DATA EQUALITY

Gender bias in artificial intelligence systems: the need for inclusive data practices.

Introduction

The rapid advancement of information technologies in recent years has contributed to the development of AI capabilities and how it collects, processes, and uses information for various purposes in society. AI is capable of simplifying processes such as medical image analysis, creating learning platforms, or generating virtual assistants to respond to customers 24/7 with relative effectiveness.

However, still prone to errors due to its design or lack of information, mistakes can occur that could cause inequalities or biases, especially in areas where problems such as the low participation of women in the development and application of AI tools often arise.

The problem lies not only in the data but also in the design and implementation. Due to a lack of diversity among development teams, coupled with insufficient oversight mechanisms, gender stereotypes and inequalities are emerging in the assistance provided by AI.

In this context, this article seeks to analyse how gender biases in AI increase data inequality, paying particular attention to the effects on the European continent. It will examine the main factors involved in these cycles and their impacts, in order to propose possible solutions for achieving greater equity in data use.

Gender, data, and algorithmic biases

Gender inequality can be understood through different concepts. The first, algorithmic bias, describes how AI can produce negative results only for certain groups due to historically observed patterns. It is in this context that the gender data gap emerges, causing technology to respond in the same way in all cases.

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Added to this is a key element: biases do not affect all women in general, but also take into account other factors, such as race or social class. Research such as that by Buolamwini and Gebru (2018) shows that system deficiencies are more pronounced in women of other races, highlighting discrimination.

Data inequality not only presents a lack of representation but also unequal access to the benefits it offers. Therefore, it could be said that AI is not neutral, but rather a reflection of the social contexts in which it is created, which is why it is necessary to incorporate a gender perspective that helps to prevent AI from amplifying inequality.

Origin of Gender Biases in Artificial Intelligence Systems

Biases in AI stem from structural and technical factors that permeate the entire data lifecycle. Historical inequalities, such as the underrepresentation of women, often contribute to this, leading algorithms to identify discriminatory patterns (Criado Perez, 2019). This is subsequently reflected in the automation of decisions, which, coupled with the underreporting of forms of discrimination, creates a vicious cycle of inequality.

Another factor contributing to bias is the lack of diversity among those who design and develop AI. Homogeneous profiles influence which data is considered relevant and how the results are perceived. Without a gender perspective, technological tools tend to ignore certain segments of the population, exacerbating existing inequalities. Furthermore, decisions that should be neutral—such as prioritising certain criteria—can generate adverse results if not critically evaluated.

These factors demonstrate that gender biases are not random errors, but rather a manifestation of social inequalities transferred to the digital realm. To solve these problems, it is necessary to improve the quality and representativeness of the data, but also to modify the processes from a perspective of equity as a central element.

Impact of gender biases in AI

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Gender biases in AI generate negative effects in different social, economic and political aspects, reducing the opportunities and well-being of women. In the labour market, automated systems can take on patterns of inequality and favour male profiles, penalising women in hiring processes (European Commission 2020), and in security, errors in facial recognition affect women much more, with risks ranging from errors in identification to violation of rights.

In sectors such as health and finance, biases are also present. Lack of data on women in clinical studies results in inaccurate diagnoses. Likewise, some algorithms used for credit evaluations can incorporate variables that cause discriminatory decisions, limiting women's access to financial services.

These impacts are not distributed evenly: Factors such as race, origin or gender can have an impact on AI discrimination. These examples show that gender biases are not abstract problems, but real consequences that require technical, regulatory and social solutions.

Institutional response in the EU and the role of Data Equality

The EU's response to discrimination has increased in recent years through regulatory frameworks and strategies that seek the ethical use of AI. ***The AI Act*** has an approach that seeks to supervise systems that may affect fundamental rights, while the ***European Gender Equality Strategy 2020-25*** seeks to integrate the gender perspective in the digital area (European Commission 2020).

Furthermore, initiatives such as ***Data Equality*** show how collaboration between public institutions, civil society and technological actors can improve the analysis of data on discrimination. These projects develop tools that seek to detect and mitigate biases, in addition to using methodologies to fill information gaps. Their work highlights the importance of combining technological innovation with inclusive and participatory approaches.

Despite the progress, there are still challenges such as the lack of data by gender, limited coordination between actors and the lack of incorporation of gender perspective in regulatory frameworks. It is necessary to increase oversight and promote algorithmic transparency to ensure the participation of diverse groups in technological design and development.

Conclusion

Advances in AI offer new opportunities but generate challenges such as inequalities and biases present in data and social contexts. Unfortunately, these systems are not yet neutral and can amplify already existing problems, especially when there is a gender data gap.

The combination of incomplete data with a lack of diversity in technological development and existing inequalities generates discriminatory results in areas such as health, safety, employment, among others, affecting women more.

Although there is an institutional commitment in the EU to promote more ethical and inclusive AI, limitations remain that require more decisive actions. Moving towards a better digital environment involves improving data and reviewing design processes, to strengthen technological growth without perpetuating inequalities in AI.

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