CO-CREATED GLOSSARY
AI WITHOUT BOSSES

EXAMPLE:

Guidelines for Contributors

– Keep definitions clear and concise (2–4 sentences).
– Provide historical background if relevant.
– Include specific examples or applications.
– Cite reliable sources when possible.

Entry Structure
Term / Concept / Event:
Definition / Description:
Historical Context (if applicable):
Example / Application:
Source(s) / References:
Contributor(s):

Example:

Term:
Mondragon Cooperative Corporation

Definition / Description:
A federation of worker cooperatives based in the Basque Country, Spain.
Mondragon has grown to include manufacturing, retail, finance, and education, employing over 70,000 people.

Historical Context:
Founded in 1956 by José María Arizmendiarrieta to address local poverty through cooperative ownership.

Source(s) / References:
Whyte & Whyte, *Making Mondragon*

Contributor(s):
Trebor Scholz

Term:
AfroBench

Definition / Description:
First multilingual benchmark created to evaluate AI models across 64 African languages, highlighting major performance gaps in large language models for non-Western linguistic contexts.

Historical Context:
Developed in 2025 by African NLP (natural language processing) researchers, including members of the Masakhane collective, to challenge English-dominated AI development and promote linguistic equity in machine learning.

Example / Application:
AfroBench demonstrated that leading LLMs, including ChatGPT, perform worse on African languages than on English, exposing systemic bias in AI training practices.

Source(s) / References:
Nature Machine Intelligence, “Localizing AI in the Global South” (2025).

Contributor(s):
Monte Ritz

Term:
AI Commercialization

Definition / Description:
The process of transforming artificial intelligence research and prototypes into marketable products, services, and business models. Commercialization often involves monetizing large datasets, deploying subscription models, licensing APIs, and capital investment.

Historical Context:
While early AI research was primarily academic or government-funded (including DARPA, et al), the rise of deep learning in the 2010s fueled corporate adoption. Tech giants in the U.S. and China (the big nine) shifted AI into a commercial race, consolidating power. OpenAI’s pivot from a nonprofit research lab to a “capped-profit” company exemplifies this.

Example / Application:

APIs for GPT-3, 4, and 5 are licensed to developers; image-generation tools like DALL·E and Midjourney are commercialized through paid tiers; AI-powered recommendation engines drive advertising revenue for Meta, Google, and TikTok.

Source(s) / References:
Amy Webb, *The Big Nine* (2019); Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Algorithmic Justice

Definition / Description:
A movement and ethical framework calling for fair and equitable AI systems that do not reproduce systemic oppression.

Historical Context:
Advanced by scholars and activists such as Ruha Benjamin and Joy Buolamwini to expose and challenge racialized and gendered harms in algorithmic systems. Buolamwini founded Algorithmic Justice League in 2016 after her MIT research revealed widespread facial recognition bias.

Example / Application:
The Algorithmic Justice League campaigns against racial and gender bias in facial recognition and advocates for greater accountability in AI governance.

Source(s) / References:
Ruha Benjamin, Radical AI Podcast: "*Love, Challenge, and Hope*" (2020); Joy Buolamwini, "*The Coded Gaze*" (2019).

Contributor(s):
Monte Ritz

Term:
Anthropic

Definition / Description:
AI company founded by former OpenAI employees, focused on developing large language models with an emphasis on safety. Known for its Claude series of models.

Historical Context:
Founded in 2021 by Dario and Daniela Amodei after leaving OpenAI, Anthropic positioned itself as a safety-focused competitor within the rapidly consolidating AI industry.

Example / Application:
Claude LLMs are marketed as more interpretable and steerable, designed to reduce harmful or biased outputs compared to competitors.

Source(s) / References:
Company website; industry reporting.

Contributor(s):
Monte Ritz

Term:
Appen

Definition / Description:
Data annotation company headquartered in Australia, providing large-scale labeling services for AI systems. Known for using a global microworkforce to deliver training data at scale.

Historical Context:
Founded in 1996 in Sydney, Appen grew into one of the world's largest annotation firms, supplying datasets for major tech companies. Its 2019 acquisition of Figure Eight expanded its role in crowdsourced data labeling.

Example / Application:
Appen has provided annotated datasets for Microsoft, Google, and Amazon, powering natural language processing and computer vision applications.

Source(s) / References:
Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Broken Windows Policing → Predictive Policing

Definition / Description:
Broken Windows policing linked minor disorder (graffiti, loitering) to serious crime; predictive policing algorithms such as PredPol automated and amplified these assumptions, embedding racial and socioeconomic bias into data-driven policing.

Historical Context:
Broken Windows theory (Wilson & Kelling, 1982) shaped U.S. policing in the 1990s. Predictive policing tools like PredPol, developed from UCLA research in the 2010s, promised "crime forecasting" but reinforced existing inequalities.

Example / Application:
Reading, Pennsylvania adopted PredPol to forecast crime "hotspots." Los Angeles also piloted PredPol before abandoning it amid bias concerns.

Source(s) / References:
Cathy O'Neil, *Weapons of Math Destruction* (2016).

Contributor(s):
Monte Ritz

Term:
ChatGPT / GPT-3

Definition / Description:
Large language models developed by OpenAI, trained on vast corpora to generate human-like text. GPT-3, with 175 billion parameters, was the largest model of its kind at launch.

Historical Context:
GPT-3 (2020) and ChatGPT (2022) marked turning points: GPT-3 as the largest model of its time (175B parameters), and ChatGPT as the fastest-adopted consumer application in history. Both illustrate the shift from nonprofit research to profit-driven corporate AI.

Example / Application:
ChatGPT has been widely adopted in education, creative industries, and workplaces while sparking debates on copyright, consent, and the exploitation of ghost workers in its training.

Source(s) / References:
OpenAI technical papers; Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
CloudFactory

Definition / Description:
A data-labeling company outsourcing AI training tasks, employing workers in Kenya and Nepal. Markets itself as mission-driven and socially responsible, but often critiqued for labor precarity.

Historical Context:
Founded in 2008 in Nepal and later expanding to Kenya, CloudFactory positioned itself as a pioneer of “impact sourcing.” Despite branding, its workforce has faced the same instability and low pay as other annotation firms in the global AI supply chain.

Example / Application:
Provides annotation services for computer vision and natural language datasets used by major AI companies.

Source(s) / References:
Karen Hao, *Empire of AI* (2025)

Contributor(s):
Monte Ritz

Term:
Coded Gaze

Definition / Description:
Joy Buolamwini’s term for the bias embedded in AI systems, particularly facial recognition, reflecting skewed training data and design choices.

Historical Context:
Introduced publicly in her 2019 Bloomberg Equality Summit talk, building on her MIT Media Lab research (*Gender Shades*, 2018), which revealed high error rates for darker-skinned women compared to lighter-skinned men.

Example / Application:
The Gender Shades study showed that commercial facial recognition systems misidentified darker-skinned women at rates up to 34%, compared to less than 1% for lighter-skinned men.

Source(s) / References:
Joy Buolamwini, “The Coded Gaze.”

Contributor(s):
Monte Ritz

Term:
Computer-Vision Annotation

Definition / Description:
The process of labeling images or video frames so that computer-vision systems can detect, classify, and interpret objects. Tasks include drawing bounding boxes, segmenting regions, and tagging attributes to enable machine learning models to “see.”

Historical Context:
Scaled globally in the 2010s–20s through outsourcing firms and gig platforms like Appen, Sama, and Remotasks. It is part of the hidden “ghost work” that sustains AI development, often performed by low-paid workers in the Global South.

Example / Application:
Annotators draw boxes around pedestrians, stop signs, and vehicles to train self-driving car algorithms. Similar annotation labor underpins facial recognition systems and medical imaging AI.

Source(s) / References:
Karen Hao, *Empire of AI* (2025); Gray & Suri, *Ghost Work* (2019, supplementary).

Contributor(s):
Monte Ritz

Term:
Data Annotation

Definition / Description:
The process of labeling text, images, or video so that AI models can learn to recognize patterns and categories. Annotation is essential for training natural language processing, computer vision, and large language models.

Historical Context:
While data labeling has existed for decades, it scaled globally in the 2010s–20s with the rise of deep learning. Outsourcing firms in the Global South supplied much of this labor under precarious conditions.

Example / Application:
Kenyan workers employed by Sama labeled harmful text for OpenAI's reinforcement learning from human feedback (RLHF) process in training ChatGPT.

Source(s) / References:
Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Data Colonialism

Definition / Description:
The extraction and appropriation of human life through large-scale data capture, treating data as a raw resource to be mined. It mirrors older colonial logics of dispossession and exploitation, now extended into the digital sphere.

Historical Context:
Coined by Nick Couldry & Ulises Mejias in *The Costs of Connection* (2019), the concept critiques how digital capitalism extends colonial patterns of resource extraction into data practices.

Example / Application:
Global South users' social media posts, location data, and search histories harvested without consent by Big Tech, then repurposed to train commercial AI systems.

Source(s) / References:
Kate Crawford, *Atlas of AI* (2021); Nick Couldry & Ulises Mejias, *The Costs of Connection* (2019).

Contributor(s):
Monte Ritz

Term:
Data Sovereignty

Definition / Description:

A concept and movement asserting that data should be goverened by the nation or community where it is collected. is subject to the laws and governance of the nation or community where it is collected, emphasizing local ownership and protection against external exploitation.

Historical Context:
Emerging in the 2010s–20s amid debates on global cloud infrastructure, cross-border data flows, and Big Tech extraction. The concept gained traction as a response to data colonialism and was advanced by Indigenous communities and Global South researchers.

Example / Application:
Indigenous Data Sovereignty movements assert ownership of community health and governance records. African NLP collectives like Masakhane insist on member-owned datasets to preserve linguistic and cultural sovereignty.

Source(s) / References:
Nature Machine Intelligence, “Localizing AI in the Global South” (2025).

Contributor(s):
Monte Ritz

Term:
Democracy Theater

Definition / Description:
The illusion of participatory governance in AI policy that appears inclusive but lacks meaningful redistribution of power, ultimately reinforcing the status quo.

Historical Context:
Adapted from political science critiques of symbolic participation, where public consultations mask exclusion. Applied in AI governance debates to describe how corporations and policymakers simulate inclusion while avoiding structural change.

Example / Application:
AI ethics boards created by tech companies without real decision-making power for affected workers or communities.

Source(s) / References:
Amy Webb, *The Big Nine* (2019)

Contributor(s):
Monte Ritz

Term:
Disaster Capitalism

Definition / Description:
The practice of exploiting crises (war, poverty, climate) to secure cheap labor or resources for AI development, leveraging vulnerability to reduce costs and expand profit.

Historical Context:
Term popularized by Naomi Klein in *The Shock Doctrine* (2007). Karen Hao applies it to outsourced AI labor, showing how companies exploit crises in the Global South to build and train AI systems cheaply.

Example / Application:
OpenAI outsourced content moderation to Kenyan workers via Sama, who were paid as little as $1.50 per hour to review traumatic material used in reinforcement learning from human feedback (RLHF) for ChatGPT.

Source(s) / References:
Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Extractive Infrastructures

Definition / Description:
The material, human, and ecological systems that sustain artificial intelligence while depleting resources and exploiting labor. “Extractive” because infrastructures rely on continuous resource extraction from people and planet.

Historical Context:
Concept emphasized by Kate Crawford in *Atlas of AI* (2021), which reframes AI not as abstract computation but as a system built on mining, labor exploitation, and ecological harm.

Example / Application:
Rare earth mineral mining for chips, massive water use in data centers, hidden labor of annotators, and mounting e-waste from outdated hardware.

Source(s) / References:

Crawford, *Atlas of AI* (2021).

Contributor(s):
Monte Ritz

Term:
Fairwork Principles

Definition / Description:
Framework developed by the Fairwork Project to evaluate digital labor platforms on fairness in pay, conditions, contracts, management, and representation.

Historical Context:
Launched in 2019 by researchers at the Oxford Internet Institute and international partners, Fairwork Principles provide a global benchmark for decent work in the gig economy. They've since been applied to AI annotation platforms in the Global South.

Example / Application:
Used to assess Sama, Appen, and Remotasks on a 10-point scale measuring compliance with basic labor standards.

Source(s) / References:
Fairwork Project (2019); Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Ghost Work

Definition / Description:
Invisible, low-paid human labor that powers AI systems, hidden behind the myth of automation. Such work is often dispersed through outsourcing platforms and microwork sites.

Historical Context:
Coined by Mary L. Gray & Siddharth Suri in *Ghost Work* (2019), the term highlights how human labor is erased in narratives of AI autonomy. Karen Hao extends the concept to annotation and moderation work outsourced to the Global South.

Example / Application:

Content moderators and data annotators labeling toxic or traumatic data to train AI models, such as Kenyan workers employed by Sama to filter harmful text for ChatGPT's RLHF process.

Source(s) / References:
Mary L. Gray & Siddharth Suri, *Ghost Work* (2019); Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Insular Development

Definition / Description:
The tendency of AI research and development to occur within insular "tribes" (academic, corporate, or geopolitical) limiting cross-cultural and interdisciplinary perspectives.

Historical Context:
Amy Webb identifies "AI Tribes" in *The Big Nine* (2019), warning that their siloed thinking and narrow values shape divergent AI futures, often at odds with democratic or global needs.

Example / Application:
Corporate AI teams design global systems with little input from the Global South, while U.S. and Chinese AI ecosystems develop along insular national lines.

Source(s) / References:
Amy Webb, *The Big Nine* (2019).

Contributor(s):
Monte Ritz

Term:
Localizing AI

Definition / Description:
Adapting AI systems to the cultural, linguistic, and infrastructural realities of the Global South. Localizing AI emphasizes designing models that reflect local languages, values, and material conditions, rather than importing Western-centric approaches.

Historical Context:

Emerging in the 2020s as a response to English-dominated datasets and models that erase non-Western contexts. Concept gained visibility through Global South research networks and was highlighted in *Nature Machine Intelligence* (2025).

Example / Application:
The Masakhane collective produces natural language processing tools for African languages, while AfroBench evaluates LLM performance across African linguistic contexts.

Source(s) / References:
Nature Machine Intelligence, “Localizing AI in the Global South” (2025).

Contributor(s):
Monte Ritz

Term:
Masakhane

Definition / Description:
A volunteer-driven grassroots research collective advancing natural language processing for African languages. “Masakhane” means “we build together” in isiZulu.

Historical Context:
Formed in 2019 to resist linguistic imperialism in AI and to promote African ownership of linguistic data, it has since grown into a global network of researchers and practitioners committed to language equity in machine learning.

Example / Application:
Masakhane has developed translation models and datasets covering more than 50 African languages, and contributed to benchmarks such as AfroBench to evaluate AI performance on African linguistic contexts.

Source(s) / References:
Nature Machine Intelligence, “Localizing AI in the Global South” (2025).

Contributor(s):
Monte Ritz

Term:
Mechanical Turk (MTurk)

Definition / Description:
Amazon's crowdsourcing marketplace launched in 2005 that allows businesses and researchers to outsource small, repetitive microtasks to a distributed workforce.

Historical Context:
Named after the 18th-century "Mechanical Turk" chess-playing automaton, which concealed a human operator inside (referenced by Walter Benjamin in his Theses on the Philosophy of History [1940]). Amazon's MTurk platform became a prominent site of ghost work in the digital economy, paying workers cents per task.

Example / Application:
Used to provide training data for natural language processing and computer vision models, as well as for psychological experiments, content moderation, and AI evaluation.

Source(s) / References:
Mary L. Gray & Siddharth Suri, *Ghost Work* (2019); Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term / Concept:
New Jim Code

Definition / Description:
Ruha Benjamin's concept describing the ways algorithms and emerging technologies reproduce and amplify racial hierarchies under the guise of technical neutrality.

Historical Context:
Coined in *Race After Technology* (2019), the term draws parallels between digital systems and the legacies of Jim Crow segregation. Benjamin elaborates on the concept in her 2020 *Radical AI Podcast* interview, highlighting how technological design can mask systemic racism while reinforcing it.

Example / Application:
Predictive policing systems and facial recognition tools disproportionately target or misidentify Black communities. Hiring algorithms trained on biased data also perpetuate racial discrimination in employment.

Source(s) / References:
Ruha Benjamin, *Race After Technology* (2019); *Radical AI Podcast* (2020).

Contributor(s):

Monte Ritz

Term:
OpenAI

Definition / Description:
San Francisco–based AI company, developer of the GPT series and ChatGPT. Markets itself as pursuing “safe and beneficial AI,” but widely critiqued for centralizing control, monetizing collective data, and relying on hidden labor.

Historical Context:
Founded in 2015 as a nonprofit research lab by Sam Altman, Elon Musk, and others, OpenAI shifted to a “capped-profit” model in 2019, securing major investment from Microsoft, and aligning with corporate interests despite its original nonprofit framing.

Example / Application:
2022 launch of ChatGPT reshaped global discourse on AI, sparking debates on copyright infringement, ghost work in annotation, and the corporate capture of AI development.

Source(s) / References:
Karen Hao, *Empire of AI* (2025); Amy Webb, *The Big Nine* (2019).

Contributor(s):
Monte Ritz

Term:
Recidivism Models

Definition / Description:
Algorithmic tools designed to predict the likelihood of someone re-offending, widely used in sentencing, bail, and parole decisions. Marketed as objective risk assessments but criticized for reproducing systemic bias.

Historical Context:
Prominent in the 2010s–20s, with COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) as the most widely known system. A 2016 ProPublica investigation revealed severe racial bias: Black defendants were far more likely to be labeled “high risk,” while white defendants were more often misclassified as “low risk.”

Example / Application:

COMPAS used in U.S. courts misclassified Black defendants as “high risk” at disproportionate rates, shaping judicial decisions in parole and sentencing.

Source(s) / References:
Cathy O’Neil, *Weapons of Math Destruction* (2016).

Contributor(s):
Monte Ritz

Term:
Regenerative AI

Definition / Description:
An approach to artificial intelligence rooted in inclusivity, ecology, and cultural sustainability. Seeks to build systems that strengthen local communities rather than exploit them, embedding ecological care and democratic governance into AI design.

Historical Context:
Advanced by Anita Gurumurthy and Nandini Chami of IT for Change (2025), the concept emerged within Global South discourses as a corrective to extractive Big Tech models of AI development.

Example / Application:
AI trained on community media archives to support agroecological farming practices and preserve cultural knowledge for sustainable development.

Source(s) / References:
Digital Watch Observatory, “*AI that Serves Communities, Not the Other Way Round*” (2025).

Contributor(s):
Monte Ritz

Term:
Remotasks / Remotasks Plus

Definition / Description:
A data-annotation platform operated by Scale AI, outsourcing micro-tasks like labeling images, video, and text for AI training. “Remotasks Plus” was introduced as a tier in Venezuela, framed as stable work but often deepening precarity.

Historical Context:
Expanded in the late 2010s–20s during economic crises, particularly Venezuela's collapse, exploiting vulnerable populations for low-cost annotation labor. Became one of the largest pipelines feeding data into AI systems.

Example / Application:
Venezuelan workers recruited to annotate data for self-driving car algorithms and large language model training, sometimes tasked with labeling traumatic content with minimal support.

Source(s) / References:
Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Reinforcement Learning from Human Feedback (RLHF)

Definition / Description:
A machine learning technique in which human workers evaluate and rank AI outputs to refine a model's responses. RLHF is essential for aligning large language models with human preferences.

Historical Context:
Popularized by OpenAI in training GPT-3, GPT-4 (2023), and GPT-5 (2025), RLHF has become an industry standard for large language models, though it depends heavily on hidden and precarious human labor.

Example / Application:
Kenyan contractors employed by Sama rated ChatGPT's outputs to help "align" the model, while being paid very low wages and exposed to harmful or traumatic content.

Source(s) / References:
Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:

Sama

Definition / Description:
An outsourcing firm (formerly Samasource) contracting workers in Kenya and other regions to provide annotation and content moderation for major AI companies. Markets itself as a social enterprise but has been criticized for precarious conditions and traumatic workloads.

Historical Context:
Founded in 2008 by Leila Janah as Samasource, rebranded as Sama in 2019. Positioned as an "ethical" outsourcing company, it became central to debates on exploitative AI labor when investigations revealed low pay and harmful working conditions.

Example / Application:
Kenyan moderators employed by Sama reviewed violent and sexual material to filter ChatGPT's outputs for OpenAI's RLHF process, sometimes earning as little as $1.50 per hour.

Source(s) / References:
Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Scale AI

Definition / Description:
A U.S.-based company specializing in data annotation and AI training pipelines, outsourcing work globally through platforms like Remotasks. Markets itself as an "AI infrastructure" provider while relying on precarious gig labor.

Historical Context:
Founded in 2016 by Alexandr Wang, Scale AI rapidly grew by securing multi-million-dollar contracts with the U.S. Department of Defense and major corporations. Its model illustrates the entanglement of AI development with both militarization and global outsourcing.

Example / Application:
Scale AI provided large-scale annotation labor for OpenAI's models, self-driving car projects, and defense applications such as Project Maven.

Source(s) / References:
Karen Hao, *Empire of AI* (2025).

Contributor(s):
Monte Ritz

Term:
Small Language Models (SLMs)

Definition / Description:
Compact AI models designed to operate on limited data and computational resources, optimized for specific use-cases rather than general-purpose text generation. SLMs are often tailored to local cultural and linguistic contexts.

Historical Context:
Proposed by Global South researchers in the 2020s as ecological and equitable alternatives to resource-intensive large language models (LLMs). SLMs reflect efforts to counter the extractive infrastructures of Big Tech AI.

Example / Application:
Community-developed models that run locally for underrepresented African or Indigenous languages, or on-device systems for agriculture and healthcare in low-bandwidth settings.

Source(s) / References:
Nature Machine Intelligence, "*Localizing AI in the Global South*" (2025).

Contributor(s):
Monte Ritz

Term / Concept:
Techno-Solutionism

Definition / Description:
The belief that complex social problems can be solved through technical fixes, reducing political and structural issues to matters of efficiency or design, and often ignoring systemic causes and lived realities.

Historical Context:
Critiqued by Evgeny Morozov in *To Save Everything, Click Here* (2013) and applied by Ruha Benjamin in *Race After Technology* (2019) to highlight how AI reproduces racialized harms under the guise of innovation.

Example / Application:

Predictive policing software promoted as a solution to crime, despite reinforcing structural inequality. Similarly, AI-driven education platforms marketed as “closing achievement gaps” without addressing systemic inequities in schooling.

Source(s) / References:
Ruha Benjamin, *Race After Technology* (2019).

Contributor(s):
Monte Ritz

Term: Myth of Replacement

Definition / Description: The belief that AI will fully replace human workers across industries. In reality, AI tends to augment and transform work rather than completely eliminate it.

Historical Context: Rooted in long-standing fears of automation-driven unemployment, resurfacing with each major technological shift from industrial machines to digital systems.

Source(s) / References: Kate Crawford, *Atlas of AI*; Ruha Benjamin; Joy Buolamwini

Contributor(s): Course materials, AI Without Bosses Week 2

Term: Myth of Neutrality

Definition / Description: The claim that AI technologies, algorithms, and infrastructures are impartial tools. In reality, they encode human choices, political values, and social hierarchies.

Historical Context: Examples include IBM punch cards in Nazi Germany, ARPANET’s Cold War origins, and Facebook’s role in amplifying extremism and fueling violence in Myanmar.

Source(s) / References: Lawrence Lessig (“Code is Law”); Langdon Winner (*Do Artifacts Have Politics?*); Crawford, *Atlas of AI*

Contributor(s): Course materials, AI Without Bosses Week 2

Term: Myth of Dematerialization

Definition / Description: The idea that AI is a “virtual” or immaterial technology. In reality, AI depends on vast physical infrastructures—data centers, rare earth minerals, energy, and labor.

Historical Context: Promoted by tech companies to obscure ecological and material costs. Reality shows massive water/electricity consumption and exploitative supply chains.

Source(s) / References: Kate Crawford, *Atlas of AI*

Contributor(s): Course materials, AI Without Bosses Week 2

Term: Myth of Autonomy

Definition / Description: The belief that AI systems are independent, self-running, or truly "intelligent." In practice, AI relies on global labor, curated data, and constant human oversight.

Historical Context: AI has often been marketed as autonomous (e.g., "self-driving cars"), but hidden human inputs (e.g., low-paid microworkers labeling data) undermine this claim.

Source(s) / References: Joy Buolamwini on algorithmic bias; Ruha Benjamin on hidden labor

Contributor(s): Course materials, AI Without Bosses Week 2

Term: Myth of Superintelligence

Definition / Description: The belief that AI will surpass human intelligence and dominate all aspects of life. Often framed as either utopian (AI solving everything) or dystopian (AI destroying humanity).

Historical Context: Popularized in Silicon Valley discourse, futurist writing, and AI hype cycles. Often distracts from real present harms of AI by focusing on speculative future risks.

Source(s) / References: Kate Crawford, *Atlas of AI*; Emily Bender et al., "On the Dangers of Stochastic Parrots"

Contributor(s): Course materials, AI Without Bosses Week 2

Term: Myth of Inevitability

Definition / Description: The notion that AI progress is unstoppable, pre-determined, and that societies must adapt rather than shape its trajectory.

Historical Context: Mirrors earlier “technological determinism” narratives that treated industrialization or digitization as unavoidable. Used by corporations to discourage regulation or democratic input.

Source(s) / References: Langdon Winner, *Do Artifacts Have Politics?*; Kate Crawford, *Atlas of AI*

Contributor(s): Course materials, AI Without Bosses Week 2

Term: Myth of Universality

Definition / Description: The claim that AI systems, models, and datasets can be universally applied across contexts. In reality, they are built on narrow, localized assumptions that often fail when exported.

Historical Context: Emerged from early computing ideals of “general purpose” systems; reinforced today by companies exporting biased models globally without accounting for cultural or political differences.

Source(s) / References: Joy Buolamwini on facial recognition bias; Ruha Benjamin, *Race After Technology*

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Ecological Costs

Definition / Description: AI depends on vast energy, water, and resource consumption. Training large models produces massive carbon emissions and draws on exploitative extractive industries.

Historical Context: Traces to the hidden infrastructures of “cloud computing,” which require data centers, lithium mining, and rare earths—often outsourced to Global South communities.

Source(s) / References: Kate Crawford, *Atlas of AI*

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Hidden Micro-Workers

Definition / Description: Behind "autonomous" AI are millions of low-paid workers who label data, moderate content, and maintain systems, often under precarious and exploitative conditions.

Historical Context: Builds on earlier histories of outsourcing and global digital piecework, such as Amazon Mechanical Turk and content moderation farms.

Source(s) / References: Mary Gray & Siddharth Suri, *Ghost Work*; Ruha Benjamin

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Bias and Racism

Definition / Description: AI systems often replicate and amplify racial and gender biases embedded in their training data and design. This leads to discriminatory outcomes in hiring, policing, credit scoring, and beyond.

Historical Context: Cases like predictive policing in the U.S. and facial recognition misidentifying Black faces show how structural inequalities get baked into AI.

Source(s) / References: Ruha Benjamin, *Race After Technology*; Joy Buolamwini's Gender Shades project

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Labor Exploitation

Definition / Description: Beyond micro-tasking, AI development relies on exploitative labor relations, including warehouse robotics, surveillance in gig platforms, and precarious digital work.

Historical Context: Reflects a continuation of colonial and capitalist patterns where marginalized workers absorb risks and costs while corporations profit.

Source(s) / References: Mary Gray & Siddharth Suri, *Ghost Work*; Trebor Scholz, *Uberworked and Underpaid*

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Militarization

Definition / Description: AI tools are used for surveillance, targeting, and weaponization in military contexts, raising ethical concerns about autonomous warfare and state violence.

Historical Context: U.S. military–industrial research funded much of early computing and AI; today projects like Project Maven connect big tech with drone warfare.

Source(s) / References: Stop Killer Robots campaign

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Disinformation

Definition / Description: AI enables the mass production of deepfakes, fake news, and automated propaganda, eroding trust in media and democracy.

Historical Context: Builds on earlier practices of computational propaganda and bot armies, now supercharged by generative AI models.

Source(s) / References: Kate Crawford, *Atlas of AI*; Shoshana Zuboff, *The Age of Surveillance Capitalism*

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Lack of Transparency

Definition / Description: Many AI models operate as “black boxes” where even developers cannot fully explain outputs, making accountability difficult.

Historical Context: Reinforces power imbalances between corporations/governments and individuals, as affected communities cannot contest or audit decisions.

Source(s) / References: Frank Pasquale, *The Black Box Society*; Emily Bender et al., “Stochastic Parrots”

Contributor(s): Course materials, AI Without Bosses Week 2

Term: AI Failures – Inequality

Definition / Description: Benefits of AI are concentrated in a few corporations and countries, while harms—ecological, economic, and political—fall disproportionately on the Global South and marginalized groups.

Historical Context: Mirrors patterns of colonial extraction and global inequality in previous industrial revolutions.

Source(s) / References: Nick Couldry & Ulises Mejías, *The Costs of Connection*

Contributor(s): Course materials, AI Without Bosses Week 2