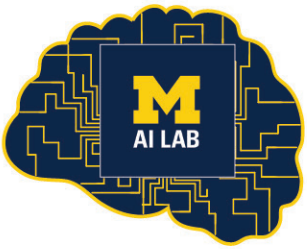


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WHITE PAPER

# Mapping Poverty Challenges to AI-driven Solutions

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# Abstract

*Although recent years have brought significant advances in AI with impact across many disciplines, we still have limited understanding of how AI can help address poverty—and conversely, how it may worsen existing inequalities. In this paper, we examine how AI can be applied to some of the core barriers faced by individuals and communities living in poverty, including food and housing insecurity, unequal access to healthcare and education, limited mobility and infrastructure, and structural imbalances in representation and power.*

*We also identify key risks associated with the use of AI, such as widening socio-economic gaps, reinforcing systemic biases, and accelerating job displacement, and suggest strategies to mitigate these harms. Our goal is to chart a path for AI innovation that meaningfully contributes to poverty alleviation while avoiding unintended consequences.*

# 1. Introduction

Poverty remains a major global challenge: nearly 700 million people (about 8.5% of the world's population) live in extreme poverty, surviving on less than $2.15 per day. An additional 3.5 billion people (44% of the global population) live in poverty on less than $6.85 per day, with little improvement since the 1990s due to population growth [1].

In this paper, we explore the use of AI to address specific challenges related to poverty. We first address the potential benefits of AI in the main areas where poverty creates barriers, including food and housing insecurity, limited access to quality education, structural power imbalances, healthcare inequities, and gaps in infrastructure. We then discuss the risks AI may pose, including the potential to widen economic gaps, reinforce existing biases, and replace jobs in ways that disproportionately affect low-income groups. By looking at both the possible benefits and harms, we aim to provide a clear view of where AI can be useful and where caution is needed.

While poverty is a worldwide issue, this paper focuses on the United States (U.S.) as the primary case study. Among the world countries, **the U.S., despite being a high-income country, has one of the highest poverty rates** among OECD nations, second only to Costa Rica as of 2022 [2]. Not only does the U.S. have relatively high rates of poverty, but the degree of economic inequality (the contrast between the highest and lowest earners) in the U.S. has grown substantially over the previous five decades. The Gini coefficient (a measure of economic inequality commonly used for international comparisons) in the U.S. was 39.8 in 2021, putting it alongside Peru, Micronesia, and Morocco [3]. In addition, recent studies found a substantial population of U.S. residents living on less than two dollars a day. These residents, often unable or unwilling to access support services, get income from irregular, usually short-term jobs [4]. Medical debt, education debt, and debt for car repairs, overdue rent, and other needs often leave impoverished families deeply underwater financially [5].

1. Laura Lein is an emerita professor of the School of Social Work.

## About this paper.

This paper is the result of a collaborative workshop that brought together nearly 30 researchers from diverse fields, including poverty studies, artificial intelligence, social work, psychology, education, and public health, to examine the potential of AI to help reduce poverty.

Participants contributed through structured roundtable discussions focused on two main topics: (1) key poverty-related challenges and (2) potential opportunities and limitations of AI in addressing them. Building on the insights from the workshop, a smaller group of researchers (the authors of this paper) synthesized the input, identified major themes, reviewed relevant literature, and outlined directions for future work. The findings and analysis presented in this paper reflect that collective effort.

While the insights presented in this paper are relevant to global contexts, our workshop and this paper focus primarily on the nature of poverty in the U.S.. Although some discussion touches on poverty in low- and middle-income countries, the data and examples are drawn predominantly from the U.S., a country with relatively high levels of both poverty and economic inequality among highly industrialized countries.

## About the authors.

The authors of this paper bring expertise across several disciplines, including poverty solutions, artificial intelligence, public health, psychology, and education. Together, they integrate domain knowledge and technical insight to analyze how AI can be applied to address core challenges related to poverty, identify risks and limitations, and propose research directions that are grounded in real-world constraints and aware of the state-of-the-art.

# 2. Poverty Solutions: Problem Space and Potential Role of AI

***Poverty encompasses many dimensions that go beyond a lack of income, and involve systemic barriers that limit access to essential resources, services, and opportunities.***

Addressing poverty requires a deep understanding of the complex factors that shape the lived experiences of individuals and communities, including food and housing insecurity, limited access to quality education, structural power imbalances, inequities in healthcare, and inadequate infrastructure. In this section, we outline key domains where these challenges manifest and explore how **AI can play a meaningful role in addressing some of these challenges by providing technological solutions to fill in gaps, optimize resource distribution, enhance service delivery, and support more equitable systems.**

## 2.1 Limited Resources

Families in poverty are more likely to experience material hardship, including food shortage, contaminated water, and unhealthy habitation. Shortages in these areas are not only related to poverty, but they in turn make it difficult to escape poverty. Furthermore, impoverished families are more likely to live in neighborhoods with poor housing stock, irregular utilities, few outlets for purchasing healthy food, and relatively underfunded community services. Deeply impoverished communities have worse health profiles and, in rural areas, in particular, limited access to healthcare facilities and other services, few opportunities for community-based employment, and low quality residence.

Lack of food, clean water, and safe housing make it difficult to escape poverty, raise healthy children, and stabilize family life. Families felt the ill effects, even before Covid [6] and these are particularly pronounced for children [7]. The years of Covid highlighted the difficulties of families and communities to sustain children's well-being when pressures on our society increase [8].

**Opportunities.** AI can help address the limited resources associated with poverty through two different approaches. Top-down approaches stress local, federal and state government services. Bottom-up approaches stress worker-owned and cooperative network economic structures and investment in local communities.

Top down approaches look to improve resource allocation for vulnerable populations through two key avenues: crisis prediction and personalized service delivery. By analyzing vast datasets of social, economic, and environmental indicators, AI systems can predict emerging crises like homelessness and food shortages. Predictive models have identified households at risk of eviction before crisis strikes, enabling early interventions that prevent families from losing their homes [9]. Similarly, AI-driven analysis of regional food production patterns and complex supply chain logistics can predict shortages, which allows agencies to deploy critical resources before communities face hunger.

AI can also enhance welfare program efficiency while customizing support to individual needs. Mobile AI applications can guide people to nearby resources like emergency shelters or food assistance programs, even in areas with weak internet infrastructure. When integrated with the existing workforce (e.g., social workers), these tools streamline housing and welfare delivery by automating burdensome administrative tasks, which can reduce staff burnout, and improve outcomes for vulnerable clients [10]. Low-power AI systems specifically engineered for regions with unreliable electricity can extend these vital innovations to underserved areas.

Bottom-up approaches can contribute to a community-based economy that repositions wealth generation at the grassroots, and actively prevent value extraction and exploitation [11], [12], [13]. In this model, AI can design models for replacing exploitation and extraction with regenerative flows of value. Specifically, AI models can help assets that are typically invisible to hegemonic economic forces, which are often those accessible to the poor [14], and make them more accessible such that they can enter into circulation as worker-owned economic activity. Mechanisms by which this can occur include informal and artisanal activity [15]; platform cooperatives [16]; and community-based financial systems [17].

## 2.2 Education and Skill Development

Our society faces profound challenges in ensuring equitable access to education, particularly as technology reshapes learning and work. For example, consider an urban public school where students share outdated computers, while peers across town use individual tablets for personalized learning. Such resource disparities in under-resourced schools directly impact academic achievement and future opportunities [18]. When a student is unable to access online research databases or complete digital assignments at home, they fall behind peers who have these tools readily available. These gaps extend beyond academics: many individuals lack crucial knowledge about their rights and available resources, leaving them unable to navigate systems effectively. Among other issues, they may miss scholarship opportunities due to unfamiliarity with application processes [19].

Technology literacy also creates economic barriers. While some students learn coding and AI concepts in advanced computing labs at their high schools, others lack basic digital literacy. This has downstream implications in the workforce, as for instance a factory worker whose job now requires interfacing with AI-powered machinery may struggle without proper training. Currently, only 40% of students worldwide receive technology literacy education [20]. Yet integrating technology also raises valid concerns. When a math program instantly solves equations, students might miss the cognitive benefits of working through problems step-by-step. Similarly, spell-checkers may weaken writing skills if students rely on them exclusively [21].

Alarmingly, younger individuals, who have traditionally been the primary participants in some form of education and schooling [22], are also the most affected by poverty. In the US alone, 17% of children under the age of 18 live in poverty [23], a rate that goes down to 11% for ages 18 and higher. This issue gets further complicated when examining racial and ethnic differences, as a disproportionate number of non-White children live in poverty. Among children under 18 who live in poverty, 30% are non-Latino White while the other 70% consists of non-Latino Black, Latino, Asian, Native American, or from other racial groups [23]. Many of these children come from households where a language other than English – the primary language of the education system – is spoken. For example, 36% of children in poverty are Latino, of which the majority natively speak Spanish, creating additional barriers to their education.

***AI tools offer transformative potential in addressing some of the most pressing challenges in education and skill development, including creating greater access to educational resources and creating personalized learning experiences that meet the unique needs of students.***

**Opportunities.** For instance, AI has the potential to make higher education more accessible to diverse learners by providing financial solutions for students from low-income families. Tools like RaiseMe, which enables students, particularly those from low-income families or first generation college students, to earn micro-scholarships for achievements often overlooked by traditional financial aid programs, exemplify how AI-driven innovations can bridge gaps in educational access [24].

Moreover, AI tutors, often referred to as intelligent tutoring systems, have been linked to improved test scores and increased student engagement with classroom material [25], [26], [27], [28]. These systems have the potential to deliver high-dose, one-on-one intensive tutoring that is accessible even to students and schools facing financial constraints [29]. Lastly, advanced machine learning algorithms can leverage vast amounts of data to more accurately and proactively identify students who are at risk of negative outcomes like chronic absenteeism and high school dropout [30], [31].

By enabling earlier interventions and supports, these tools help address challenges before they escalate, thus improving students' chances of academic success.

## 2.3 Power Imbalances and Economic Empowerment

The U.S. economy has developed in the context of weaker unions, fewer protections for wage workers, the growth of the "gig economy" and the declining share of the rewards of production going to workers. Since it is increasingly designed to extract as much labor, social, and ecological value as possible, while remitting a meager fraction of returns to labor, it is no surprise that poverty is one result. The extraction process and the current planning process are, moreover, self-reinforcing: the less money you have, the less political influence and economic leverage available to you as a means of avoiding that exploitation. AI systems exacerbate this systemic property by forcing lower income communities out of previously available jobs, and by commodifying what were previously public services.

For example, transportation decisions often disproportionately benefit specific communities while marginalizing others, as investments frequently favor affluent areas. Underserved groups, such as low-income individuals and minorities, may face inadequate public transit, restricted access to jobs, and environmental harms like increased pollution in their neighborhoods. These inequities perpetuate systemic inequalities, reinforcing existing injustices and limiting opportunities for disadvantaged communities [32].

Such inequities can become embedded in the algorithms that increasingly control both the development of systems, and the conditions for labor across economic arenas. In some ways, AI-driven algorithms control platform-based workers' workflow and incentive structures (e.g., Amazon delivery, food delivery workers). Algorithms often restrict precarious workers' agency instead of empowering them, contributing to further social marginalization and restricted social mobility [33]. The conservative bias in AI algorithms prevents us from examining whether algorithms deliver social goods or accentuate poverty and inequalities [34].

The planning process urgently needs clear definitions and equity measures to guide choices about the transit system, in our example above, and across other economic domains. When social equity goals and objectives are not translated into clearly specified objectives, and there is a lack of meaningful measures to assess the achievement of various projects toward equity, inequity and poverty are likely to grow [35].

**Opportunities.** Shifting from algorithmic bias to algorithmic justice is a critical step in evaluating how algorithms affect various intersections of the supply chain, not just the consumers or the companies that own the platforms [36]. While reducing algorithmic bias is essential, algorithms that are supposed to empower workers can also be appropriated to augment managerial control. So, it is critical to involve workers in the design and implementation process of algorithms [37].

AI's potential for reversing these trends can be carried out in two ways. Public services provided by federal, state and local governments can be enhanced (by efficiency, data analysis, integration of multiple data sources, and so on) using AI. This however is dependent on the current political climate, and even when achieved, can be overturned in the next election. An alternative approach shifts AI ownership to the community, and embeds less extractive forms of economic activity, such as solidarity economies, community-based economies, and generative justice, into business ownership, horizontal value flows and other elements that avoid exploitation [38], [12], [13], [39].

One advantage of the top-down government approach is that it makes large scale system planning more tractable. A public transportation system, for example, can be simulated by AI, accounting for more variables and scenarios than might normally be intractable for human researchers. It could also have its operations utilize real-time adjustments, resulting in better responses to emergencies, and more efficiency targeted in particular ways (e.g., when higher energy efficiency is needed, versus other priorities). Other large-scale systems in which AI might optimize planning, design, and data analysis to address poverty include sewage, water, energy, and health systems.

Bottom-up frameworks, in contrast, offer opportunities for less centralized approaches, but these can incorporate more decolonized elements, and long term "emergent strategies" [40] may be utilized to expand that to larger scales. For example, at the small scale, Robinson et al. [41] examined the problem of machine-made kente cloth fakes being sold as hand woven cloths in Ghana. They used a machine learning process to develop an application that can distinguish between hand-woven and authentic clothes, with the aim of reducing it to a cellphone size app in the near future. At larger scales, Eglash et al. [12] developed computational support for a community-based economy in Detroit. They explored this at three levels. At the microscale, AI apps specific to low-income artisanal labor were developed.

These included AI for waste stream "upcycling" [42]; for clothing design and other applications. At the mesoscale, they investigated AI for worker-owned e-delivery. And at the macroscale, they explored supports such as AI search applications that would redirect consumers to worker-owned businesses [43].

Outside the U.S. context, Nayebare et al. [44] examined a decolonial approach to AI in the context of low-income African artisans. The platform (https://ubuntu-ai.net/) currently supports 400 artisans from Ghana, Kenya, Namibia, Nigeria, South Africa and Uganda. The uploaded images, bios and other information are used internally to develop AI applications that they are co-developing with the researchers, focusing primarily on assistance to their design and marketing process. Visitors to the platform can license images for use in generative AI, but only in direct negotiation with the contributing artisan (thus avoiding the extraction of overhead or transaction costs that occur with privately owned platforms like Etsy). Investing in inclusive transportation systems (continuing our example above) can reduce social disparities by improving access to underserved areas. For instance, extending transit services to low-income communities can connect residents to jobs and education, fostering upward mobility. A report by the Urban Institute notes that inclusive transport boosts regional equity and creates a more cohesive economy [45]. Designing a lenient algorithmic management system can empower workers. For example, a study of platform delivery workers in Aarhus, a mid-sized Scandinavian city in Denmark, Kusk and Bossen [46], found that a lenient algorithmic management system that is not harsh, when implemented with no penalties or wage reductions, and embedded in a supportive ecosystem can empower workers. Such a compassionate algorithmic design embedded in a supportive environment will contribute to workers' social mobility.

## 2.4 Disparities in Healthcare

Healthcare disparities persist due to systemic challenges that undermine equitable access, quality, and outcomes for vulnerable populations. While generative AI has significantly expanded its potential in clinical care, research, and training, it also presents substantial challenges around privacy and data security, transparency and interpretability, equity in outcomes, and model evaluation and validation [47].

A major barrier lies in the unequal distribution of healthcare resources, such as clinics, hospitals, and specialized services [48]. Rural and underserved urban areas often lack sufficient healthcare infrastructure, leaving residents with limited or no access to timely care [49]. These geographic disparities are compounded by workforce shortages [50], particularly in primary care and specialty fields, which disproportionately affect low-income and minority communities.

Another significant challenge is the prevalence of socioeconomic and cultural barriers that inhibit access to care. Financial constraints, such as the inability to afford insurance premiums, copayments, or out-of-pocket costs, prevent many individuals from seeking necessary treatment and navigating systems to address these challenges [51]. Additionally, language differences, mistrust of the healthcare system, and cultural misalignment between providers and patients contribute to communication gaps and suboptimal care. Structural biases and discrimination within healthcare systems further exacerbate disparities, resulting in unequal treatment and poorer health outcomes for marginalized groups, including racial and ethnic minorities, LGBTQ+ individuals, and people with disabilities [52]. These challenges collectively perpetuate cycles of poor health and limited access, underscoring the need for systemic reforms to address the root causes of healthcare inequities.

**Opportunities.** AI has the potential to mitigate healthcare disparities by improving access, enhancing quality, and promoting equity in care delivery. One application is leveraging AI to identify and address gaps in healthcare infrastructure and workforce distribution. Predictive models can analyze population data to pinpoint areas with the greatest unmet needs, enabling policymakers and healthcare organizations to allocate resources more effectively. For example, AI tools can map underserved regions lacking primary care providers or specialty services and guide the establishment of clinics or mobile health units [53]. Another opportunity lies in using AI to provide targeted education and training for healthcare practitioners [54], which is especially valuable in regions where medical expertise is limited.

AI-driven solutions can also bridge socioeconomic and cultural barriers to care, for instance through real-time translation tools, which, while imperfect, have been found to facilitate communication and support diagnostic processes [55]. AI systems can also analyze social determinants of health such as income, housing, and employment status to offer tailored interventions and connect patients to community resources that address underlying barriers to health [56].

Virtual health assistants and telemedicine platforms, powered by AI, can expand access to care in remote or underserved areas, making it easier for patients to receive timely medical advice without geographic or financial constraints [57].

***Integrating AI into clinical decision-making for healthcare providers can reduce biases and improve the quality of care for marginalized groups [58]***

Machine learning models trained on diverse datasets can help clinicians make more accurate diagnoses and treatment plans, minimizing the impact of implicit biases that often contribute to health inequities. Additionally, AI tools such as those offered by TailorMed can streamline administrative tasks, such as processing insurance claims, navigating financial support for patients, or managing patient records, freeing up resources and reducing costs that disproportionately burden low-income patients [59].

## 2.5 Limited Accessibility and Lack of Trust in the System

Accessibility barriers to bureaucratic processes and institutional systems often exclude underprivileged populations, creating additional hurdles for those already struggling to navigate complex AI infrastructures [60]. Additionally, the rise of conspiracy theories [61] and political polarization [62] amplifies mistrust and hinders public confidence in digital systems. These challenges are compounded by the lack of inclusive design in technological systems, which often overlook the needs of marginalized communities [63]; [64]. Additionally, the digital divide stemming from disparities in education, income, and infrastructure reinforces systemic inequalities, leaving several underprivileged communities without the tools to engage meaningfully with technology [65], [66], [67].

Inconsistent transportation services and limited accessibility negatively impact individuals with disabilities, senior citizens, and low-income groups, creating frustration and a lack of trust in the system. Inadequate infrastructure results in significant social exclusion for vulnerable populations. A study by the National Council on Disability [68] identifies how the systemic lack of accessible infrastructure perpetuates barriers to mobility and autonomy [69]. Further, research shows that traditional transportation models—often focused narrowly on job accessibility and travel times—overlook the broader social and emotional costs experienced by low-income populations. These models fail to capture the daily stress, unpredictability, and relational burdens caused by unreliable or unstable transportation systems [70].

**Opportunities.** Focusing on universal design principles and advanced technologies opens opportunities to make transit systems more inclusive and trustworthy. Features like real-time transit tracking and AI-driven route planning can improve accessibility, reliability, and user satisfaction. A study by the World Economic Forum outlines how smart transportation systems enhance inclusivity by integrating real-time updates and predictive scheduling [71].

Beyond transportation, AI can serve as a powerful tool to navigate bureaucratic processes, such as social welfare, housing, and healthcare systems. For instance, AI welfare program finders can match individuals' circumstances with relevant support, streamlining access to childcare, clean water, and subsidies [72].

These systems can also connect people to verified information about resources in their communities, reducing misinformation and fostering trust [73], [74]. Moreover, the development of low-resource AI models that operate efficiently on mobile devices without requiring Wi-Fi can bridge the digital divide, ensuring underprivileged populations are not excluded from technological advancements [75]. To further build trust and encourage adoption, providing accessible training on how to protect oneself from the pitfalls of technology, while harnessing its potential can create a positive perception of AI [76]. For example, digital literacy and data privacy efforts have been shown to empower users and increase their confidence to engage with AI systems [76]. By integrating solutions from inclusive transportation to AI-driven welfare navigation, we can create equitable and trustworthy AI ecosystems for everyone.

# 3. AI-Induced Poverty Concerns

***While AI development holds significant promise for addressing poverty, it also carries the risk of deepening existing inequalities and introducing new forms of exclusion.***

As AI technologies become more integrated into public and private systems, concerns have emerged about their role in widening the socio-economic divide, reinforcing systemic biases, and displacing vulnerable workers. These unintended consequences can undermine the very goals that AI-driven solutions aim to achieve, especially when they are designed without input from affected communities or deployed in contexts with limited oversight. This section examines three critical areas of concern: the potential for AI to exacerbate socio-economic gaps, the persistence of bias in algorithmic systems, and the potential implications of automation on employment.

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## 3.1 Technology Increasing the Socio-Economic Gap

The unequal distribution of technological advancements and the centralized deployment of AI widen existing inequalities between privileged and underprivileged communities [77], [78]. A critical gap persists between technology developers and the specific needs of underprivileged populations, resulting in solutions that often fail to address their realities [79], [80]. The concentration of power in AI deployment exacerbates these inequities, as decision-making authority and resources remain predominantly in the hands of a few well-resourced stakeholders, sidelining less privileged regions. This increases socioeconomic inequality, with AI systems disproportionately benefiting those in high-resource settings while leaving underserved populations behind [81], [82], [83].

Furthermore, the exclusion of diverse perspectives and data from AI training increases biases, making these systems ill-equipped to tackle the challenges faced by underprivileged groups [84], [85], [86]. Barriers such as inadequate education and limited digital infrastructure prevent many communities from accessing or benefiting from these technologies [87]. The lack of robust regulations to ensure equitable AI practices further increases these issues [88].

Building and deploying AI models is an expensive endeavor [89], [90]; thus, it is not surprising to see that a majority of AI research and development takes place in resource-rich communities, e.g., University labs and Industry setups in the Global West and China. Since humans are likely to innovate based on the problems with which they are most familiar, the design process, data collection, and issues addressed represent the perspective of the AI developers. The ratio of people involved in AI innovation to the rest of the global population is small and homogenous. According to [81], they possess life experiences of Western, Educated, Industrialized, Rich, and Democratic people. Therefore, we see these characteristics in the AI technology we interact with every day. For example, the development and use of AI models in English is most popular, cheaper, and has the best performance compared to other languages [91], [92], [93], [94], and these tools are mostly accessible to people who have access to stable electricity and Internet access [67].

However, these models are marketed to the global community and adopted by corporations and governing bodies that preside over communities with different needs from what was envisioned by the developers of the AI models. Therefore, a disconnect exists between the developers, usually those with resources and power to build and design an AI solution for a problem envisioned from their point of view and the end users, usually those with less resources who rely on tech and decisions made for them by those in power and are normally not invited to give constructive input during the ideation/development process [95], [96]. These end users feel the brunt of the impact of these technologies, yet have little say in how these solutions are developed [97], [98]. We see this dynamic in AI models deployed to improve worker efficiency in industries and increase profit for stakeholders. At the same time, overlooking employee needs for a safer work environment and devaluing crucial human experiences [99], [100]. We also see this dynamic in AI performance inequality, where models perform worse for certain communities whose culture, income, language, or beliefs differ from those of the developers [101]. When the requirements for accessing AI continue to increase, with no solution to lower barriers for those with fewer resources, the digital divide is further widened by AI.

**Opportunities.** The digital divide can only be reduced when developers work to incorporate community needs from the perspective of the end users. While many researchers engaged in AI model design do not experience poverty, they can seek to understand the issues that lower-income communities face when using AI technology by conducting adequate user studies. Participatory design is an HCI framework that encourages the addition of end users from communities of focus to join the model design teams as domain experts who are experienced in their needs and the best kinds of solutions that will solve their issues [102], [103], [104]. By adopting a user-first approach as opposed to a create-first approach, we can improve the AI technology development process and design models that sustainably solve societal problems. CVQA [105] and World Cuisines [106] are excellent examples of leveraging participatory design principles in cultural dataset development.

## 3.2 Systemic Bias and Algorithmic Fairness

Biases continue to create critical issues that hinder equitable outcomes in AI applications targeting poverty alleviation [107]. Embedded biases in the AI pipeline, from training data to models and evaluation often perpetuate systemic inequalities leading to the marginalization of vulnerable communities [108], [109]. Furthermore, algorithmic decisions can amplify existing disparities [110]. The lack of stakeholder accountability in evaluating the disparate impacts of AI systems exacerbates the issue [111], [112]. The under-represented population that is hardly included in the data, design, and development process [113] are the most impacted, which leads to a lack of trust in AI systems [114], [115]. For example, in genomics, approximately 80% of collected data represents Caucasian populations, leading to algorithms less accurate for underrepresented groups [113].

Many AI models are created to replace systems previously handled by humans. To train these models, we feed the data generated by the expert humans who handled these tasks previously to the models to help them learn what factors lead to successful task completion. While the models learn patterns from the data and become excellent at performing these tasks, they also pick up the biases, hidden contexts, and beliefs of the humans/institutions whose data was used in training [116]. Unfortunately, when the models are used to cater to a market with a different context from what was captured in the data, problems arise.

Take, for instance, a financial institution that has been lending money to a certain group of people determined as worthy of a loan by their financial experts. When an AI model is trained on this data, and the model is deployed to expand access to other regions, the model continues to see new customers with the perspective of the financial experts and factors such as neighbourhood of residence, education status, gender, or income bracket become implicit goalposts that customers must overcome to get a positive response from the AI lending model [117], [118], [119]. In situations where these factors could be adapted to suit the context at hand, these models struggle to generalize [120]. Most of these processes are built on assumptions, some of which are fair, unfair, or only applicable in certain contexts. But since most competent models today are complex and lack interpretability, it is often difficult to distinguish what factors have been learned as biases [121], and therefore decrease the likelihood of removing/reducing the effect of these factors. AI technology is modeled after processes and institutions that already exist in our world.

**Opportunities.** Researchers need to understand the assumptions underlying the processes they wish to model and ensure that they fit the end goal/end user need. This can be achieved through including domain experts during the early phases of model design. Foundation models, usually very large pretrained models that are finetuned for applications on different downstream tasks, are trained on a lot of data from different sources. However, the nature and source of the data are often not made publicly available [122]. Publicly accessible datasets and dataset statistics help developers and users reason and make informed decisions about how much trust to give to an AI model's inferences. Since datasets can never be all-encompassing and AI models are not perfect, it is important to have periodic comprehensive evaluations with respect to the user's needs to ensure that the model is still aligned with the set end goals [101], [123]. Policies should be enacted to incentivize developers of AI models to share information about training data, market models according to the corresponding context, and perform comprehensive evaluations that are reflective of the customer needs (with respect to culture, income status, age, gender, and race) [124], [125], [126].

Additionally, algorithmic auditing frameworks can play an important role in ensuring **fairness** and accountability by systematically identifying and mitigating biases in AI systems [127]. These frameworks should be complemented by tools that enable continuous testing and bias correction throughout the system lifecycle [128]. Furthermore, inclusion of diverse perspectives in algorithm design is pivotal to creating equitable systems that account for diverse social and cultural contexts [129].

Educating users about AI's capabilities and limitations is also very important to combat and foster informed engagement with AI technologies [130], [131], [132]. Thus, combining transparent data practices, robust auditing, inclusive design, and user education can lead to technically advanced and socially responsible AI. For example, recent studies have highlighted that participatory design approaches, where stakeholders from marginalized communities are actively involved in the development process, lead to AI systems that address unique needs and challenges [133], [134].

## 3.3 Job Displacement

AI-driven automation is expected to continue eliminating routine and repetitive tasks, displacing workers particularly in industries such as manufacturing, finance, healthcare, and retail [135]. This shift has disproportionately affected low-wage and middle-class jobs while increasing the demand for high-skilled jobs centered around AI, which intensifies wage polarization [136]. Nevertheless, higher-paying jobs have also been displaced by the advent of AI automation, as demonstrated by the mass tech layoffs in the wake of the pandemic, particularly in 2022 and 2023 [137]. Similarly, a case study in China revealed that companies initially trained employees on AI to improve efficiency but later leveraged the resulting productivity gains as a rationale for mass layoffs, prioritizing cost reduction over workforce retention. This shift illustrates a broader trend where AI transitions from an augmentation tool to a means of worker surveillance and control [37]. Moreover, insufficient re-skilling programs worsen the displacement effects on low-wage workers, increasing anxiety about job security and fueling skepticism toward AI's growing role in traditional employment sectors.

**Opportunities.** While job displacement trends remain uncertain, by 2030 it is projected that AI will transform 60% of jobs while creating at least 78 million new ones [138]. As seen in past technological revolutions, AI is reshaping work by automating repetitive tasks while increasing the demand for critical thinking, problem-solving, and creativity. This shift shows that adaptive learning and lifelong education will be crucial, where individuals continuously acquire new skills to remain relevant in an AI-driven economy.

***Research suggests that AI can enhance worker productivity and career opportunities when implemented as an augmentative tool rather than a replacement mechanism, fostering job satisfaction and skill development [142].***

Additionally, AI-driven platforms for re-skilling and job readiness can address workforce needs in underserved areas [139]. To ensure a smoother transition for displaced workers, developing human-AI socio-technical systems that prioritize equity, worker protection, and sustainable career pathways will be essential.

To address these challenges, governments and businesses must actively invest in vocational training and upskilling initiatives. Research shows that digital skills help protect workers from **AI-induced** job losses, ensuring they remain competitive in evolving industries [140]. As AI integration grows in sectors like healthcare and finance, the demand for human-AI collaboration is increasing, emphasizing the need for AI ethics, decision-making, and human-centered development.

In response to these challenges, policymakers and institutions worldwide have ramped up efforts to ensure the responsible deployment of AI and mitigate the risks of job displacement. Ethical frameworks such as the OECD AI Principles [141] emphasize transparency, fairness, and accountability in AI-driven decision-making, ensuring that AI-driven economic benefits are shared inclusively rather than exacerbating inequality. By fostering inclusive economic empowerment and protecting workers, these measures aim to strike a balance between technological advancement and social responsibility.

# Conclusions

**AI holds transformative potential to reshape poverty alleviation efforts. By enhancing systems for food and housing security, healthcare access, education, infrastructure, and civic engagement, AI technology can help dismantle persistent barriers, yet realizing this promise requires advances that are equitable, context-aware, and ethically grounded, through collaborations that center low-income and underserved communities.**

Future research should prioritize co-designing tools with underserved communities and rigorously evaluating them for unintended consequences, thereby bridging the gap between technical innovation and social policy. It should also deepen our understanding of the **structural impacts** that AI systems can have on equity and inclusion. Only through such integrated efforts can AI advance beyond innovation to become a meaningful force for inclusive poverty reduction, empowering communities rather than compounding disadvantage.

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