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LABOUR AND EXPLOITATION PROCESSES IN ARTIFICIAL INTELLIGENCE: EXAMPLE OF DIGITAL TAYLORISM IN DATA LABELLING

Yapay Zeka'da Emek ve Sömürü Süreçleri: Veri Etiketleme Sürecinde Dijital Taylorizm Örneği

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Abstract

The advancement of artificial intelligence (AI) depends on vast datasets that require extensive human labour for annotation and labelling. Despite being framed as autonomous and intelligent, AI systems rely on precarious digital labour, particularly in the Global South. Data labelling, essential for AI training, is often outsourced or crowdsourced, exposing workers to low wages, job insecurity, and exploitative conditions. This study explores AI, labour, and global inequalities, demonstrating how Digital Taylorism and datafication intensify worker surveillance while reducing human labour to fragmented, repetitive tasks. The rise of digital sweatshops and a digital underclass reflects historical economic dependencies between the Global North and South. Crowdsourcing platforms and outsourced labour markets create a new form of exploitation under the guise of technological progress. This research challenges the prevailing narrative of AI as a purely technological advancement by unveiling its socio-economic dimensions. Findings emphasize the necessity of ethical AI development, transparency in labour practices, and structural reforms to protect workers from exploitation. Without intervention, AI risks deepening global inequalities, concentrating wealth and power while reinforcing systemic disparities in the digital economy. Addressing these issues requires a critical approach that situates AI within broader socio-political and economic structures, ensuring technology serves equitable and just purposes rather than perpetuating historical injustices.

Keywords: Artificial intelligence, Digital labour, Crowdsourcing, Digital taylorism, Global inequality, Datafication, Precarious work

Öz

Yapay zekanın (YZ) ilerlemesi, açıklama ve etiketleme için kapsamlı insan emeği gerektiren geniş veri kümelerine bağlıdır. Özerk ve zeki olarak çerçevelenmesine rağmen, YZ sistemleri özellikle Küresel Güney'de güvencesiz dijital emek süreçlerine dayanmaktadır. Yapay zeka eğitimi için olmazsa olmaz olan veri etiketleme genellikle dış kaynaklı veya crowdsourcing kaynaklıdır ve çalışanları düşük ücretlere, iş güvencesizliğine ve sömürücü koşullara maruz bırakmaktadır. Bu çalışma yapay zeka, emek ve küresel eşitsizlikleri inceleyerek Dijital Taylorizm ve verileştirmenin işçi gözetimini nasıl yoğunlaştırdığını ve insan emeğini parçalanmış, tekrarlayan görevlere nasıl indirgediğini göstermektedir. Dijital sweat shopların ve dijital alt sınıfın yükselişi, Küresel Kuzey ve Güney arasındaki tarihi ekonomik bağımlılıkları yansıtmaktadır. Kitle kaynak platformları ve dış kaynaklı emek piyasaları, teknolojik ilerleme kisvesi altında yeni bir sömürü biçimi yaratmaktadır. Bu araştırma, sosyo-ekonomik boyutlarını ortaya çıkararak yapay zekanın salt teknolojik bir ilerleme olduğu yönündeki yaygın anlatıya meydan okumaktadır. Bulgular, etik yapay zeka geliştirme, emek uygulamalarında şeffaflık ve çalışanları sömürüden korumak için yapısal reformların gerekliliğini vurgulamaktadır. Müdahale olmadan, yapay zeka küresel eşitsizlikleri derinleştirme, dijital ekonomideki sistemsel eşitsizlikleri güçlendirirken serveti ve gücü yoğunlaştırma riski taşımaktadır. Bu sorunları ele almak, yapay zekayı daha geniş sosyo-politik ve ekonomik yapılara yerleştiren, teknolojinin tarihi adaletsizlikleri sürdürmek yerine eşitlikçi ve adil amaçlara hizmet etmesini sağlayan eleştirel bir yaklaşım gekektirmektedir.

Anahtar Kelimeler: Yapay zeka, Dijital emek, Kitle kaynak, Dijital taylorizm, Küresel eşitsizlik, Verileştirme, Prekarya emeği

Introduction

Artificial intelligence (AI) has evolved significantly since its conceptualization in the mid-20th century. Initially conceived as a means to develop machines capable of mimicking human reasoning and problem-solving, AI has expanded beyond its theoretical foundations to become an integral part of contemporary digital infrastructure. The term itself has been subject to multiple interpretations, ranging from basic automation processes, such as thermostat-controlled environments, to more advanced machine learning applications that continuously adapt and improve based on data inputs. Today, AI operates as both an enabler of technological efficiency and a transformative force reshaping various sectors, including healthcare, finance, security, and labour markets.

However, alongside its rapid advancement, AI has also introduced complex ethical, social, and economic concerns, particularly regarding its reliance on vast amounts of human-labelled data. Indeed, a crucial yet often overlooked component of this technological evolution is the labour-intensive process of data labelling, which functions not merely as a preliminary technical step but as a core site of data training. Far from being a simple categorisation task, data labelling constitutes the pedagogical foundation through which human workers teach machines to interpret, classify, and act upon the world. This human-guided training makes possible the very capacities AI claims as autonomous. Yet this essential process remains largely invisible and structurally devalued within dominant AI narratives. Moreover, the dynamics of neoliberal capitalism further shape and exacerbate this invisibility. As a regime that prioritizes deregulation, profit maximization, and cost-cutting, neoliberalism drives the outsourcing of labour to regions with the lowest wages and weakest protections. In the AI sector, this manifests in the systematic relocation of data labelling tasks to the Global South, where workers often earn as little as $1.50 per hour under precarious and unregulated conditions. This model reflects not merely a search for efficiency, but a deliberate strategy of global labour exploitation that reinforces structural inequalities between the Global North and South (Regilme, 2024, p.76).

The development of AI is dependent on machine learning models trained through extensive datasets, a process requiring rigorous data labelling and annotation. This necessity has given rise to a global workforce dedicated to preparing AI training data, often operating under precarious conditions. While AI is frequently framed as a revolutionary technology that automates cognitive functions, its training and refinement remain deeply reliant on human labour, particularly in data labelling tasks outsourced to low-wage economies. Countries such as India, Kenya, the Philippines, and Madagascar have become key hubs for this labour, where workers are tasked with annotating images, videos, and text under conditions that resemble digital sweatshops. The emergence of crowdsourcing platforms, such as Amazon Mechanical Turk and Appen, has further decentralized this labour market, allowing corporations to source data annotation services globally while minimizing costs and circumventing labour protections. This outsourcing model reinforces existing global economic disparities, wherein AI ownership and technological benefits are concentrated in the Global North, while workers in the Global South perform the foundational tasks that enable AI systems to function.

Indeed, the data labelling process -often overlooked in mainstream AI narratives- is better understood as a process of data training, where human workers effectively teach machines how to "see" and interpret the world. As Altenried (2022, pp.99–100) observes, human labour is indispensable in creating the massive annotated datasets required to develop complex AI applications such as autonomous vehicles. Workers across the globe spend countless hours labelling images, identifying objects, and refining outputs for machine learning systems, yet their labour remains invisible beneath the veneer of automation. This hidden human input sustains the illusion of autonomous machine intelligence, masking the exploitative conditions under which much of AI's so-called intelligence is produced.

Beyond its implications for economic inequality, the AI labour process is increasingly governed by principles of Digital Taylorism, where workers are subjected to algorithmic surveillance, task fragmentation, and constant performance monitoring. Unlike traditional Taylorist principles, which sought to maximize factory efficiency through standardized workflows, Digital

Taylorism leverages AI-driven tools to track and optimize human labour in real-time. This transformation has led to heightened job precarity, as AI simultaneously depends on human labour while threatening its obsolescence through continuous automation. Moreover, the commodification of digital labour under AI-driven capitalism is intricately linked to datafication, where workers are reduced to "data generators" producing vast amounts of information for machine learning models. This process exacerbates concerns related to worker agency, privacy, and the devaluation of human expertise, raising critical questions about AI's role in shaping future labour dynamics.

1. Methodology

This study adopts a qualitative, interpretive approach grounded in close reading and contextual analysis (Finn, 2020, p.247) to examine labour exploitation in artificial intelligence (AI) training processes and its articulation within the global division of labour. While theoretically oriented, the research is empirically supported by a purposive sample of investigative news articles, functioning as primary data sources. These texts, selected from journalistic outlets such as The Guardian, WIRED, The Conversation, Noema Magazine, Context News, and Vice, provide vivid accounts of working conditions in AI-related data annotation and moderation, thereby illustrating the invisible labour behind so-called autonomous systems. The selection criteria for these sources included both geographical diversity and thematic relevance, ensuring a representation of labour experiences from countries including Kenya, India, China, the Philippines, Madagascar, and Venezuela.

These articles report on human labour conducted via widely used data labelling platforms such as Amazon Mechanical Turk, Appen, Scale AI, and Remotasks. Each of these platforms plays a distinct role in the crowdsourcing or outsourcing of annotation work -often in low-wage economies of the Global South- facilitating micro-tasks such as image classification, toxic content filtering, and object recognition for AI training. For instance, investigative reports detail how Kenyan workers, employed through Sama to filter traumatic content for OpenAI, were paid under $2 per hour while enduring severe psychological distress. Similarly, Indian and Filipino annotators using Amazon Mechanical Turk and Appen perform repetitive labelling tasks for meagre pay and under algorithmic control.

Through a close reading of these sources, the study identifies three recurring discursive and empirical patterns: (1) the global distribution and exploitation of AI labour, particularly the displacement of annotation work to the Global South while ownership and profits remain concentrated in the Global North; (2) the structural invisibility of labour in AI production processes, with emphasis on the epistemic and economic marginalization of data workers; and (3) the emergence of digital Taylorism, wherein labour is governed through surveillance technologies, algorithmic management, and performance metrics that intensify the pace and fragmentation of work.

By situating these journalistic narratives within broader theoretical frameworks of digital exploitation, platform capitalism, and data colonialism, the study critically analyses how AI development both reflects and reinforces global inequalities in labour organization. Furthermore, it reasserts the necessity of recognizing data labelling not as a peripheral technical task, but as a politically and ethically significant form of cognitive and affective labour.

2. Artificial Intelligence and Labour Issues

Artificial intelligence began as a legitimate science around 1955. John McCarthy, a mathematics professor at Dartmouth, decided to launch a project to explore the possibilities and limitations of the term "artificial intelligence," which he had coined the previous year. The goal was to enable machines to use language, form abstractions and concepts, solve problems that humans can currently solve, and improve themselves. To achieve this, he brought together four computer scientists who were already working on machines capable of thinking: himself, Marvin Minsky, Nathaniel Rochester, and Claude Shannon. The broadest definition of artificial intelligence is a technology that responds to data or its environment, meaning that a sprinkler system with a sensor is a type of artificial intelligence. A more active definition is that it is a technology that learns from its surroundings. In this sense, a thermostat in your room that adjusts to the desired temperature is considered artificial intelligence, while a sprinkler system is not (Reese, 2020, pp.75-76).

In everyday language, the term artificial intelligence is used with two meanings, often without awareness. The first corresponds to the concept of weak (limited) artificial intelligence, which represents the only type of artificial intelligence we currently possess. Weak artificial intelligence refers to the ability of a computer, machine, or any artificial system to solve problems or perform specific tasks. Weak or limited artificial intelligence is present in all technological devices that we now refer to as "smart." Weak artificial intelligence works by imitating the human mind to a limited extent, performing only the tasks it has been programmed to do (Doğan, 2021, p.86). Technological progress has often developed before the ethical rules required for the use of these technologies, which may lead to ethical issues such as the breakdown of social conflict and social solidarity. Technology can pose a threat to individual autonomy by violating privacy rights and may cause financial and physical harm to individuals. Technological ethical assumptions are defined as the biases and values that are inadvertently or deliberately applied in the design of a product, leading to unforeseen consequences during its use. Biases are considered one of the prominent ethical issues in artificial intelligence technologies (Pehlivanlı, 2021, p.29).

Artificial intelligence, no matter its form, is inherently biased, just as we are. AI carries political implications because it functions in ways that influence global power dynamics and shapes political tendencies, borders, and distinctions. The AI system forms feedback cycles with the broader society. As AI spreads across industries, it tends to result in the growth of repetitive and precarious jobs, rather than leading to widespread job loss (McQuillan, 2024, pp.9-11). Work can be defined as a set of tasks that individuals regularly perform based on a contract or some other type of agreement, and for which they are compensated, either financially or in another form, for fulfilling these duties according to the terms of the agreement. Of course, it is also possible to provide a broader definition of "work," which could include unpaid care work or volunteer activities where no compensation is provided. Artificial intelligence is commonly understood as any form of technology capable of performing tasks that humans typically conduct using their natural intelligence. If AI operates simply as a computer program, the computers used are not labelled as robots. However, when machines are equipped with sensors and actuators, and are able to directly "perceive" their surroundings and then respond to them, these AI systems are typically referred to as "robots” (Nyholm, 2024, pp.31-32).

The development and deployment of artificial intelligence cannot be viewed in isolation from the dominant logic of global capitalism. Rather than offering a rupture from neoliberal orthodoxy, AI and digital technologies have become integral to its deepening. Far from softening the neoliberal project, the rise of tech giants and platform-based economies has exacerbated core tendencies such as labour precarity, monopolistic concentration, and financialisation (Rendueles, 2024, pp.13-14). Artificial intelligence, which can be encountered in various sectors such as healthcare, education, and entertainment in every aspect of our daily lives, is also being used in areas that directly impact the security of individuals, society, and the state (Bekar, 2021, p.133). The expansion of artificial intelligence across various sectors also closely intersects with transformations in digital labour and production processes. In particular, the rise of cognitive labour as communicative work highlights how AI-driven systems are reshaping labour dynamics. AI technologies accelerate the fragmentation and coordination of tasks within digital infrastructures, creating interconnected yet autonomous production nodes. Consequently, workers increasingly depend on their cognitive skills, creativity, and communicative abilities, positioning themselves as essential actors who continuously reorganise informational flows within these AI-enabled labour networks (Berardi, 2012, pp.82-83). Another important point in the relationship of artificial intelligence with society is labour processes and exploitation processes.

This reorganisation of labour under artificial intelligence is inseparable from the broader logics of platform capitalism and data extraction economies. The coordination of labour through digital platforms has led to the fragmentation of tasks into micro-units -what scholars refer to as "microwork," "crowd labour," or "crowdsourcing." These forms of labour, often mediated by platforms such as Amazon Mechanical Turk, operate through extreme task decomposition, where workers are paid mere cents to perform repetitive and isolated duties -liking posts, labelling images, or moderating content- without any understanding of the final product to which their labour contributes. This structure obscures both the value produced and the social relations embedded in the labour process. Far from representing innovation in employment, such platforms intensify alienation and precarity while transforming the labouring subject into a data-producing node. These forms of digital labour constitute a new regime of exploitation, where surplus value is extracted not only from time and productivity but also from affect, attention, and data traces. Thus, digital labour in the age of AI must be situated within the expanding literature on platform capitalism, data colonialism, and algorithmic governance, where the human becomes a modular input in the service of opaque algorithmic economies (Huws, 2015, p.104).

3. Training the AI

Creating AI systems requires large sets of data. Supervised machine learning, such as those used for object or facial recognition, relies on extensive datasets composed of numerous distinct images. For example, to design a computer vision system capable of distinguishing between apples and oranges, developers must collect, label, and train a neural network on thousands of images of both fruits. The algorithms then analyse the data statistically, creating a model to differentiate between the two categories. If successful, the model should be able to identify apples and oranges it has never seen before. Training datasets are essential to the operation of modern AI systems. They define how AI interprets and interacts with the world, creating the boundaries that guide how these systems function. These datasets are central to addressing important social and ethical issues in AI. However, when we closely examine the training images used in many computer-vision systems, we discover that they rest on shaky, biased assumptions. Despite the efforts of institutions like MIT and tech giants such as Google and Facebook, interpreting images is a complex and relational task. Images are inherently ambiguous, with multiple potential meanings, unresolved issues, and contradictions (Crawford & Paglen, 2021, pp.1106-1108).

Recent advancements in machine learning have significantly accelerated the development of artificial intelligence, driven by the convergence of advanced computational power, sophisticated algorithms, and vast datasets, commonly referred to as "big data." A key factor behind this rapid progress is the increasing speed of hardware improvements, with chip designers reporting advancements that exceed the predictions of Moore's Law. The emergence of quantum computing is expected to further enhance this trajectory, enabling even greater processing capabilities. The exponential growth of available data, with approximately 2.5 billion gigabytes generated daily, provides AI systems with an extensive foundation for continuous learning and refinement, contributing to the unprecedented pace of AI innovation (Reese, 2020, p.79).

In the training of artificial intelligence algorithms, the most important ethical issue is that they should not contain human biases. Training AI systems properly requires a large amount of data/observations. The selection of data plays a crucial role in the training of AI. Biases present in the selected data or scenarios can lead to bias in the trained system. Therefore, it is essential to use unbiased data in the selection process (Pehlivanlı, 2021, pp.31-32). Training artificial intelligence systems involves a meticulous process that relies heavily on the collection and utilization of large datasets. In supervised machine learning, such as systems designed for image or facial recognition, vast amounts of labelled data are required to train the algorithms. For instance, to develop a system capable of distinguishing between objects or people in images, datasets containing thousands, if not millions, of labelled images are gathered. These datasets are used to teach the system how to identify specific features or patterns in the data. The labelled data serves as the foundation for the algorithm to develop a model that can accurately identify or predict new instances based on the patterns it has learned. As this process progresses, the AI system is expected to make predictions or classifications on data it has never seen before. This method of training is essential for the system to perform complex tasks, ranging from recognizing objects in photographs to understanding spoken language. However, the quality and accuracy of these models depend significantly on the datasets used, making the selection of training data a critical factor in the development of AI technologies (Morreale et al, 2024, pp.2392-2396).

Training artificial intelligence (AI) systems involves extensive use of data, often collected from vast and varied sources. In the case of text-to-image AI, such as popular applications based on diffusion models, large datasets containing millions of image-annotation pairs are gathered using web crawlers and scrapers. These datasets are used to train machine learning algorithms, which in turn produce models capable of generating images based on textual descriptions provided by users. The training process involves extracting relationships between images and corresponding text annotations, allowing the system to reverse the typical process of image annotation by taking a text prompt and generating an image that corresponds to it. However, this process raises significant ethical concerns, particularly regarding the sources of the data used to train these systems. The images used in training datasets are often scraped from the internet without the explicit consent of the creators, which has led to accusations of AI systems engaging in a form of "theft" of creative labour. Artist-protesters argue that AI image generation is a form of intellectual property theft, where the work of human artists is effectively stolen to train models that produce images without giving credit or compensation to the original creators. These concerns are particularly amplified in the context of marginalized artists who are already vulnerable within the global economy. The use of their work without consent or compensation is seen as an exploitation of their creative labour, and the proliferation of AI-generated art exacerbates existing inequalities within the art industry. This issue highlights the complex intersection of technology, creativity, and ethical considerations in the development of AI systems (Goetze, 2024, pp.189-192).

One key issue is the exploitation of creative labour, where AI systems are trained on vast datasets without obtaining consent from the original creators. This raises concerns about intellectual property rights, as artists argue that their work is effectively being used without recognition or compensation. Furthermore, this issue is not merely a legal or financial dispute; it also reflects broader structural inequalities within the creative industry, where marginalized artists are disproportionately affected. AI-generated art, by replicating and commodifying artistic styles, risks devaluing human creativity while reinforcing economic disparities. While AI training depends on vast datasets and increasing computational power, the ethical and methodological challenges surrounding data selection, bias, and intellectual property rights remain critical considerations in the development of responsible AI systems.

4. Beginning of the Training Process: Data Labelling

Despite optimistic narratives from major tech corporations claiming that artificial intelligence will lead to widespread societal benefit, empirical evidence suggests a far more uneven distribution of its impacts. While AI systems are increasingly able to perform complex tasks in fields such as law, medicine, and finance, these technological advances have not translated into inclusive progress for all. Instead, the expansion of AI has been marked by workforce reductions, intensified automation, and the growing marginalisation of lower-skilled workers -those already made vulnerable by previous waves of digital transformation. At the heart of these systems lies a largely hidden foundation: human labour, particularly in the form of data labelling. This process, often performed under precarious and low-paid conditions, enables the training of machine learning models by transforming raw data into meaningful inputs. Far from being an incidental or minor step, data labelling represents the indispensable human contribution that sustains the functioning and evolution of AI (Acemoğlu & Johnson, 2023, p.284).

A crucial step in AI training is data labelling, where raw data is systematically categorized and annotated to enable machine learning models to recognize patterns, make accurate predictions, and function effectively across various applications. One of the important processes in artificial intelligence training is data labelling. Data can be categorized based on its content, and for AI to generate appropriate outputs, it must recognize the predefined classifications of that data and understand the characteristics of each category. Raw data, in itself, holds no meaning for AI, so it is essential for the system to first comprehend what the data represents. The process of assigning meaningful labels to data according to the necessary categories is known as data labelling. This can be viewed as introducing the meanings embedded within the data to artificial intelligence. The labelled data is then gathered to form the training set, which is used to train the AI model. Through these labels, the learning process of the AI is enriched with valuable information, allowing it to make informed predictions and decisions based on the labelled data (Samancı, 2024). In other words, human labour lies at the basis of the phenomenon that develops artificial intelligence day by day: This labour begins with data labelling.

Data labelling is crucial in various databases and machine learning applications, as it forms the foundation for training accurate models. Traditional methods typically depend on humans -whether workers or experts- to assign labels, but this process can be costly, especially with large datasets. Active learning approaches aim to address this by labelling a small subset of data with significant uncertainty, training a model on these labelled examples, and then using the model to label the remaining data. Despite their advantages, these methods face two key limitations. First, they struggle to effectively select the most appropriate data (task selection) and assign the tasks to the right individuals (task assignment). Furthermore, they treat task selection and task assignment as separate processes, failing to capture the correlation between the two. Second, active learning methods infer the truth of a task based solely on human answers and the trained model, without considering the relationship between them. This approach overlooks the potential noise in the labelled data caused by human biases, and the model, trained on this noisy data, may introduce further biases, leading to inaccurate inference results (Li et al., 2021, p.289). While data labelling is fundamental to the accuracy and functionality of AI models, its implementation raises concerns regarding efficiency, cost, and ethical implications, particularly when considering the global labour structures that sustain this process.

Building on this, Couldry and Mejias (2024, pp.89-90) argue that data labelling must be understood not merely as a technical prerequisite for machine learning, but as a core site of what they call "data colonialism" -a new form of appropriation where human life is rendered as raw material for capital. In this framework, the extraction of labelled data is legitimised through civilising narratives that frame AI development as a universal good, while masking the asymmetrical relations of power and exploitation it relies upon. The convenience and progress promised by AI technologies often obscure the global labour inequalities that underpin their training processes, particularly in the Global South, where precarious workers carry out the repetitive, low-paid annotation tasks. Thus, data labelling is not only an epistemic operation of meaning-making for machines but also a political act of dispossession, where the knowledge and labour of marginalised populations are expropriated under the guise of technological advancement.

5. Outsourcing and Data Labelling

At the core of artificial intelligence systems lies an indispensable yet often invisible resource: human-labelled data. These datasets serve as the lifeblood of AI models, enabling them to learn, adapt, and generate outputs that power everything from recommendation engines to generative text platforms. Yet, the process of data labelling -critical to AI functionality- is rarely conducted within the same institutions that develop these technologies. Instead, global tech giants such as Meta, Google, Microsoft, and OpenAI outsource this labour to annotation firms and digital labour platforms. While companies such as Scale AI and iMerit now command valuations in the billions, the human workers on whose backs these profits are built often endure precarious conditions, meagre wages, and algorithmic control (Pogrebna, 2024).

In response to the high costs and labour-intensive demands of data annotation, AI companies increasingly rely on outsourcing as a strategic solution. This approach delegates data labelling tasks to low-wage economies, thereby forming a globalized workforce composed of precarious digital labourers. Outsourcing has become a structural feature of the AI production process, enabling companies to lower development expenses while accessing a broad pool of human annotators, particularly in the Global South. In these contexts, workers perform essential annotation tasks under precarious conditions, often through digital labour platforms or third-party firms that offer minimal labour protections. Although this model accelerates AI development and reduces operational costs, it also reproduces global inequalities by transferring labour-intensive work to regions with weak regulatory frameworks. Workers engaged in repetitive and cognitively demanding tasks receive low pay and lack security, despite the critical role they play in enabling machine learning systems to detect patterns and improve predictive accuracy. Thus, outsourcing in the AI industry not only reflects a shift in the spatial organization of labour but also reinforces systemic exploitation and uneven power relations within the global digital economy (Le Ludec, Cornet & Casilli, 2023, pp.2-3).

Data labelling for AI systems is frequently outsourced to low-wage economies such as India, Kenya, the Philippines, Venezuela, Bulgaria, and Mexico, where precarious workers annotate vast datasets for machine learning models. This labour, often facilitated through digital platforms like Amazon Mechanical Turk and Appen, is characterized by low pay, job insecurity, and algorithmic management, reinforcing global inequalities in AI development (Williams, Miceli & Gebru, 2022). This dynamic unfolds in tandem with what has been termed peripheral Fordism -a process through which digital technologies and the global circulation of capital reorganise production on a planetary scale. The decentralisation of labour, enabled by communication infrastructures and platform-based work arrangements, reflects a broader shift in capitalist accumulation strategies. Through this shift, production is fragmented across regions with abundant and inexpensive labour, allowing firms to reduce costs while maintaining tight control over workflows. The invisible labour behind AI -particularly data annotation- is emblematic of this logic: geographically dispersed yet digitally connected workers contribute to core technological advancements while remaining structurally marginal within the global economy (Aydoğan, 2019, p.62).

For example, French AI companies outsource data annotation and verification tasks to workers in Madagascar, a former French colony, where precarious labour conditions persist. These workers perform repetitive yet essential tasks, such as outlining human figures in images or correcting algorithmic errors, enabling AI systems to function effectively. This outsourcing model reflects a broader historical pattern of economic dependence, where France's high-tech sector benefits from low-cost labour in the Global South, reinforcing structural inequalities in the AI industry (Le Ludec & Cornet, 2023).

In another example, Kenyan workers earning less than $2 per hour are tasked with labelling harmful content, such as hate speech and violent imagery, to improve AI models like ChatGPT. Despite managing distressing materials for long hours, these workers receive minimal support, and many report lasting psychological harm. Meanwhile, the global data annotation market, valued at $800 million last year, is projected to reach $3.6 billion by 2027, highlighting the growing demand for outsourced data labelling while reinforcing disparities in AI labour conditions (Cheng, 2023). In addition to labelling harmful content, Kenyan workers employed by OpenAI through Sama were exposed to extremely graphic and distressing materials, including child abuse, bestiality, and violent acts. Many workers reported experiencing recurring traumatic visions due to the nature of their tasks, yet they received little psychological support. Sama, which marketed itself as providing "dignified digital work" in developing countries, ended its contract with OpenAI in early 2022, partly due to the severe mental health toll on workers. However, this decision left many labellers unemployed or forced them into even lower-paying projects, demonstrating how outsourcing both exploits and discards precarious labour (Xiang, 2023). In addition, the labour processes experienced in these countries, which are former colonies, bring to mind the phenomenon of colonialism.

The exploitative nature of data labelling and content moderation work in Kenya has prompted organized resistance. In a recent open letter addressed to ex U.S. President Joe Biden, 97 African workers affiliated with the African Content Moderators Union publicly condemned the labour practices of tech giants such as OpenAI, Meta, and Scale AI, characterizing them as "modern-day slavery." These workers, many of whom are based in Kenya -a hub for tech outsourcing- detailed their daily exposure to graphic content, including depictions of murder, child abuse, and sexual violence, often underpaid and overworked for more than eight hours a day. In addition to psychological trauma, they reported abrupt dismissals and withheld wages, particularly after Scale AI's Remotasks platform unexpectedly banned workers from Kenya, Nigeria, and Pakistan. The letter demands accountability for U.S.-based tech companies operating abroad, citing violations of labour and human rights, and calls for dignified, fair, and safe working conditions for African workers (Haskins, 2024).

Another example is India, where a significant portion of the global online freelance workforce is engaged in data labelling. Workers rely on platforms such as Amazon Mechanical Turk to perform annotation tasks, often competing for low-paying gigs. With AI's growing demand for vast training datasets, India has become a crucial hub for digital microwork, reflecting the broader trend of outsourcing AI-related labour to precarious workers in developing economies (Chandran, Smith & Ramos, 2023). In India, the scarcity of stable employment opportunities has driven many educated young workers into precarious digital labour, including AI data annotation. The country, home to one of the largest and fastest-growing gig economies, has become a critical hub for data labelling, with up to one million Indians expected to work in the field by 2030. However, these jobs offer low wages and little security, with freelancers earning only a few cents per task on platforms like Amazon Mechanical Turk. Many workers, particularly in small towns, face erratic work availability and inconsistent pay, as completed tasks are often rejected without explanation. Despite the growing demand for AI training datasets, Indian data annotators remain at the bottom of the AI value chain, with limited prospects for upskilling or wage increases. While some full-time managed service providers offer salaries between 15,000 and 25,000 rupees per month, most workers operate under precarious conditions, highlighting the imbalance between India's role as a global AI outsourcing hub and the lack of long-term labour protections. As AI automation advances, even these low-paying annotation jobs may become obsolete, further deepening employment insecurity for workers in the country (Khanna & Chandran, 2023). In this way, it can be said that these jobs, which are outsourced to workers from Global South countries, are precariat jobs.

Building on the convergence of racial capitalism and data colonialism, the labour structures underpinning contemporary AI and digital economies can be understood as a continuation of extractive logics rooted in colonial modernity. Digital Taylorism, as it manifests within platform capitalism, reproduces the historical dynamics of dispossession and control -now through algorithmic management and the commodification of cognitive and affective capacities. Workers in the Global South, drawn into the AI value chain through precarious digital microwork, exemplify the new "data proletariat," whose fragmented, invisible, and undervalued labour fuels technological development in the Global North. This labour is not only surveilled and quantified but also racialised and classed, as platform infrastructures disproportionately target and extract value from marginalised populations through processes of predatory inclusion. As the production of data becomes central to capital accumulation, these workers are positioned at the intersection of value extraction and social stratification, embodying the uneven geographies of exploitation that data capitalism both inherits and intensifies. In this sense, platform-mediated digital labour cannot be separated from the broader coloniality of data extraction- it is a contemporary articulation of a much older logic, wherein dispossession and profit generation are naturalised through technological rationality (Couldry & Mejias, 2023, p.792).

While outsourcing has become a dominant strategy for AI companies to reduce costs and access a global workforce, crowdsourcing represents another crucial approach that leverages distributed human intelligence for large-scale data labelling. By decentralizing labour through digital platforms, crowdsourcing introduces both opportunities for efficiency and significant ethical concerns regarding worker protections and fair compensation. However, when the examples given up to this point are summarized, it can be seen that the human labour used in the AI training process is subcontracted to workers in regions that can be defined as the Global South at low wages. The companies that subcontract this AI work are owned by the Global North.

6. Crowdsourcing and Data Labelling

The task of data labelling in artificial intelligence is often misrepresented as a marginal or mechanical function. In reality, it constitutes the very foundation of data training -a critical stage in which human workers teach machines how to interpret and respond to the world. Far from being a passive or purely technical operation, data labelling requires workers to make culturally and linguistically nuanced judgments that machines are fundamentally incapable of performing. These labourers, often operating through platforms like Amazon Mechanical Turk, classify images, moderate content, transcribe audio, and structure unorganised text-enabling AI systems to simulate human understanding. This labour is not simply preparatory; it is constitutive of AI's capacity to function. Without this human-guided training phase, artificial intelligence systems would remain incapable of distinguishing satire from spam, violence from humour, or relevance from noise. As such, what is commonly framed as low-skill annotation work must be re-understood as an essential form of cognitive and cultural labour-one that underpins the very possibility of intelligent automation (Irani, 2019, pp.27-28).

Artificial intelligence systems depend on vast volumes of labelled data for effective training. In response, crowdsourcing has become a widely adopted and scalable method, allowing companies to outsource data annotation tasks to a dispersed global workforce via digital platforms. Within this model, human intelligence is mobilized to support machines in tasks they cannot autonomously perform-a process often referred to as human computation. Crowdsourcing enables the rapid and cost-effective generation of large annotated datasets, which are crucial for supervised machine learning. Platforms such as Amazon Mechanical Turk (MTurk) and CrowdFlower facilitate the distribution of annotation tasks, including image classification, video tagging, and ranking exercises. Although expert labelling remains more accurate, it is financially burdensome and lacks scalability. In contrast, crowdsourcing offers economic efficiency but often suffers from inconsistency in annotation quality due to variations in worker expertise, motivation, and evaluation criteria. This inconsistency has led to a growing body of research focused on improving data quality and managing noise in labelled datasets (Zhang, Wu & Sheng, 2016, pp.545–546). Ultimately, the widespread reliance on crowdsourcing reveals how major AI firms generate substantial profits while depending on low-cost, underregulated labour to sustain their data infrastructures.

Crowdsourcing in data labelling work has created a global workforce where precarious labour conditions persist, particularly in regions such as South America, East Asia, and the Philippines. Investigations have revealed that some data labellers work more than 18 hours per day for wages below their country's legal minimum, highlighting the exploitative nature of the industry. Companies like ScaleAI, which employs at least 10,000 workers in the Philippines, have been reported to pay extremely low rates, delay or withhold payments, and offer minimal avenues for workers to challenge unfair treatment. As the demand for AI training data increases, the expansion of the data labelling industry raises concerns about the ethical implications of relying on an underpaid and invisible workforce (Taylor, 2023). When it is looked at the countries where the workers used in artificial intelligence training come from, it can be said that they belong to Global South countries.

For example, in China, data labelling has become a critical component of the country's AI industry, with vocational school students increasingly being incorporated into the workforce as low-cost labour. Many are required to complete internships at data annotation centres as a condition for graduation, where they engage in repetitive tasks such as tagging images, filtering videos, and processing audio files. These internships often involve long working hours and subminimum wages, despite government regulations introduced in 2022 that mandate fair compensation and prohibit institutions from requiring students to perform routine, repetitive tasks. However, enforcement remains limited, and data labelling continues to be a precarious sector that sustains China's AI development through undervalued labour (Zhou & Chen, 2023). At this point, it can be said that China being a state with a communist party in power does not lead to any improvement in the working conditions of the working class.

The case of Uganda exemplifies how crowdsourcing in AI data labelling exploits a global workforce under precarious conditions. Business Process Outsourcing (BPO) firms employ workers to perform repetitive, attention-intensive tasks -such as reviewing driver behavior for autonomous vehicle systems- at very low wages. Crowdsourcing platforms enable AI companies to delegate these tasks to countries in the Global South, where labour protections are minimal and wage standards are low. This arrangement benefits AI firms by reducing costs and increasing scalability, while workers endure mentally exhausting labour for minimal compensation. The decentralized structure of this work undermines job security and limits workers' ability to seek redress when mistreated. Despite their critical role in training AI systems, these workers remain invisible in broader ethical debates surrounding artificial intelligence. As the demand for AI-generated data continues to grow, the expansion of this labour model risks further entrenching global inequalities (Muldoon, Graham & Cant, 2024). When looking at the issue of crowdsourcing in artificial intelligence, it can be said that the working conditions are similar to sweatshops. In this context, these environments can be called digital sweatshops.

In the data labelling process, human labour plays a crucial role, but it is often subjected to exploitation, particularly in crowdsourced or outsourced data work. Workers, often from the Global South, are paid low wages for repetitive, labour-intensive tasks such as labelling images, categorizing data, or verifying AI outputs. While crowdsourcing platforms offer a cost-effective solution for AI companies needing vast amounts of labelled data, they often fail to provide adequate protections for workers. These platforms typically do not guarantee fair compensation or offer job security, resulting in precarious working conditions for data labellers. Furthermore, the work is often fragmented, and labellers are treated as interchangeable cogs in the system, with little recognition of the value they add. This exploitation mirrors the broader patterns seen in other industries where labour is outsourced to low-wage workers, creating a situation where workers contribute significantly to the development of advanced AI systems but receive minimal compensation. The quality of data labelling is also inconsistent due to varying levels of expertise and dedication among workers, leading to further challenges in ensuring the reliability of AI models. Thus, while data labelling is essential for AI development, the conditions under which this labour is performed raise significant ethical concerns about exploitation and fairness (Vijeyarasa, 2014, p.2).

Building on this, Gray and Suri (2019, pp.23-25) conceptualise this form of labour as *ghost work* -a hidden, yet foundational, layer of human input that sustains seemingly automated digital systems. Platforms like Amazon Mechanical Turk and Appen obscure the presence of workers by presenting AI outputs as purely machine-driven, thereby naturalising the invisibility of human contributions. These workers, dispersed across geographies yet connected through algorithmic infrastructures, perform micro-tasks that are vital to machine learning, from identifying objects in images to filtering toxic content. However, their labour remains underpaid, unprotected, and structurally devalued. The fragmentation and invisibility of this work not only reinforce global inequalities but also uphold a techno-capitalist illusion of automation, where machines appear intelligent precisely because human input is systematically erased. As AI becomes further integrated into critical decision-making systems, the failure to acknowledge and compensate the human labour underpinning these technologies raises urgent questions about digital justice, algorithmic accountability, and the ethics of global labour extraction. The labour processes experienced in the data labelling process bring to mind the issue of Taylorism.

7. From Traditional Taylorism to Digital Taylorism

Digital Taylorism is a modern adaptation of traditional Taylorism, reshaped by digital technologies. At its core, it aims to increase efficiency and productivity by dividing work into standardized, repetitive tasks and continuously monitoring performance. In this system, human labour is supported by computers, artificial intelligence, and algorithms, often reducing work to menial tasks performed by low-skilled workers. Digital Taylorism focuses on global workforce control through intensified surveillance, where workers are monitored using wearable technologies, big data, GPS tracking systems, and customer rating tools. This surveillance aims to increase worker speed, thereby maximizing surplus value production. Furthermore, work conditions are modified to ensure higher productivity, with adjustments such as shortening lunch breaks or extending workdays. As a result, while digital technologies enhance workforce control, they also deepen insecure working conditions, making workers' labour more precarious. Digital Taylorism thus seeks to maximize capital accumulation through the exploitation and heightened control of labour, reinforcing both the surveillance of workers and their increasingly unstable working conditions (Yılmaz, 2024, pp.65-67). In this respect, the surveillance processes that have developed with the increasing use of technology can actually be seen as a "one-sided class war" intensified by capital. On the one hand, the working class is being distanced from being defined as a historical bloc, while on the other hand, capital is intensifying the process of its disintegration.

Unlike traditional Taylorism, which was primarily confined to the physical optimisation of factory labour through time-motion studies and rigid task specialisation, digital Taylorism extends managerial control into the cognitive and affective realms of work. Traditional Taylorism was bounded by space and co-presence -supervision required physical proximity, and labour control operated through direct observation and mechanical discipline. In contrast, digital Taylorism leverages algorithmic systems and real-time data flows to monitor, assess, and reconfigure labour processes remotely and continuously. This shift enables not only the decomposition of tasks but also the commodification of knowledge work and emotional labour. Furthermore, digital Taylorism embeds control mechanisms into the very infrastructure of digital platforms, where surveillance is ambient rather than direct, and where workers internalise discipline through metrics, gamified evaluations, and customer feedback loops. While classical Taylorism mechanised the body, digital Taylorism seeks to modulate the entire subjectivity of the worker- transforming thought, behaviour, and emotion into measurable and optimisable inputs. Hence, its scope is not limited to production sites but permeates service industries, logistics, and remote gig work, reflecting a new regime of labour governance tailored to the needs of platform capitalism (Brown, Lauder & Ashton, 2011, p.72).

As digital Taylorism amplifies the fragmentation and surveillance of labour, it further entrenches the asymmetry between capital and workers. The more this logic intensifies the antagonism between labour and capital, the less feasible any coordination of mutual interests becomes, making reliance on coercive measures increasingly inevitable (Burawoy, 2015, p.70). In this context, algorithmic management replaces negotiated regulation, and consent is gradually substituted by control mechanisms embedded in code, metrics, and automated feedback. Rather than fostering collaboration, the system fosters compliance -through constant evaluation, fear of deactivation, and opaque performance thresholds -revealing that the digital augmentation of Taylorism does not resolve historical labour-capital tensions, but reconfigures them under a new digital architecture of domination. Under the hegemony of neoliberalism, Taylorism should not merely be understood as a model of capital accumulation, but more profoundly as a model of social transformation. It extends beyond the reorganisation of physical labour to encompass the restructuring of cognitive and affective capacities in line with the demands of efficiency and control. In this framework, Taylorism becomes a regime of subjectivation that reshapes how individuals think, work, and relate to themselves and others within the production process. The fragmentation of labour -once confined to the factory floor- is now applied to intellectual and creative work, dissolving boundaries between manual and mental labour.

This transformation is especially evident in how subjectivity is managed under the guise of professional objectivity. As Paddy Scannell (2020, p.56) notes, Taylorism no longer only disciplines the body but also alienates the mind. The journalist who suppresses their own convictions to adopt the editorial voice of a media institution exemplifies this condition of "reified consciousness." Here, the worker's subjectivity is disassembled, repurposed, and commodified to fit institutional templates, reducing complex mental activity to functionally neutral output. Thus, digital Taylorism operates not just as an economic tool but as a cultural and ideological mechanism that reshapes the fabric of everyday life, regulating not only what is produced but also how individuals come to understand and perform their roles within the production apparatus.

Data labelling processes in the digital age are increasingly influenced by the principles of Digital Taylorism, where tasks are fragmented, and workers' efforts are systematically monitored and optimized for maximum efficiency. As artificial intelligence (AI) systems take over more repetitive and predictable tasks, data labelling has become one of the key areas where human labour is exploited. Workers, often from low-wage regions, are tasked with labelling data that AI models use for training. This process, while crucial for the advancement of AI, is heavily reliant on crowdsourcing or outsourcing, where workers are often paid meagre wages to perform monotonous tasks. These workers become "data generators," similar to the workforce model envisioned by Taylor, but now under the watchful eye of AI-driven surveillance systems. As AI models learn from the data labelled by humans, these workers are not only contributing to efficiency but are also at risk of being replaced as AI systems evolve to automate these tasks. Digital Taylorism is thus transforming the nature of work, shifting more responsibilities onto low-paid, precarious workers while threatening their job security as AI continues to advance. This cycle of exploitation mirrors the broader trend of technological innovation that increasingly decouples economic growth from job creation, deepening the inequality between technological advancement and the demand for human labour (McCullen, 2024). At this point, it is seen that with Digital Taylorism, business processes are increasingly subjected to the "datafication" process over tasks. In this way, tracking of the work done becomes easier, performance tracking creates greater pressure on the worker, and workers with low performance can be easily dismissed.

Data labelling constitutes a central pillar of contemporary workforce management within the framework of digital Taylorism. This management approach, exemplified by companies such as Amazon, employs advanced artificial intelligence, robotics, and pervasive surveillance to decompose complex tasks into smaller, repetitive units that can be executed by minimally trained workers. While sharing the efficiency-oriented logic of classical Taylorism, digital Taylorism introduces a new layer of control through algorithmic tools used for task assignment, performance monitoring, and labour optimisation. These systems transform workers into "data generators," responsible for producing large volumes of labelled information essential for machine learning models. Frequently outsourced or crowdsourced, this labour is performed by individuals from low-income regions who engage in monotonous annotation tasks involving images, videos, and text. Although fundamental to AI development, this work remains low-paid, highly monitored, and increasingly subject to automation. The integration of algorithmic control mechanisms exacerbates worker precarity, undermines opportunities for collective organisation, and deepens labour-capital asymmetries. This dynamic is sustained by an ideology of disparity that normalises unequal treatment. Workers are compelled to internalise exploitative conditions as inevitable, thereby limiting their ability to resist or demand improved wages and labour standards (Rogers, 2023, pp.59–62).

In the domain of data labelling, both Taylorist scientific management and gamification share a common objective: the rationalization of labour processes to maximize efficiency. By fragmenting tasks into standardized and repetitive units, both approaches aim to optimize productivity through systematic observation and data-driven performance monitoring. Data labelling -an essential stage in AI model training- frequently adopts these methods, assigning low-skill, repetitive tasks to workers who are often employed through outsourcing or crowdsourcing in low-wage regions. These workers are subject to constant monitoring and assessment based on standardized metrics. As in classical Taylorism, which sought to eliminate inefficiencies through rigid task design, gamified training systems intensify this control by embedding performance metrics into learning environments. Although gamification claims to enhance engagement, it often overlooks the individuality of workers, reducing performance to conformity with pre-set rules. This mirrors the limitations of standardized testing in educational contexts, where the measurement of compliance overshadows the recognition of creative or critical capacities. The increasing integration of surveillance mechanisms into both gamification and Taylorist systems raises significant ethical concerns. In digital Taylorism, surveillance becomes pervasive, facilitated by algorithmic tools that govern worker behaviour and output in real-time. As AI-driven crowdsourcing expands, these mechanisms reinforce exploitative labour structures, relegating data labellers to an invisible digital underclass, marked by precarious employment and growing vulnerability to automation (DeWinter, Kocurek & Nichols, 2014, pp.11–12).

Conclusion

This study has critically examined the labour dynamics underlying the development of artificial intelligence, with a particular focus on data labelling as a structurally invisible yet essential component of AI systems. Contrary to dominant discourses that celebrate AI as a fully automated and autonomous technological revolution, this research reveals how the apparent intelligence of machines is, in fact, contingent upon the repetitive and precarious labour of a global workforce - particularly from the Global South. These workers, often operating through outsourcing and crowdsourcing arrangements, are subjected to algorithmic management, low wages, and severe psychological stress, especially when moderating toxic and harmful content. Their invisibility is not incidental but is rather systematically produced by the political economy of platform capitalism and digital Taylorism.

By analysing empirical data from investigative journalism alongside theoretical insights from critical political economy and decolonial thought, the study demonstrates how AI development reproduces and intensifies global asymmetries of labour and value. The practices of data extraction, content moderation, and platform-based task fragmentation reflect broader patterns of digital colonialism and the perpetuation of historical North–South dependency relations. Companies in the Global North benefit from the commodified cognitive and emotional labour of workers in former colonies, while these workers remain excluded from both the economic gains and the epistemic recognition of their contributions.

Furthermore, the research shows that digital Taylorism does not merely represent a transformation of labour processes but also entails a reconfiguration of subjectivity. Labour is decomposed into micro-tasks, monitored through algorithmic metrics, and subjected to performance evaluations that leave no space for negotiation or agency. This mode of labour governance not only amplifies the exploitation of digital workers but also erodes their social and psychological well-being, revealing the human cost of AI's apparent neutrality and efficiency.

Ultimately, the findings underline that AI, far from being a neutral tool, functions as a socio-technical system embedded within the logic of neoliberal capitalism. Without structural interventions aimed at protecting workers' rights, ensuring fair compensation, and regulating outsourcing practices, the development of AI technologies will continue to deepen existing global inequalities. A just and equitable AI future requires the recognition of labour not merely as a technical input but as a political and ethical issue. This necessitates a critical reassessment of how knowledge, value, and agency are distributed in the digital economy- and for whom technological progress truly serves.

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