Development of AI: Role of "invisible workers" in the AI value chains

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Abstract

The past decade has observed a rise in artificial intelligence (AI) systems or tools for a range of tasks or occupations. The development of AI systems requires an iterative value chain process involving different phases: data collection and annotation, analysis and model development, and data verification, which then function as a loop. Workers are intrinsic to this process (human-in-the-loop) due to the need for human judgment. This policy brief explores the characteristics of these workers, their working conditions and the content of tasks performed by them. It shows how this process of AI development could undermine the progress towards attaining decent work (SDG 8). The policy brief concludes with a call for a responsible and ethical AI development process and highlights the need for labour disclosure in the AI supply chain for ensuring decent working conditions for all.

The past decade has observed a rise in artificial intelligence (AI) systems or tools for a range of tasks and occupations, thanks to the availability of finance from venture capitalists and advancements of digital technologies and computing power. The development of AI systems requires an iterative value chain process involving different phases: data collection and annotation, analysis and model development, and data verification, which then function as a loop. Workers are intrinsic to this process (human-in-the-loop) due to the need for human judgment. These workers are dispersed globally and perform such tasks as 'invisible workers' either on microtask or crowdsource platforms or in business processing outsourcing (BPO) companies under precarious working conditions. The rise of AI systems has resulted in an increase in the number of BPO companies, including those set up by multinational companies in developing countries in pursuit of cost optimization, and with the aim to offer employment opportunities to young graduates and individuals from disadvantaged groups.

Based on a global survey as well as country surveys conducted with workers in India and Kenya, this policy brief explores the characteristics of workers, their working conditions and the content of tasks performed by them. Furthermore, it will unravel whether there is an emergence of digital sweatshops – in terms of piece rate work, low pay, lack of work-related and social protection benefits - which can undermine the progress towards attaining decent work (SDG 8). It will also assess the match between workers' skills and the tasks performed, to understand whether their skills are being fully utilised or under-utilised. The policy brief concludes with a call for labour disclosure in the AI supply chain, and for responsible and ethical AI development process to ensure decent working conditions for all.

Reliance of AI systems on "invisible workers"

Despite developments in AI, many data-processing methods require tasks that are to be carried out by humans, such as tagging, classifying, categorizing, cleaning, structuring and organizing, largely because AI cannot be fully automated (Rani and Dhir, 2024; ILO, 2021; Casilli, 2021). Microtask platforms such as Amazon Mechanical Turk (AMT), emerged in 2005 largely "due to the failure of AI to classify images, sounds and texts, as human intelligence is required to process such data" (Irani, 2015 in ILO, 2021). In 2007, Stanford Human-Centred AI Institute trained its machine to recognise objects and images by distributing 3.2 million images to be labelled by about 49,000 workers in 167 countries (Gray and Surie, 2019). The use of such workers on microtask platforms or in BPO companies who are often based in developing countries is quite widespread. For instance, Appen, a platform company, has access to a global "crowd" of more than 1 million workers from about 170 countries to support the multiple phases of AI development. [1]

Autonomous vehicle manufacturing

Autonomous vehicle manufacturers, rely on machine-learning algorithms and they require large high quality AI training datasets with appropriately labelled and annotated information, such as images of pedestrians, dogs, traffic lights, or other vehicles (Rani and Dhir, 2024; Schmidt, 2019). This process requires human input, which is often outsourced to microtask workers through platforms or to BPO companies (ILO, 2021). A full semantic segmentation of an image can often take a

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[1] See: https://www.appen.com/services, accessed 27 February, 2024. This information is no longer available on the website but the authors have saved the information and is available on request.

worker up to two hours to complete, which is one of the reasons to outsource as it reduces costs immensely for these companies (Schmidt, 2019).

Content moderation for social media platforms and websites

Similarly, AI systems for content moderation are far from being fully automated and rely on “invisible workers”, who keep social media platforms as well as web 2.0 clean and free from toxic content. Workers go through disturbing or objectionable content such as videos, images or texts of violence, abuse, pornography, among others to keep the internet clean, which have strong mental health implications (Ahmad and Krzywdzinski, 2022; Berg et al. 2018; Glaser 2018; Cherry, 2016; Roberts, 2014). Further, large language learning models (LLLMs) like ChatGPT also use such “invisible workers” to remove toxic element such as violent, sexist, or racist responses. Perrigo (2023) in his Times investigation found that companies like Open AI outsource such tasks to BPO companies such as Sama in Kenya, who were paid less than US$2 per hour, with long working hour shifts and were “mentally scarred by the work”.

Consumer products, like “robot” vacuums

The use of “invisible workers” for AI systems is also prevalent in consumer products such as ‘robot’ vacuums, wherein workers spend time taking more than 250 photographs of ‘dog poop’ to train a vacuum cleaner to avoid animal excrements and are paid few cents for each photograph (Matheus et al., 2023: 17). It has been estimated that Scale AI platform has annotated two million images for a robotic vacuum manufacturer (Loten, 2021).

Secretarial services and security systems

Finally, another area where AI is gaining popularity is in AI powered tools such as secretarial services or security systems that are available today in the market, which are not purely AI driven but human-powered. For example, X.ai or Clara relied on workers pretending to be chatbots for calendar scheduling services (Solon, 2018), and this aspect has also been documented in the case of a virtual assistant, which operates with a human-in-the-loop as natural language processing still requires human intervention (ILO, 2021). Similarly, Ludec et al. (2023) document the case of an AI company which offers automated video surveillance of theft detection for retail stores in France. In practice, this tool does not operate with an AI system but with “invisible workers” based in Madagascar who detect thefts through livestreamed video using CCTV.

Thus, the development and maintaining of an AI system relies heavily on “invisible workers” on microtask platforms and in BPO companies. These workers now constitute a fundamental part of the global AI supply chains. The transnational nature of AI production, servicing and deployment enables companies to maximise commercial benefits, as regulatory systems are not yet in place (Cobbe et al., 2023). It is crucial to consider the challenges arising from AI systems, which are sustained by workers in developing countries, who are often paid low wages and do not have any protections. Addressing these challenges is crucial to realizing the vision of the 2030 Agenda.

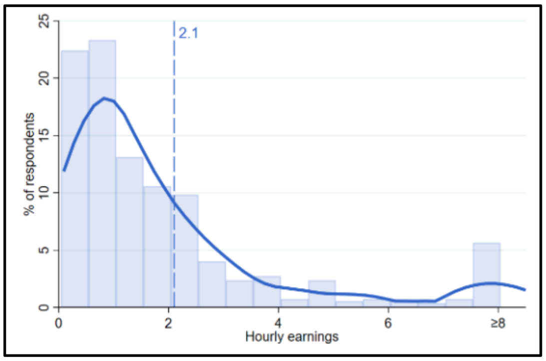
Workers behind AI: Challenges to achieving SDG8

Based on the global survey on microtask platforms conducted between Feb. and May 2017, and country level surveys on microtask platforms and in BPO companies in India and Kenya in 2022, we present some of the demographic characteristics of these workers as well as some of the challenges they face. The survey data reveals that both men and women participate in AI development tasks. These workers are generally young, and the average age is around 27 to 32 years in developing countries, as well as in India and Kenya.

These workers are well-educated and often have a graduate and post-graduate degree. In addition, about 47 per cent of the workers in developing countries are specialized in STEM education. Country level surveys also show that more than 50 per cent of the AI workers in India and about 40 to 50 per cent of them in Kenya have STEM education in both microtask platforms as well as BPO companies. The AI development tasks performed by these highly educated workers include data collection, categorization, text and image annotation, content moderation, transcription, and audio and image recording, are similar across microtask platforms and BPO companies.

How much do the AI workers earn, given these high levels of education in specialized fields? The analysis shows that in developing countries, AI development workers on average earn about US$ 2.1 per hour (Figure 1) and about 50 per cent of the workers earn less than US$1.2 per hour. There are no major differences in hourly earnings between men and women, and their earnings are similar to the overall average. Across different types of tasks, audio and image recording as well as content moderation have slightly higher earnings compared to other AI tasks. The median earnings is nearly half of the average earnings across all types of tasks, which highlights the significant disparities in earnings (table 1).

Figure 1: Average hourly earnings (in US$) in AI development tasks in developing countries



Data source: Authors' calculations based on ILO global survey of workers on microtask platforms, 2017.

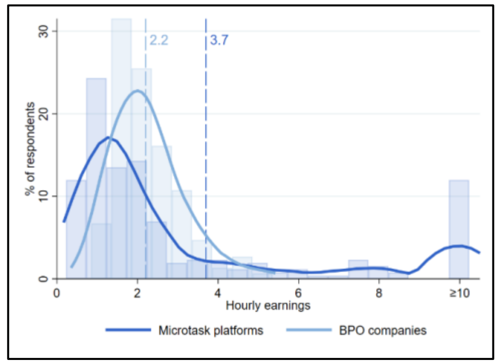
Table 1: Average and median hourly earnings (in US$) by types of task and gender in developing countries

	Mean	Median
Total	2.1	1.2
By gender		
Male	2.1	1.2
Female	2.0	1.2
By type of task		
Categorization	2.0	1.2
Data collection	1.8	1.2
Content moderation	2.3	1.0
Audio/image recording	3.2	1.6
Verification	1.7	1.0
Transcription	2.2	1.4

Data source: Authors' calculations based on ILO global survey of workers on microtask platforms, 2017.

At the country level in India, the AI workers on microtask platforms earn on average US$ 3.7, which is more than the earnings of workers in developing countries as well as the BPO companies (US$2.2) (figure 2). The difference in earnings between microtask platforms and BPO companies primarily arises from the distinct nature of tasks (table 2). Female workers on microtask platforms earn twice as much as their male counterparts, while the earnings are almost similar between genders in BPO companies.

Figure 2: Average hourly earnings (in US$) in AI task on microtask platform and BPO companies in India



Data source: Authors' calculations based on ILO-IIHS survey of workers on microtask platforms and BPO companies, 2022.

Although there exists a significant difference between the average and median earnings on microtask platforms, the disparity is small in BPO companies, suggesting that the inequalities are small. Within BPO companies, earnings are slightly higher for annotation compared to other tasks (table 2).

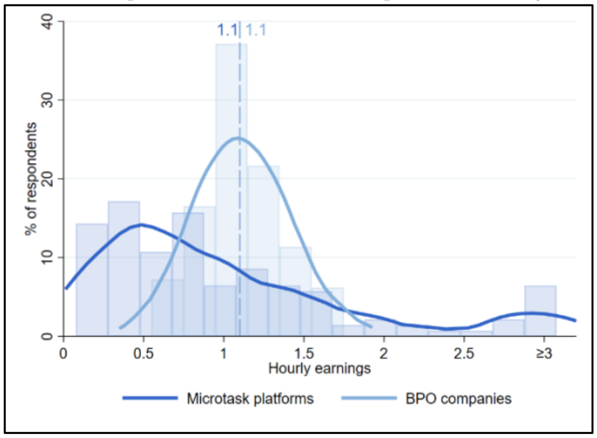
Table 2: Average and median hourly earnings (in US$) by types of task and gender in India

	Microtask platforms		**BPO**	
	Mean	Median	Mean	Median
Total	3.7	1.7	2.2	2.0
By gender				
Male	2.1	1.1	2.3	2.1
Female	4.3	2.0	2.1	2.0
By task				
AI Training	3.7	1.7	-	-
Annotation	-	-	2.5	2.4
Content moderation	-	-	2.0	2.0
Quality analyst	-	-	2.0	1.8

Data source: Authors' calculations based on ILO-IIHS survey of workers on microtask platforms and BPO companies, 2022.

The AI workers in Kenya on microtask platforms and BPO companies earn on average US$ 1.1 per hour, which is quite low compared to the earnings in developing countries and in India (figure 3). The average and median earnings are also quite similar, and the differences between genders are also quite minimal (table 3). There are also no differences between the different types of tasks in the BPO companies.

Figure 3: Average hourly earnings (in US$) in AI task on microtask platform and BPO companies in Kenya



Data source: Authors' calculations based on ILO-Thunderbird School survey of workers on microtask platforms and BPO companies, 2022.

In both India and Kenya, conventional wisdom would indicate that workers in BPO companies would earn more than those on microtask platforms, given the latter is part of the global labour market, and the fierce competition could potentially lower the piece rates for these tasks. However, surprisingly, earnings in BPO companies are either similar or lower than those on microtask platforms. In addition, one would expect that BPO companies would provide work-related and social protection benefits as they are formal companies.

Table 3: Average and median hourly earnings (in US$) by types of task and gender in Kenya

	Microtask platforms		**BPO**	
	Mean	Median	Mean	Median
Total	1.1	0.8	1.1	1.1
By gender				
Male	0.9	0.8	1.2	1.1
Female	1.1	0.8	1.1	1.1
By task				
AI Training	1.1	0.8	1.1	1.1
Annotation	-	-	1.1	1.1

Data source: Authors' calculations based on ILO-Thunderbird School survey of workers on microtask platforms and BPO companies, 2022.

But, the majority of workers do not receive such benefits, largely due to the contractual nature of employment. A very small proportion of them are salaried employees with formal contracts, while the remaining are engaged on temporary contracts or paid on daily or hourly basis, or on the basis of tasks.

Despite the low earnings and lack of protection, *why do such highly educated workers engage in AI development tasks which are quite repetitive and do not add any value addition to their careers?* This is largely due to a lack of labour market opportunities and access to well-paying jobs, which has forced many workers to turn to microtask platforms and BPO companies for work. In addition, many BPO companies lure these workers by promising them that they would become data scientists over a period of time. As one annotator in a BPO company in India who was aspiring to be a data scientist, realized three months into the job that the skills required to annotate automotive data had no relation to the data science training camp she had attended prior to the job.

This type of AI development tasks risks deskilling workers, as they do not require specialized STEM skills to perform them. Many workers in both India and Kenya expressed that "attention to minor details" was the most important skill to perform the tasks. And a medical image annotator in India noted that she relied heavily on her class 10 biology knowledge to be able to annotate CT scan data at her job. The earnings and experiences of AI workers on both microtask platforms and BPO companies suggests that the premium on higher education in the AI-BPO market is quite ambiguous, and in addition there are questions around how to use these experiences to advance their careers.

Lastly, there are notable concerns regarding the psychosocial ramifications stemming from tasks like content moderation, both on social media platforms and in large language learning models such as ChatGPT. Workers tasked with filtering through thousands of pornographic images, violent content and objectionable material daily bear the brunt of these effects on their mental well-being, which can significantly impede their professional and personal lives. Workers, particularly in BPO companies, are required to adhere to non-disclosure agreements, and they find themselves unable to share their experiences and to seek support from their families or friends. This type of AI development has significant implications on workers in developing countries, potentially leading to erosion of skilled workers in specialized fields, thereby adversely impacting the socio-economic development of these economies. At the same time, this process leads to a race to the bottom due to the availability of surplus labour at a very low cost.

AI Development: Measures to be taken towards achieving SDGs

This brief has highlighted some of the risks that workers in developing countries face as a result of the on-going development and deployment of AI systems. The rapid acceleration of AI development poses a significant risk of deepening existing inequalities between those who benefit from technological progress and those exploited within the AI value chain. In developing countries, invisible workers are often tasked with repetitive and routine work that underutilizes their skills and does not offer meaningful opportunities which could lead to their skill development or career advancement. In addition, the specialised education of workers in STEM fields are wasted on these routine tasks instead of utilizing it for bringing about a productive transformation of their economies. Further, these workers bear the brunt of precarious labour conditions without adequate recognition or protection, exacerbating economic and social disparities on a global scale.

How can we ensure labour rights and decent working conditions for these workers? This would require policymakers, technologists, and labour advocates to take action and address these urgent challenges by fostering a collective commitment to ethical and equitable AI development. It would require better policies, practices, and international cooperation to ensure that AI development does not compromise ethical standards or exploit workers. As a way forward, this brief calls for digital labour disclosure in the AI supply chain for informed policies and investments for ethical AI development.

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