# AI-augmented Collaboration in Crowdsourcing: Threats and Opportunities*

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**Abstract**

Digital labor platforms have evolved and diversified under the influence of artificial intelligence (AI) technology over the last couple of years due to the multimodal transformative capabilities of large language models (LLMs) and generative agent-based models. These platforms are now established and offer scalable solutions to solve macrotasks of varied levels of complexity and demands. However, the challenges associated with the inappropriate use of AI in digital labor settings are enormous. This emphasizes the need of collaboration mechanisms enabling crowds, large groups, or self-organizing teams to create new solutions or just responsibly oversee AI-generated outputs. Despite growing scholarly interest in macrotask-based digital labor platforms, there remains a significant gap in understanding how AI-augmented collaboration can shape the socio-technical dynamics of the digital economy. This paper contributes to this stream of research by providing a new lens on the potential threats, enablers, and open questions at the intersection of human-centered AI and large-scale collaboration in digital labor platforms with crowdsourcing at the heart of it.

**Keywords**

artificial intelligence, collaboration, crowdsourcing, digital economy, digital labor platforms, inequalities, large language models, optimization workflows

## 1. Introduction

Digital labor platforms have become well-established and widely used in a wide range of problems encountered daily by companies and institutions worldwide. Online workers operating remotely in real-time or asynchronous modes can be effective in contexts that involve product feature development, interface design, transcription, film production, etc. Traditionally, digital labor platforms have primarily supported microtask-based models, where online workers perform decontextualized tasks that can later be aggregated by requesters [1]. These platforms typically emphasize independence and efficiency rather than collaboration. Nonetheless, a shift has emerged with the rise of macrotask-based crowdsourcing. Unlike microtasks, macrotasks usually need coordination efforts among multiple contributors, more time allocated to each task, and specialized expertise from crowd workers [2, 36]. These tasks are inherently complex, interdependent, and involve new forms of workflow support and interaction within the crowd.

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As the digital economy evolves towards more knowledge-intensive and creative tasks, the role of artificial intelligence (AI)-augmented collaboration has gained increasing attention. Collaboration offers a promising path forward for optimizing processes and overcoming workflow fragmentation. To support this transition, platforms must provide mechanisms beyond basic coordination by facilitating coalition-based ensembles where contributors build on each other's work and make joint decisions mediated by AI [3]. In this line of thought, AI-augmented platforms play a critical enabling role. Rather than replacing humans, they are increasingly deployed to augment collaboration by assisting online workers in executing complex tasks, dynamically allocating subtasks, and providing intelligent feedback throughout the crowdsourcing process. In fact, many new terminologies have been used to describe the relational aspects between humans and AI systems (for a detailed discussion of the conceptual tensions in the existing scholarly literature, see [19]). By way of example, AI can serve as a "mediator" by monitoring task progress, recommending complementary skill matches among workers, flagging inconsistencies, and optimizing communication between a crowd ensemble. In some applications, AI functions as a "partner" by participating directly in problem-solving, especially in settings requiring teams comprised of humans and autonomous agents.

Extensive field experiments have been carried out to demonstrate the transformative effect of AI-augmented collaboration. In domains such as tissue image annotation, for instance, human annotators working alongside AI-driven preprocessing tools have achieved improved accuracy and efficiency [4]. In writing and analytical tasks, some experiments showed that workers using large language models (LLMs) completed them more quickly and with higher levels of quality [20]. These cases exemplify a broader shift toward human-centered AI systems able to reshape the way collective human capabilities are leveraged within the digital economy.

This paper seeks to provide a descriptive account of the key challenges, potential directions, and existing gaps in AI-augmented collaboration for crowdsourcing applications. We focus specifically on the potential of designing AI systems that enhance collaboration in macrotask environments. To this end, we continue our effort to consolidate research and practical insights outlining foundational pathways for further investigation and technological advancement in this area of work.

## 2. AI-augmented Digital Labor in Crowdsourcing Platforms: Is the Road to Collaboration Too Far?

The rise of digital labor platforms has transformed the work landscape by offering new ways to outsource tasks that are either expensive or too complex to automate. As these platforms gain traction as viable solutions for addressing economically infeasible tasks through traditional means, researchers have turned their attention to the collective intelligence that emerges from coordinated crowd activity mediated by AI [6, 37]. Among the most promising developments in this domain is the use of collaborative mechanisms, wherein groups or teams of crowd workers interact explicitly or implicitly. While aggregating individual contributions has long been a hallmark of crowdsourcing, a transition to collective problem-solving represents a fundamental shift in operationalizing digital labor. In practice, these interactions often extend beyond simple task completion, fostering joint cognitive and creative processes that benefit from the diversity of human skills involved in such settings. Figure 1 illustrates different levels of complexity found in crowdsourcing tasks.

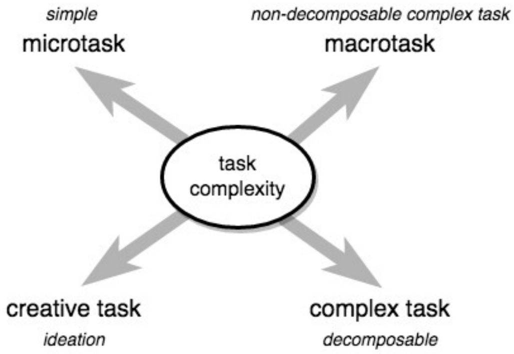


**Figure 1.** Balancing the dimensions of task complexity in crowdsourcing (adapted from [1]).

Despite the growing academic interest in AI-augmented collaboration, many digital labor platforms lack built-in support for communication or coordination among workers who use external tools such as social forums or mobile messaging apps to exchange knowledge and provide information about ongoing tasks [5]. These emergent behaviors underscore a latent demand for more structured, AI-augmented collaborative frameworks.

Recent initiatives have begun to address such limitations through intelligent systems and algorithms that facilitate the dynamic assembly and coordination of groups or teams of online workers. Here, the role of AI is not merely to mediate the workflow but a key enabler of enhanced collaboration able to actively augment human abilities through informed decision-making support or real-time feedback. Advanced task assignment algorithms now factor in social affinity, worker compatibility, and motivational incentives [6]. Furthermore, interactive crowdsourcing applications are being developed to facilitate real-time collaboration between requesters and online workers aided by AI agents capable of orchestrating workflows and solving ambiguities while promoting equitable participation.

The convergence of AI and collaborative crowdsourcing introduces critical challenges and research opportunities. From a design perspective, questions of transparency, trust, and fairness become central as AI agents take on greater roles in mediating human labor. Equally important is the need to examine the multidisciplinary nature of human-AI mixed-initiative systems. This intersection forms the basis for a research agenda intended to unpack the socio-technical elements that characterize AI-augmented collaboration in digital labor platforms.

## 3. Can AI Augment Collaboration in Crowdsourcing?: 'The Dark Side of the Moon'

From mixed-initiative evaluation to chat-based anonymous communication, generative AI and LLM-based multimodal tools now support an increasingly diverse range of interactive features. As illustrated in Figure 2, certain aspects must be considered when integrating AI into digital labor platforms. In this section, we list some of the opportunities, threats, and prominent areas of application of AI-augmented collaboration in crowdsourcing settings.

### 3.1. AI-based Optimization Workflows

AI-augmented collaboration offers significant potential for optimizing both collective output and the workflows associated with task assignment in crowdsourcing. Traditional models of crowd work have often relied on simplistic assumptions about worker capabilities and random or rule-based task distribution. However, AI-based methods enable more nuanced and adaptive strategies matching tasks to individuals based on multifactorial models. These models account for a range of attributes, including worker skills, preferences, motivation, and historical performance indicators such as accuracy and response time. Such personalization has been shown to enhance output quality while also reducing task completion times. This approach was discussed by Retelny and co-authors [7], who emphasized computationally-supported team assembly and further expanded upon in subsequent debates on the role of interactive systems in guiding teams to solve complex, non-decomposable macrotasks.

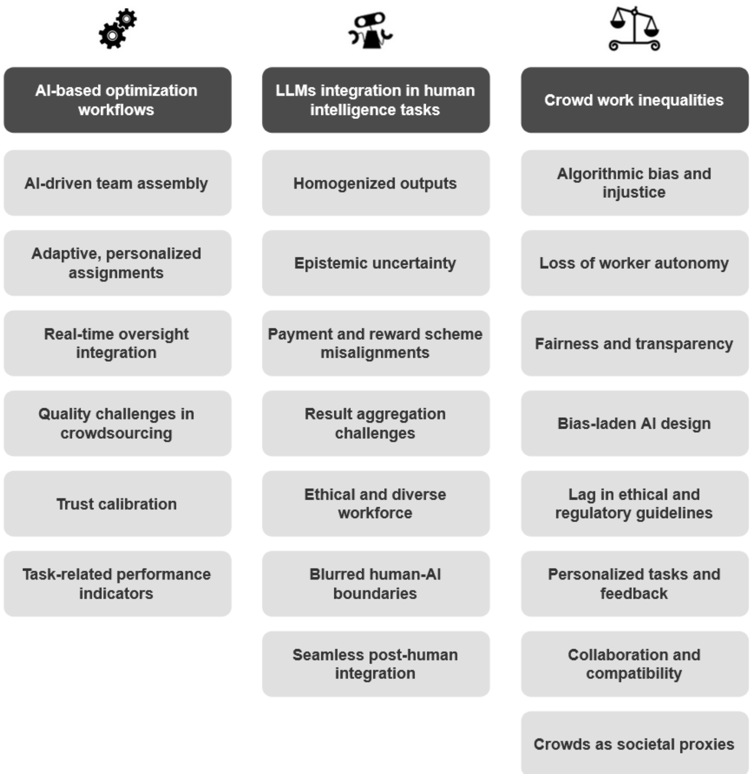


**Figure 2.** Promises and perils of AI-augmented collaboration in crowdsourcing.

A persistent challenge in open-ended crowdsourcing environments lies in managing quality control amidst the inherent variability of crowd workers' reliability and expertise [8]. AI-driven collaborative models address this challenge by incorporating real-time oversight, intelligent task allocation, and predictive analytics. These systems not only enable dynamic adaptation to worker performance but also actively monitor for signs of inconsistency, low reliability, fatigue, or potential malicious activity [32, 33]. By analyzing task completion data such as deviations in response time or inconsistencies with gold-standard responses, AI-augmented systems can infer levels of trustworthiness and optimize team configurations accordingly. This aligns with broader literature emphasizing the role of team assembly in shaping collaborative dynamics and performance outcomes [9]. Moreover, AI systems can facilitate the formation of synergistic teams whose combined capabilities align with the cognitive and procedural demands of specific crowdsourcing tasks.

### 3.2. LLMs Integration in Human Intelligence Tasks

In the context of crowdsourcing challenges on business ideation, hybrid teams using an iterative prompting strategy (where humans guided the LLM to explore diverse solution directions) outperformed both independent human teams and unguided AI, demonstrating the potential of combining human strategic guidance with AI's generative capacity [21]. As LLMs become increasingly integrated into crowdsourcing workflows, the boundary between human- and AI-generated contributions has blurred, raising critical concerns about trust, authorship, and the epistemic validity of collected data [10]. While such models enhance productivity and streamline processes by enabling tasks such as algorithm training and data collection from user studies [11], they also introduce significant uncertainty about the extent to which outputs reflect genuine human cognition and judgment. This is particularly problematic in contexts that rely on subjective input, where LLM-assisted responses may distort or homogenize data meant to capture diverse human perspectives [30, 31]. As a result, conventional feedback loops and compensation mechanisms, which assume a direct correlation between performance metrics and individual worker input, are increasingly rendered obsolete. Furthermore, a key aspect that should not be overlooked is the potential for LLMs to introduce subtle biases into their training data, potentially introducing inadvertent distortions to collective human intelligence. This underscores the need to develop methods and strategies for detecting and mitigating AI-induced biases in crowdsourced data.

The execution of human intelligence tasks (HITs) with the computational support of AI systems underscores the need for a more ethically aware, diverse, skilled, and AI-literate crowd workforce. There is growing recognition that the unregulated use of LLMs may lead to homogenized outputs, which undermines the goal of many crowdsourcing initiatives aimed at capturing heterogeneity in attitudes, behaviors, and lived experiences. In response, hybrid frameworks have been proposed and tested in complex tasks such as misinformation detection, content moderation, and deepfake identification [12]. However, further research is required to develop effective design principles for human-LLM interaction within digital labor contexts. One possible avenue is investigating optimal strategies for task decomposition between humans and AI agents based on user interface (UI) designs that clearly delineate AI contributions and facilitate human oversight and correction.

Given its importance, the aggregation and interpretation of results generated by both human and non-human agents present novel methodological challenges. As pointed out in [13], the success of AI-crowd interactive systems depends on the development of robust mechanisms to reconcile outputs from mixed-agent teams and to ensure that the collective intelligence produced remains trustworthy, diverse, and aligned with the task's epistemic goals. This entails exploring new aggregation techniques that can account for the different levels of human and AI influence on the generated data, which could be leveraged through differential weighting or qualitative analysis of contributions. In the context of AI recommendations, if the AI's reasoning or criteria are opaque, users tend to distrust its outputs or feel that the process is unfair. Providing explanations for AI recommendations can increase user trust and achieve more accurate results [22], despite recent evidence indicating that this may be insufficient to ensure critical evaluation and appropriate incorporation of human and AI contributions in decision-making [34].

The integration of LLMs into collaborative settings also raises important questions about the skill sets required from workers. Although AI is expected to automate routine tasks and enable crowd workers to engage in higher-level cognitive activities, the growing use of generative AI in these contexts often diminishes perceived work value and enjoyment while simultaneously introducing new ethical concerns [23]. This underscores the need for training and upskilling initiatives to equip the collaborative workforce for new roles in AI-augmented environments and to mitigate potential inequalities among workers [24]. Moreover, the legal and ethical implications of authorship and intellectual property underlying content co-created with LLMs require careful consideration. A recent example is the viral spread of Studio Ghibli-themed, prompt-generated animations which have raised concerns regarding ownership and privacy. Therefore, guidelines and frameworks are needed to address issues of accountability, opacity, responsibility, and fair attribution of contributions in AI-enabled collaborative crowdsourcing. To create and implement such policies, it is important to bring experts from different fields to define ethical principles that can contribute to avoid the misguided and misunderstood usage of AI. Digital labor platforms should then implement these principles and regulations in their terms of service, offering tools to track contributions and resolve disputes by establishing effective social conventions among humans and LLM populations [38]. Among the vast amount of possibilities, potential solutions include providing clear usage policies, ethical instructions, and training to enhance workers' AI literacy.

### 3.3. Crowd Work Inequalities

Introducing LLMs into digital labor platforms has amplified existing power imbalances. Algorithmic biases are usually rooted in opaque model training and therefore amplify social injustices and inequalities [14, 35]. These dynamics are particularly concerning in crowdsourcing contexts where the labor force is often diverse but socioeconomically precarious. To mitigate this, inclusivity must be embedded within AI-augmented systems [15]. Preserving worker autonomy and ensuring equitable task allocation across demographic and cultural lines are essential steps toward fostering a fairer digital labor ecosystem [27]. On top of all of this, the lack of transparency in how AI algorithms evaluate workers' performance can exacerbate feelings of injustice and hinder opportunities for skill development and social inclusion on these platforms [28, 29]. It is thus paramount to explore explainable AI and other related strategies within collaborative settings. Also, it is necessary to develop mechanisms as proposed by Tubella and co-authors [25] to understand the behavioral constraints of the AI system and how they influence its outputs.

AI-driven collaborative crowdsourcing offers a potential way of addressing structural imbalances inherent in digital labor markets. These markets often operate asymmetrically, concentrating power in the hands of platform owners and requesters. This may lead to systemic inequities in how tasks are assigned and assessed [16]. As mentioned by Colón Vargas [26], the operation of the AI industry is often characterized by intellectual appropriation and extreme exploitation of workers (e.g., data labelers) from minority workforces. This asymmetry undermines worker wellbeing, limits agency, and contributes to an ongoing sense of precarity.

In rapidly evolving domains like user experience (UX) design, AI systems that learn from user-generated data may inadvertently replicate and reinforce these problems over time [17].

Addressing these issues demands a paradigm shift toward more ethical, culturally sensitive, and worker-centered design in both academic and industrial AI research. This involves a deeper exploration of alternative platform governance models able to empower workers by providing them greater agency over platform policies and operations. Furthermore, it is crucial to consider mechanisms that facilitate collective negotiation for crowd workers, enabling them to advocate for their rights and interests more effectively. In addition to governance, developing fair compensation models is essential. As noted in [33], such models should move beyond metrics that exclusively prioritize speed or work volume. Instead, they should account for the inherent complexity of tasks and the actual value of the contributions made by individual workers. By moving towards a more nuanced compensation model, we can help establish a digital labor ecosystem that is more equitable in the long term, ensuring fairer rewards for the expertise and effort involved.

Despite the growing reliance on AI in crowdsourcing, collaboration has historically received limited attention in the literature [18]. As the field progresses, a more humanized approach to crowd work is needed, one that recognizes workers not merely as task solvers but as active agents with different cultural contexts, learning trajectories, and social motivations. Socio-algorithmic approaches offer a promising path forward by enabling adaptive personalization of tasks, feedback mechanisms, and social incentives in ways that align with each worker's skills and characteristics. Additionally, crowd workers can play a more participatory role within AI auditing by helping to detect bias, uncover model vulnerabilities, and correct hallucinations [33]. This approach repositions crowd workers as co-creators and "stewards" of ethical AI systems toward empowerment and shared responsibility. To advance this humanistic approach of crowd work, more research should be conducted on how AI-mediated communication affects online community formation within these platforms. Understanding how AI can facilitate trust-building and mutual support among workers is critical for fostering a more equitable and sustainable digital labor ecosystem. As AI evolves, design approaches that reduce algorithmic aversion by aligning system functionality with users' expectations must be prioritized as a way of ensuring an inclusive and effective crowd-AI digital workforce.

## 4. Concluding Remarks

This paper critically examines the role of AI-augmented collaboration in addressing both decomposable and non-decomposable macrotasks within crowdsourcing environments. Our agenda opens up new avenues for inquiry by highlighting the threats underlying workers' engagement with both harmful and beneficial AI-generated content. Moreover, the paper explores the socio-technical arrangements and inequalities faced by workers in relation to the integration of AI into digital labor platforms. However, our work still faces significant limitations in clarifying how AI affects the labor conditions of crowd workers, including wages and income distribution. Addressing this requires more case studies and concrete examples of how digital labor platforms are being used to train LLMs. Furthermore, data is still lacking to contextualize the AI-augmented collaborative crowdsourcing phenomenon and its relevance and distribution across countries, sectors, and occupations.

## Declaration of Generative AI

The authors have not employed any Generative AI tools.

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