a social phenomenon; it is also a technical feature of AI systems. It is central to one of the foundational architectures of large language models: the transformer. Transformers encode vast amounts of data into layers of internal representations and then decode these representations to produce responses that align with patterns humans interpret as meaningful or relevant in context. The novelty and success of transformers lie precisely in their ability to direct attention (Vaswani et al. 2017). During encoding, attention mechanisms determine the relationships among representations; during decoding, they guide the model in selecting which elements to prioritize when generating output. These operations are not intended to mirror human cognition – but the responses are ultimately evaluated, and made legible, through human judgment. In this sense, in the process of determining what to pay attention to, transformers effectively answer the question: *What would we pay attention to?*

This interplay enacts attention as a bridge – a space where AI systems and everyday life mutually shape each other. On one hand, we train large language models explicitly to respond according to our preferences – using techniques such as reinforcement learning from human feedback (Bai et al. 2022; Christiano et al. 2017). This training reflects value-laden choices: not necessarily unethical in themselves but shaped by the social and institutional contexts in which they are made. While prioritization is a computational necessity, the perspectives embedded during training often reflect systemic power dynamics, raising ethical questions about whose preferences guide the model's development and whose experiences are excluded.

On the other hand, we increasingly examine what transformers themselves attend to, hoping to discover new insights from patterns revealed in data. Attention is not just a mechanism through which models process information; it also becomes a mirror, revealing what we value, prioritize, and overlook – offering insights not only into AI systems, but into ourselves. To understand attention, then, is to trace how power moves – across the uneven configurations of what we choose to see and what we risk overlooking when computational agency meets human agency.

E Conclusion

To reckon with AI development from the standpoint of the global majority is to follow the subtle yet persistent struggles of people navigating systems they did not design but must nonetheless contend with. It is to recognize that computational agency is not something out there, in abstract technical systems, but something lived and negotiated in ordinary life – in missed services, misread identities, improvised workarounds, and tacit refusals. This chapter has traced how impact is measured, how stories are told, and how attention is organized – not to isolate these dimensions, but to show how they converge in the process of building the global infrastructure that makes AI possible. Impact is often anticipated before deployment, storytelling emerges in the aftermath, and attention moves across these moments – marking when, where, and why algorithmic systems become objects of action and concern. In the face of these concerns, reclaiming human agency means making room for the perspectives, standpoints, and shared experiences of those at the receiving end of these systems and most affected by them. Their knowledge and experience is not peripheral; it is foundational.

What makes the standpoint of the global majority distinct is not just their numerical scale, but their proximity to adaptation, improvisation, dysfunction, and refusal. To see AI from this position is to recognize it not as a neutral tool, but as a social force embedded within histories of inequality, extraction, and survival. The challenge ahead is not only to make AI systems more just, but to redistribute the very power to define what justice, relevance, and harm mean. That work begins – not in moments of crisis or wonder – but in the slow, ongoing, collective labor of listening to the ordinary. And it grows with the practices that follow: in citizen assemblies convened around questions of technological design; in community-held data infrastructures rooted in care, consent, and accountability; in experiments that treat publics not as endpoints of impact, but as architects of the possible. After all, only systems built with us – not just for us – can begin to meet the enduring work of contending with the making and management of computational agency.

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