A Material Lens to Investigate the Gendered Impact of the AI Industry

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Abstract

Artificial Intelligence (AI), as a collection of technologies, but more so as a growing component of the global mode of production, has a significant impact on gender, specifically gendered labour. In this position paper we argue that the dominant aspect of AI industry's impact on gender is more that the production and reproduction of epistemic biases which is the focus of contemporary research but is rather a material impact. We draw attention to how as a part of a larger economic structure the AI industry is altering the nature of work, expanding platformisation, and thus increasing precarity which is pushing women out of the labour force. We state that this is a neglected concern and specific challenge worthy of attention for the AI research community.

1 A Critique of the Critique

The arc of technological development has been historically blind to its impact on gender and is erroneously considered both gender neutral and apolitical, with structural flaws in research being overlooked. [Wajcman, 2000] Even when this issue got recognised, the response was confined to addressing bias and diversity within the existing structures of technological development without investigating the root cause of how those structures impact gendered labour[Adam, 1996].

Gender roles in the technological sector have been normalised to a point where extremely skewed gender ratios in education and workplaces, lack of women and non-binary people in leadership are commonplace visible issues[Cockburn and Ormrod, 1993]. The glaring problem of women dropping out of the STEM academic pipeline has taken a while to be recognised[London *et al.*, 2011]. Once recognised, this problem has been critiqued from the point of bias, i.e. epistemic bias in knowledge production due to people who create these technologies [Adam, 1995] and the bias inherent in the artefacts the AI industry produces. Contemporary critique on gender disparity in the AI industry stresses thus on how knowledge is created and culture reproduced, on bias detection/correction of data sets and algorithms etc, transparency of decision making, and diversity as solutions.

This position paper argues that such criticisms are not deep enough to comprehend gendered labour in the AI industry, and we assert that to frame solving diversity and bias reduction of tech as optimisation problems is a technosolutionist approach which ignores structural issues. We draw attention to the fact that despite the existence of comprehensive arguments for unbiased and fair AI, not only are ineffective datasets and models still being employed, but crowdwork, which has the potential to be exploitative towards the marginalised is endorsed and actively pushed by this industry [Daugherty and Wilson, 2018]. The answer to this lies in the fact that AI development does not happen in vacuum but in the realm of political economy [Trajtenberg, 2018]. The profit seeking impulse at both company and state-policy level leads the AI industry to both benefit from and contribute to the platformisation of work, something which disproportionately hurts marginalised workers, especially women workers [Berg *et al.*, 2018]. The same impulse leads the AI industry to increasingly use machine learning in hiring and surveillance of workers [Moore *et al.*, 2018], where the limitations like gendered[Scheuerman *et al.*, 2019] and other biases, inherent problems in gendering via ML [Hamidi *et al.*, 2018], reductionist and non-deterministic nature of these artefacts are ignored. It also fuels the industry wide policy apathy towards wage depression, job displacements and annihilation due to AI and automation, something which disproportionately affects women and the marginalised.

Thus, it is important to investigate the problem from the lens of political economy which is thoroughly intertwined with AI tech which is gradually becoming a general technology [Trajtenberg, 2018]. Gendered impact of AI is relatively understudied, the effects of which are still being explored [Parsheera, 2018]. Our position paper attempts to open some new and unexplored lines of investigation.

Machine learning makes decisions based on patterns in vast amounts of past data [Carbonell *et al.*, 1983] and consequently reproduces and reifies the material relations of the past. This exacerbates extant social relations which has the elements of inequity and gendered oppression rooted in it. As ML identifies collective and individual behavioural patterns, reproduces and alters them, a certain level of political responsibility is expected from the people who generate, design, and assess AI.

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2 Political Economy of AI and Gendered Labour

The problem of gendered labour being impacted by the AI industry has material roots, namely that technology development is dependent on ownership of capital [Walker and Storper, 1989; Morozov and Bria, 2018]. To illustrate this, let us examine how material inequality operated in the pre-AI digitisation era. In 1974, the number of men and women who expressed an interest in coding as a career was equal, however by 1981-84, the number of women with a degree in computer and informational science had sunk to 37.1% [Light, 1999]. Researchers from science and technology studies and gender studies suggest that initially, computing (and, programming) was considered to be low-skilled and clerical work. As the field became culturally, socially and most importantly economically more valuable in the early 2000s, a culture of women not being hired in these jobs arose [Dillon and Collett, 2019]. To understand inequality among workers, we must examine the nature of the work and its relation to capital.

2.1 Microwork: neglected labour in AI Industry

Let us examine these workers in the AI industry. It is easy to ignore that a major part of them consists of those not formally recognized but doing "microwork"on distributed platforms [Altenried, 2020]. This kind of work is done under the piece wage system by geographically dispersed and atomised workers. These workers perform two vital functions for the AI industry. First, they perform the generation and curation of data which is the largest (and most invisible) part of work needed for machine learning [Altenried, 2020]. Second, they provide expert knowledge to monitor and moderate machine learning systems, often referred to as "human in the loop", "artificial artificial systems", "human intelligence units" etc [Link *et al.*, 2016].

In-house production of this volume of data is too expensive and hence there is a constant impetus to downplay how much of this is "work" and a global push for dilution of labour norms in this area. So in need of continuous data and human experts, the AI industry heavily relies on the platformisation of work. However, these platforms themselves are heavily dependent on the AI industry, as they also use the machine learning centered software (like Uber, Amazon etc), to run themselves and be competitive in the first place. The AI industry is thus central in both propagating platformisation as well as is one of the largest consumers.

Thus, the AI industry is implicated in the transformation of the nature of work from conventionally waged work to crowd work on platforms. This new form of work is distinctly exploitative and its effects are deeply gendered. It is exploitative as its very nature promotes worker atomization and replaceability [Irani, 2015], by demolishing the work/home boundaries, [Huws *et al.*, 2018] by creating small replaceable ill paid tasks, by erasing the differences between who is an employee and who is an "associate", by making possible a distributed digital Taylorism [Altenried, 2020]. These effects are harsher on the already marginalised, in this case women who already lack representation in unions etc. Also, this new form of work disproportionately discourages women to enter as it has none of the usual protections (gendered health benefits and leaves being the most important) as waged work. When entire sectors get automated and platformised, re-skilling is also non trivial for women who have domestic constraints in patriarchal societies, as they also have to unpaid domestic work. As per the 2017 ILO survey on crowd workers, [Berg *et al.*, 2018] 15% of women mention domestic care work as a factor compared to 5% of men. Thus for women corwd work is specifically unattractive and the transition of conventional work to platforms more harmful. In increasing platformisation women have a larger chance of exiting the workforce altogether and the AI industry is a factor. That same report mentions that only one out of three crowd workers were women. There is a similar gender imbalance on Amazon Turk Workers, CrowdFlower workers, etc.

There is a popular idea that this kind of work is liberating, that one may structure one's time, care for the children or the elderly etc. but what gets forgotten is that due to atomization, replaceability or workers, and digital Taylorism, the bargaining power of the worker [Johnston *et al.*, 2018; Vandaele, 2018] as a class has sharply decreased, and their wages thus depress. Both are harsher for women workers.

2.2 The visible AI workers

Now let us examine the conventionally recognised work of the AI industry. The almost universal rule of tech monopolies has been that the pattern of diminishing representation of women on the higher rungs of the career [Dabla-Norris and Kochhar, 2018] ladder holds true here. A gender imbalance at decision making roles effects the research and product decisions of what AI products get made, but the problem has always been more than that of representation. The profit motive compels the AI industry like any other industry to continuously attempt to cut costs and a major consequence is greater reliance on AI technologies in hiring, surveillance, etc. There is an increased use of ML at the hiring stage itself, [Liem *et al.*, 2018] from the vetting of resumes to the more notorious use of "emotion detection" [Bendel, 2018] in interviews. To repeat an oft belabored point, these technologies are premised on bad, unscientific assumptions that need to be challenged, but also the consequence of unthinkingly replicating the past via ML has the consequence that past bad behavior of the industry gets perpetuated.

One infamous case was Amazon's attempt at automating the recruitment process. [Meyer, 2018] Amazon assembled a team of engineers in Edinburgh to create an AI tool to economize the hiring process. The tool indiscriminately rejected female applicants, exposing the underlying sexist recruitment practices of the company. Underlying because the tool must have had training data to learn its behaviour from, and this training data comes from Amazon thus revealing an existing pattern that got amplified. The tool had to be scrapped ultimately.[Meyer, 2018] An arbitrary and biased system which makes direct contact with the society has major consequences. It inhibits gender diversity in the job market, furthers the production and absorption of biased actions and knowledge by AI systems influencing policy and legal frameworks in many countries which consume and interact with AI-driven products on a regular basis in the public sphere.

Within the industry the problem does not stop at the hiring level, we have a plethora of companies now peddling AI products for the continuous monitoring of workers, and aside from the argument that these products are disenfranchising, oppressive, and unscientific, there is also the problem that they disproportionately hurt women and harm their chances of advancing in ranks. Take for example emotion detection, one such monitoring technology. It is a rehash of the pseudoscience of pathognomy, [Jandl *et al.*, 2017] relying on the unscientific assumption that one can detect internal states of emotions from facial expressions. The priors of these datasets are not just unscientific but also misogynist (and racist [Rhue, 2018]). [Barrett *et al.*, 2019] suggest that these technologies use value neutral terms like "pattern of facial movements" instead of "emotional expression".

The usage of these arbitrary technologies often dnce capital driven digital economy is the continuously diminishing bargaining power of AI tech-workers which aggravates the marginalization of vulnerable social groups. The question is whether the creators are aware of this and attempt mitigation.

3 Gendered Impact of the AI Industry

The impact of AI industry on gendered relations is not limited to women tech workers, everything from academia, policy, politics, and finally how society runs gets affected. An immediate and adverse consequence of a gendered pipeline into the AI industry is how it diminishes the prospects of women researchers in the AI academia. Studies have found that only 18% of the authors in leading AI conferences are women and more than 80% of AI professors identify as cisgender men.[Gagne *et al.*, 2019] No public data exists on the composition of transgender people and other gender minorities in AI-related professions. The causes of lack of representation of women and LGBTQIA+ in academia are multidimensional, however, better job prospects in the industry and correcting the lack of exposure in technological avenues for young women and the marginalised will only help.

Outside industry and the academia, one rapid result of increasing use of AI technologies in the economy has been the function creep of AI artefacts [Safdar *et al.*, 2016] taking over policy, policing, [Marda and Narayan, 2020] and governance functions without much democratic pushback or understanding that the machine learning powered software which is replacing human policy decision making is essentially replicating past patterns of decision making. We argue this is a failure to properly internalise and communicate the nature of machine learning which is excellent at replicating the past, something we as researchers and the larger AI community don't want to do where gender is concerned. The larger issue here is not bias on which there is research attention, but the interventions of the AI industry and thus machine learning non-determinism in areas which should be in ambit of considered and transparent democratic policymaking. While the larger issues like FRT(Facial Recognition Technology) is being challenged by AI researchers albeit within the framework of bias, the impacts of smaller more ubiquitous presence of machine learning in artefacts running our day to day lives that will disproportionately affect women remain unnoticed.

A worrying impact of the AI industry is not just on women workers involved in its production but its role in the transformation labour market in general which influences how women workers are treated. The AI industry is rapidly creating technologies which will result in wage depression of middle workers and in some sectors the elimination of entire categories of jobs. There is a lack of literature on what, if any, new jobs in sufficient numbers will arise to replace the ones getting annihilated. Similarly, while some researchers insist that these technologies can barely replace jobs [Grace *et al.*, 2018] and would in majority be assisting workers, [Wilson and Daugherty, 2018] the point remains that assisting technologies mean lesser lower and middle jobs, the same kind of jobs which the technology industry pushes women into.

IMF's Staff Discussion Notes [Brussevich *et al.*, 2018] estimate that 11% of jobs currently held by women are at risk of elimination as a result of AI and other digital technologies which is a higher percentage than those men risk to lose. Also, older women across the globe are disproportionately in clerical, services, and sales positions and it is these jobs which are easiest to automate. This is further exacerbated in the countries of global south with a gaping digital gender divide in terms of access to digital infrastructure and education in the areas which might mitigate the problem to an extent. The presence of AI technologies automating away some jobs and radically altering others will in many cases force workers to transition jobs and that is harder for women to do as they are burdened with domestic work and because the monetary and time cost of reskilling is high. This is especially true in the global south with lack of public healthcare, lack of social security, and lack of gendered benefits will make it harder for women to remain in the workforce.

4 What is to be done?

In this position paper, we have argued for a lens informed by the political economy to examine how the AI industry impacts gendered labour and thus gendered oppression. The AI industry is more than a set of technologies but rather a transformation in the production, distribution and exchange processes under capitalism, and thus we examine how the woman worker is situated in this industry and out of it as well. The AI industry is much larger than imagined as it is inter meshed with platforms, its effects spill over into the labour market, into knowledge production, and into policy making. Its effects on women are much larger than biased decisions. We argue that as AI researchers if we care about the social impact of what we help create, it should not be limited to interrogating our artefacts for bias or transparency but also analysing how they transform social and economic relations.

This paper is nowhere near exhaustive in even framing the problem but we hope to incite a direction of research rooted in investigating the political economy of gendered labour, of job displacement and loss, of gendered impact of AI driven policy making. It must be stressed here that looking at AI artefacts in isolation is futile if one is to understand their social implications including that on gender. In this paper, we have argued for a direction of research and asked some questions which we hope would facilitate future research and discussions.

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