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Research Article

The ethical and regulatory challenges of AI and their impact on income inequality

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ABSTRACT

The accelerated expansion of artificial intelligence, also known as artificial intelligence (AI), is restructuring productivity, employment, and income distribution. Empirical evidence shows efficiency and learning gains, but other effects on wages and opportunities, with risks of gaps between workers, sectors as well as in countries. This article analyzes the main ethical dilemmas, opacity, vigilance and concentration of being able to compare regulatory frameworks, as well as the advances in Latin America and Mexico. The main mechanisms through which AI influences income inequality are analyzed. It was concluded that directing the development and use of AI is essential for complementarity with human work and social inclusion.

Keywords: algorithmic, inequality. Ethical, Governance, Regulatory

Introduction

Artificial intelligence (AI) has become a systematic factor in economic transformation, this after only being developed in specialized fields such as computer systems, having an important impact both culturally and socially. AI has spread from industrial production and financial services to health as well as in public management, generating a new technological paradigm that redefines the way value is generated, work is organized and income is distributed. The ability of intelligent systems to process large volumes of data, learn autonomously and execute complex tasks has driven a revolution almost equal to that generated by electricity or the internet, with direct implications on the productive structure and employment dynamics.The advancement of artificial intelligence not only opens up new possibilities for improving productivity and efficiency in the different sectors of the economy, but also poses ethical and social challenges of great relevance. The replacement of certain human tasks by automated systems raises concerns about the future of employment and working conditions. At the same time, the concentration of technological development in the hands of a few corporations raises questions about the equitable distribution of the benefits that this technology can generate. In many cases, the speed with which AI evolves outpaces the ability of legal frameworks and institutions to establish appropriate standards, limits, and oversight mechanisms. This gap creates an imbalance between innovation and social protection, which requires urgent attention from public policy.The advancement of artificial intelligence has opened up new possibilities for improving productivity, as well as efficiency in different economic sectors, posing ethical and social challenges of great relevance within society. The replacement of various human tasks by automated systems has generated concern about the future of employment and the working conditions that this type of system brings with it. At the same time, the concentration of technological development in the hands of a few corporations raises questions about the equitable distribution of the benefits that this technology can generate. In many cases, the speed with which AI evolves outpaces the ability of legal frameworks and institutions to establish appropriate standards, limits, and oversight mechanisms. This gap creates an imbalance between innovation and social protection, which requires urgent attention from public policies.On a global scale, the expansion of AI has shown a growing gap between countries with greater capacity for technological investment and those that still lack digital infrastructure and specialized talent. This difference not only limits development opportunities, but can also translate into deeper economic asymmetries, widening the gap between developed and developing nations. At the same time, labour markets are transforming rapidly, which requires new skills, greater adaptability and public policies that guarantee continuous training and digital inclusion of the working population.Today, the debate on artificial intelligence is no longer focused exclusively on technical advances or its productive potential, but on its ethical, regulatory and social dimensions. Governments and international organizations face the challenge of finding a balance between fostering innovation and protecting human rights, privacy, and social justice. In this context, regulation becomes an essential instrument to ensure that the development of AI responds to the public interest and contributes to the reduction, not the increase, of inequalities.This paper addresses four fundamental axes of analysis: (i) the ethical dilemmas related to algorithmic bias, transparency, privacy and concentration of power; (ii) the international regulatory frameworks promoted by UNESCO, the OECD and the European Union; (iii) the economic and labor effects of AI on income inequality, both in its microeconomic and macroeconomic dimensions; and (iv) public and corporate policy proposals aimed at promoting human-centered artificial intelligence, with special attention to the Latin American and Mexican context.

DEVELOPMENT

Algorithmic Biases: The Automated Reproduction of Discrimination

The most immediate and pernicious ethical concern arising from the application of Artificial Intelligence (AI) in the workplace and economy is the existence and persistence of algorithmic biases. It is crucial to understand that these biases are not random technical glitches or bugs inherent in the code, but are the reliable and often amplified reproduction of historical biases and discrimination structures embedded in the large datasets (training data) with which AI systems are fed and trained (Castillo, 2024).When algorithms are deployed in critical functions within the labor and economic sphere, such as personnel selection, promotion management, performance evaluation, or even salary determination, the system operates under a fundamental premise: learning from history to predict the future. This principle, inherently logical from a machine learning perspective, becomes the primary vector of inequality. The AI system is trained on vast datasets that are the digital reflection of past human decisions. If these historical data reflect that certain demographic groups, such as women or ethnic minorities, have been systematically underrepresented or segregated in high-value and high-pay positions (e.g., technical leadership or executive roles), the algorithm interprets this pattern as a criterion of suitability (Rivas, 2022). This is not a code error, but a reliable statistical inference from historical reality.This is the essence of indirect algorithmic bias or adverse impact discrimination: a category that is prima facie neutral (such as "continuous experience", "project history" or "geographical mobility") ends up causing a disproportionate differential effect on certain historically marginalised subjects, replicating the discrimination without an intention per se to discriminate (Maldonado Smith, 2024). The algorithm is not aware of the social or ethical context; it simply optimizes the function entrusted to it based on the data that has been provided to it.

Amplification and the Vicious Circle of Discrimination

The mechanism automatically perpetuates disparities by shielding them under an apparent layer of technological objectivity. Not only does AI inherit the biases of the past, but, through its ability to scale and automate decisions to thousands of candidates simultaneously, it amplifies them exponentially and applies them uniformly, quickly, and indisputably to the entire candidate population (Guzmán Napurí & Salinas Atencio, 2024). This speed and scale transform latent prejudices into automated structural barriers, making it extremely difficult to break the patterns of occupational segregation and economic inequality.A canonical example of this impact is observed in the gender pay gap. An AI system that overvalues continuous experience, long-term loyalty to a single employer, and uninterrupted trajectories indirectly penalizes individuals, predominantly women, who have had career breaks or interruptions for reasons related to maternity, family care, or domestic responsibilities (Meritxellbeltran, 2024; Rosàs, 2022). By not considering the value of soft skills, management experience acquired outside of formal working hours, or the potential for professional reintegration, the system consolidates and justifies the existing wage inequality. The decision, although based on "objective" metrics, reproduces the economic and social cost of gender dynamics. In addition, the algorithm confuses correlation with causation: it confuses what has been (that a group has been overrepresented in success) with what should be (that that group is inherently more suitable). By codifying this historical correlation as a fitness criterion for the future, AI not only registers inequality, but actively prescribes it as the operating standard.

Impact on Social Mobility and Economic Opportunities.

The impact of these biases transcends the strict scope of labor contracting and extends to the allocation of basic economic opportunities, closing the way to social mobility. Credit and financial profiling models are perhaps the clearest examples of how the financial past is used to deny future opportunities. These systems may deny access to loans, mortgages, or microcredits to groups that, for historical reasons of marginalization, geographic segregation, or lack of access to traditional banking, have more precarious financial histories or lack a robust track record altogether (the problem of the credit-invisibles). By denying them investment capital or access to housing, the algorithm perpetuates intergenerational poverty. Similarly, in insurance pricing or risk assessment for access to housing, AI can redesign the old practice of redlining. By basing their decisions on proxy variables that highly correlate with race or socioeconomic status (such as zip code or credit score), systems replicate geographic and economic discrimination, condemning certain communities to lower-quality infrastructure and opportunities. AI systems, in essence, end up acting as "discrimination filters" that limit access to basic economic rights and opportunities, accentuating already existing digital and social divides (Flores Anarte, 2024). These filters are particularly dangerous because they are opaque and ubiquitous, and affected individuals are often unaware that an automated decision was the cause of their exclusion. The end consequence is a concentration of capital and opportunities in groups that were already in a position of historical advantage, while technology ironically becomes a tool to reinforce the status quo of economic and social inequality. The ethical urgency lies in dismantling these automated mechanisms before inequality is irreversibly embedded in society's digital infrastructure. The Ethical Requirement: Transparency and Explainability in the Face of the Algorithmic "Black Box" The existence of hidden algorithmic discrimination gives inequality a new layer of danger, since prejudice, instead of being neutralized, is automated and technified, becoming considerably more difficult to challenge both in the legal and social spheres. The adoption of decision-making based on algorithmic "black boxes" operates a subtle but profound transfer: inequality moves from the explicit social plane (where it could be detected and challenged) to the implicit technical level, which consequently makes it difficult to assign responsibilities, identify errors in the design and effectively correct systems (UNESCO, 2024). Algorithmic opacity thus emerges as the greatest epistemic and legal obstacle to justice and equity in the digital age. This opacity is not a unitary phenomenon, but is manifested in a duality that reinforces the inaccessibility of the decision-making criteria:

Technical Opacity: It is due to the intrinsic complexity of advanced Machine Learning models, especially Deep Learning or Neural Networks. In these models, the computational logic that leads to a specific inference or decision is elusive, even for developers and data science experts themselves.
The vast number of parameters and non-linear interactions make understanding the "why" of a classification or prediction extremely difficult, leading to an intelligibility gap (Dykinson, 2024).
Legal and Commercial Opacity: This is because the source code and, crucially, the training data of the algorithms, are usually protected under strict legal figures such as trade secrets or intellectual property rights. This protection, although necessary for business innovation, prevents independent auditing and, therefore, direct access to information by those affected, regulators or the courts (Iturmendi Rubia, 2024).
This combination of lack of transparency and intelligibility creates a vacuum of accountability. This lack of access and understanding makes it extremely difficult for a worker, a consumer or a citizen to know that they have been discriminated against or to initiate a procedure for the effective protection of their fundamental rights, since they cannot prove the causal criterion underlying the unfavourable decision (Dykinson, 2024). In this scenario, technology, far from acting as a neutral agent or an engine of pure meritocracy, becomes an instrument that automates exclusion, exacerbating the unequal allocation of opportunities and, consequently, increasing income inequality (Castillo, 2024).

The Ethical Response: Transparency, Explainability and Auditability

Faced with this structural dilemma, the ethical and regulatory response is the imperative requirement of Transparency and Explainability (XAI), complemented by Auditabili**ty.**

1. Algorithmic TransparencyThe concept of Transparency is not limited to showing the code, but involves ensuring proactive publicity about in which areas (e.g. personnel selection, credit scoring) algorithmic decisions are made, what data is used, and what potential impact they have on citizens' rights (Iturmendi Rubia, 2024).
2. Effective transparency must go beyond mere notification and provide clear and accessible information about the purpose, overall logic, and performance metrics of the system.2. Explainability (XAI)Explainability focuses on the mechanism for unveiling internal logic. It involves developing user-friendly methodologies and tools (known as XAI, Explainable AI) that allow both regulators and those affected to understand the reason for a specific algorithmic decision, beyond just knowing the final result (Wachter et al., 2017). The explanations must be humanly understandable and faithful to the functioning of the model, allowing the identification of which variables decisively influenced a particular result.
3. Data Auditability and GovernanceThe practical implementation of these principles lies in the need for Auditability. This implies that AI developers and users must ensure that decision criteria are auditable, understandable, and fair, allowing for the detection and mitigation of biases before they become structural factors of economic inequality (Delgado López, 2024).It is crucial to implement specific algorithmic audits that address the entire system lifecycle:

- Data Audit: Evaluate data processing and ensure that models are trained with representative and balanced data that includes equitable information from different demographic groups, identifying and correcting spurious correlations that lead to discrimination (Mehrabi et al., 2021).
- Model Auditing: Apply fairness metrics to verify that the system does not produce significantly different error rates among protected groups (Raji et al., 2020).

Only by institutionalizing these rigorous governance processes, moving from the vague "transparency fallacy" (where the publication of the code does not guarantee understanding) to true algorithmic accountability and effective human oversight, can the risk of technology perpetuating inequality be mitigated.

Regulatory Impact on Wealth Concentration and Data Colonialism

The effect of Artificial Intelligence on income inequality transcends the microeconomic level of individual discrimination in hiring, extending to the macro level through the disproportionate concentration of economic power and wealth. AI, being a General Purpose Technology (GPT), demands huge hardware infrastructures and, crucially, vast data sets for its development and training. This dependence has cemented an oligopolistic ecosystem where a handful of global technology giants (the so-called Big Tech) concentrate the key assets: data capital, specialized talent, and cloud computing infrastructure (Alonso et al., 2020).}

The Concentration of Strategic Assets and the Winner-Take-All

EffectAI development is not subject to traditional diminishing marginal returns; rather, it operates under a virtuous circle of positive feedback: more data leads to better models, better models attract more users, and more users generate more data. This phenomenon, known as the network effect or "Winner-Takes-All", ensures that the companies that first accumulated large volumes of data (the "cloud giants") are the ones that obtain the greatest competitive advantage and, therefore, the largest portion of the economic value generated by AI (Acemoglu and Restrepo, 2019).The direct implication of this concentration is an increase in inter-firm inequality. While leading companies experience exponential growth in productivity and market value, the rest of the companies — unable to access or replicate those vast data sets and cloud infrastructure — lag behind.
This translates into a concentration of capital in a few hands and a stagnation in workers' wages in lagging companies, exacerbating the income gap (OECD, 2023).

The Global Fracture: Colonialism and Neocolonialism of Data

On a geopolitical scale, this concentration of assets creates a new form of economic domination known as Data Colonialism.Data Colonialism is an extractive model in which data generated by citizens in the Global South (developing countries) or in regions with weaker regulatory frameworks is systematically collected, processed, and monetized by corporations located in the Global North (developed technology hubs), without the value or benefits of that data returning to the communities of origin (Couldry and Mejias, 2019).
This process manifests itself in two critical ways:

1. Unequal Value Extraction: Knowledge and economic value are transferred from the periphery (where the raw and contextual data is generated) to the center (where AI models and patents are developed). Countries and communities of origin lose control over a fundamental strategic resource of the twenty-first century, which compromises their digital sovereignty and their ability to develop their own AI technology (Mazzucato, 2023).
2. Imposition of Governance Frameworks: The corporations that control the AI infrastructure export their own ethical and governance standards globally. This creates a normative neocolonialism where decisions about what data is valuable, how it should be used, and what biases are tolerable are made in distant power centers, without respecting the cultural, legal, or ethical contexts of the regions where the data is mined (Couldry & Mejias, 2019).

The Regulatory Response and the Need to Share Value

The main ethical concern fueling this inequality is that the enormous benefits of AI, often built on socially generated data (public interactions, crowdsourcing, government information) or even on data stolen or extracted without informed consent, end up being privately appropriated (Mazzucato, 2023).Regulatory intervention is vital to prevent this dynamic from cementing an era of data feudalism. This requires:

- Antitrust Data Policy: Regulate access to and interoperability of large data sets to mitigate the advantage of incumbent actors, promoting competition.
- Data Sovereignty: Implement legal frameworks that allow countries or citizens to have greater control over where their data is stored, how it is processed, and under which jurisdiction their data falls.
- Value Sharing Models: Develop mechanisms that ensure that the economic and social value generated by AI reverts, at least partially, to the communities or individuals who provided the essential raw material: their data.

In short, AI not only widens inequality at the individual level, but reconfigures global power structures, concentrating wealth and technological control in a way that demands concerted and global regulatory action to ensure equitable development.

Absent Governance and Data Colonialism

The absence of an effective global and adaptive regulatory framework for Artificial Intelligence (AI) is a critical factor that allows the immense productivity gains generated by this technology to be concentrated in an unbalanced way. This lack of international governance facilitates the deepening of the structural gap between rich nations, which develop, patent, and export AI technology, and developing countries, which are limited to being users, consumers of services, and, crucially, passive providers of data. This imbalance is not a minor side effect, but the main mechanism that turns AI into a force for concentrating wealth on a planetary scale. The critical need for strong governance and ethical guidelines to address these issues is emphasized, urging the academic community to actively participate in the creation of policies that ensure that the benefits of AI are equitably shared and its risks effectively managed (Paić and Serkin, 2024).

This phenomenon of asymmetric extraction and value transfer has been accurately conceptualized as data colonialism, in this new extractive paradigm, the information assets generated by the social, economic and cultural interactions of populations are massively extracted by global platforms and used as the essential "raw material" for the training of AI models, all this without an equitable return in the form of profits, local investment, or sovereign control (Zuboff, 2019). Companies residing in global technology centers, by controlling the cloud infrastructure and the most advanced algorithms, manage to accumulate and monetize this information, exponentially strengthening their power, market value and wealth.

The accumulation of data as capital generates a new dimension of global economic heterogeneity. Not only is historical inequality between nations reproduced (the traditional industrialization gap), but a deep and unidirectional technological dependence is established. This reliance makes it extremely difficult for developing nations to establish sovereign AI policies, that is, to design, train, and implement their own AI systems that respond to their specific cultural, ethical, and economic needs (Couldry and Mejias, 2019). They are forced to operate within the parameters and biases pre-established by the models developed abroad. The most serious implication of this absent governance is the loss of digital sovereignty. The legal and ethical frameworks governing the use of data and the development of AI are usually established de facto by large corporations and subsequently adopted or imitated by states. This "normative neocolonialism" means that decisions about AI's ethics, privacy, and value distribution are made in distant centers of power, without adequate representation of affected communities (Morozov, 2018).

Therefore, the regulatory problem of AI is not merely a technical or individual ethical issue; It is a fundamental issue of global economic justice, distribution of technological dividends and geopolitical fairness. Concerted action is urgently required at the level of international bodies and economic blocs to establish mechanisms for sharing the value of data and ensure interoperability and fair access to AI infrastructure. Only in this way will it be possible to mitigate the risk that the most transformative technology in recent history will become, by default, the engine of an unprecedented concentration of wealth.

The Challenge of Fiscal Policy and Social Protection

To mitigate this polarization, regulation must go beyond abstract ethical principles and have an impact on fiscal and social protection policy. One of the central debates in AI governance is how to tax automation that replaces human labor. The lack of clarity on whether to tax robots, data transactions, or the revenues generated by algorithms leaves potential compensatory programs unfunded (Gómez Mont, 2023).

Proactive regulation is critical to ensure that the economic benefits of AI are reinvested back into society to mitigate the risks of inequality. This includes:

- Financing of Labor Retraining: Creation of funds for the continuous training of displaced workers, ensuring an inclusive transition to the new digital labor market.
- Adaptive Social Protection Mechanisms: Exploration of schemes such as Universal Basic Income or technological income, financed with concentrated digital wealth, to protect those who are excluded by structural automation (IDRC, 2023).

Initiatives such as the European Union's AI Act represent a step towards creating a fairer and more transparent market for AI, requiring compliance with fundamental rights and promoting non-discrimination (Sarría et al., 2023). However, multi-stakeholder governance that actively engages civil society and trade unions is needed to redefine labour rights in the algorithmic era and ensure that the wealth generated benefits society as a whole and not just its creators.

Conclusion

The accelerated expansion of Artificial Intelligence (AI) has generated a profound economic transformation, but the systematic analysis of its effects shows that, without political and regulatory intervention, this technology operates as a powerful accelerator of income inequality at the global and domestic levels. The evidence presented confirms that this phenomenon is driven by the confluence of inherent ethical risks and structural failures in governance. On the one hand, AI perpetuates and amplifies historical discrimination through algorithmic biases. These biases, by learning from biased social data, automate exclusion in wage determination, promotion, and access to opportunities, turning social injustice into a technological design problem. The lack of transparency and explainability in these opaque systems hinders accountability and effective mitigation of employment discrimination. On the other hand, at the macro level, AI intensifies economic polarization by concentrating profits and power in a handful of corporations, resulting in the phenomenon of data colonialism and a growing gap between developed and developing nations. In addition, AI drives labor polarization, eliminating middle-class jobs and increasing precariousness through algorithmic management and excessive control over the worker, which puts downward pressure on the wages of the least protected segments. The fundamental conclusion is that AI is not an inevitable fate, but an instrument whose social impact depends directly on its governance. Therefore, directing the development and use of AI is imperative to ensure complementarity with human labor and social inclusion. To achieve this, proactive policy action is required focused on two pillars: (a) establishing the right to algorithmic explainability and the protection of the digital worker to mitigate bias; and (b) implement innovative fiscal policies that tax the wealth generated by automation to finance mass reskilling and social protection mechanisms. Only through ethical and multi-stakeholder governance can it be ensured that AI becomes an engine of shared prosperity rather than a source of socio-economic fragmentation, a particularly urgent need in the context of structural inequalities in Latin America and Mexico.

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