Towards Hybrid Crowd-AI Centered Systems: Developing an Integrated Framework from an Empirical Perspective

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***Abstract*—Crowdsourcing has shown to be a valuable problem-solving approach to handle the increasing complexity and scale of tasks for which the current AI algorithms are still struggling. Crowd intelligence can be particularly useful to train and supervise AI systems in a symbiotic, co-evolutionary relationship that raises long-term research challenges to the hybrid, crowd-computing design space. With the increase in the scale of mixed-initiative approaches, we need to gain a better understanding of the implications of crowd-powered systems as a scaffold for AI through the study of massive crowd-machine interactions. In this paper, we identify some open challenges and design implications for future crowd-AI hybrid systems. A framework is also proposed based on the practical challenges of addressing human-centered AI methods and processes.**

Keywords—artificial intelligence; crowd-AI hybrid interaction; crowdsourcing; human-centered AI; taxonomy

I. INTRODUCTION

The past several decades have fostered different forms of interaction and Information Technology (IT) has been shaped to redesign socio-technical systems in the context of human-AI collaboration [14]. Despite this interest, it fails to incorporate hybrid intelligence in complex settings and dynamic scenarios as a socio-technical construct in which both humans and algorithms can co-evolve over time [43]. With crowdsourcing and AI becoming ever more prevalent features of science, such symbiosis is beneficial for several fields and disciplines in terms of novel design possibilities and a more holistic evaluative practice [21]. This implies that crowd-computing applications need to be studied "in the wild" considering the role of AI and its potential consequences to the social context of its use.

This paper outlines some ways in which existing research on crowd-AI hybrids can inform the development of intelligent systems while contributing to redesign some aspects in order to keep pace with the important and rapid transformation of IT-enabled practices. More specifically, we focus on the process of identifying key characteristics behind the socio-technical infrastructure of crowd-AI interaction towards the creation of a theoretical framework. In order to do this, we undertook a descriptive review to meaningfully structure relevant literature with the support of a concept matrix and taxonomy development method [22]. Thus, our work is aligned with a descriptive literature study to reveal interpretable attributes in the Human-Computer Interaction (HCI) body of literature. This approach seeks to systematically portray and examine actionable insights by categorizing research into a literature classification scheme. We take a socio-technical view of human-centered systems design [23], which acknowledges that both human and technical aspects must be taken into account in the functioning of a system. By documenting the breadth and variety of conceptual units from studies that seek to address the integration of crowd inputs into AI systems we try to make a new set of heuristics based on literature research found. In the ensuing sections of this paper, we try to accomplish these goals by first introducing the theoretical background of human-centered AI while discussing the use and adoption of hybrid crowd-machine systems as socio-technical configurations.

I. BACKGROUND

The research on the benefits of harnessing both human and machine intelligence has a long record. In 1960, JCR Licklider [18] defined a set of stages for how humans relate to machines: human-computer interaction, human-computer symbiosis, and ultra-intelligent machines. In this scenario, synergetic interactions occur between embodied cybernetic systems influenced by evolving processes such as expertise and attention. Engelbart [24] coined the term 'intelligence augmentation' to describe symbiotic interactions between individuals and AI concerning their inherent weaknesses. Such interplay between humans and algorithmic components interacting as a 'cooperative intelligent entity' constitutes a new class of socio-technical systems. Using this perspective, Hancock [26] offered insights on this question by defining 'hybrid human-machine systems' as "those in which human and machine have to engage in some form of collaborative action in order to achieve a defined goal".

The current advances in AI have profoundly changed the information environment with implications for reaching new scientific breakthroughs [27]. Machine learning algorithms have been employed to a wide range of scientific disciplines, requiring large and unbiased training data sets to work effectively [28]. Among other uses in medicine and biology, automated-based approaches such as text mining have been fruitfully applied for extracting information on cancer risk assessment and research [29], processing tumor genomes in brain cancer patients to provide personalized treatments [30], and establishing relationships among subsets of genes or proteins [31]. For instance, text mining can be particularly useful in recognizing instances of concepts like drugs and medical conditions, synonyms/variant forms of concepts, and relationships between concepts (e.g., which drugs are used to treat a particular medical condition) [28]. In addition, such methods allow search engines to perform automatic suggestions in more intelligent ways.

When considering situations involving a combination of both humans and machines, most studies agree on the use of crowdsourcing as a reliable method for supervised and semi-supervised machine learning (e.g., active learning), from feature generation to prediction, deeper analysis, and classification of mass volumes of data [33]. Crowdsourcing, a term that usually refers to work practices performed by a broad and open mass of participants [34], has been adopted for executing tasks such as collecting ratings for data to be used in supervised machine learning [10]. AI can help make the crowd more efficient and accurate through machine intelligence. On the other hand, "crowd intelligence can help train, supervise, and supplement automation" [13]. As these technologies develop, attention to ethical issues, quality control, and complex methodologies is critical.

II. Hybrid Crowd-AI Systems

We employ principles from human-centered computing research as a starting point to understand the complementary way in which human crowds interact with AI systems. Our work draws on three main bodies of prior research to construct a conceptual framework of crowd-AI hybrids that arise as a product of co-evolution between human and automatic agents and their relations to other socio-technical attributes. As can be seen from Figure 1, the taxonomy development method is derived from Nickerson and co-authors [22] following the design science approach.

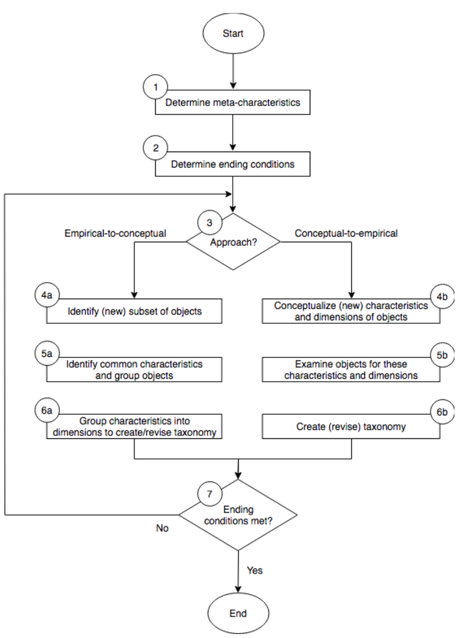

Figure 1. Taxonomy development method (adapted from [22]).

A. Human-Centered AI Framework

The past few years have witnessed a growing interest on explaining human-machine interaction and how algorithmic actions can impact people's lives by means of behavioral experiments using crowdsourcing platforms [10]. This line of work goes beyond the development of models of human behavior to better inform the development of interfaces and algorithms. As previously noted, it also exploits the evolving relationship between humans and machines in collaborative settings taking a co-evolutionary perspective [43]. At first sight, crowdsourcing can be used to help train, supervise, and supplement automation, while machine intelligence can help make the crowd more efficient, skilled, and accurate [13]. That is, the concept of human-centered AI has to take into account both automation-supported human and human-supported automation concepts related to system autonomy in terms of capabilities and limits [20].

Although there has been long-standing interest in understanding human-machine interactions, to the best of our knowledge, no other study has provided an integrated framework for human-centered AI at a crowd scale. Figure 2 presents the characteristics of the resulting taxonomic units. The aspects of the proposed framework are discussed in the ensuing subsections.

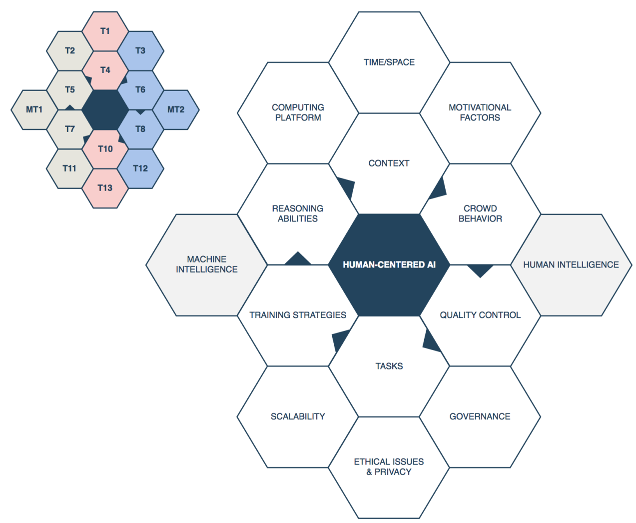

Figure 2. Human-Centered AI Framework.

1) *Time/Space*

Crowd work can occur in the same time (e.g., emergency response) or asynchronously (e.g., image labeling). The *time-space matrix* originally proposed by Johansen [45] also classifies technological configurations when participants are working at the same space (co-located) or remotely (i.e., different places). Moreover, it should be noted that crowd members can be virtually or physically dispersed [46]. A relevant aspect in crowd work settings is the availability and contribution time of crowd workers [48]. Thus, the level of engagement can be classified according to the daily-devoted time, activity duration, and periodicity of interactions.

2) *Crowd Behavior*

A crowd can be defined as a complex system constituted by a large, definable group of people with a diversity of selforganized behaviors and transient identities [46]. At the same time, such ensembles can vary in terms of size, roles, motivation, skills/domain expertise, social structure, strength of ties, preferences, emotions, among other aspects [49]. As a brief example, some crowds are socially networked or organized into teams, while others are arbitrary.

There is some evidence to suggest that crowd workers are not independent units but actually "a rich network of collaboration" [50]. That is, a wealth of studies has revealed the existence of communication networks in social spaces (e.g., forums) used by crowd workers connected through social ties to "build socializing spaces at work" [53]. Some concerns that are often overlooked include credibility and trust, fairness, and responsiveness. Workers are allowed to share (or make visible) their true identity, executed actions (e.g., endorsements), and traces concerning their social interaction behavior.

3) Tasks

Crowd behavior can be strongly influenced by aspects inherent to workers (such as trustworthiness) and others that are induced by the nature of the task [54]. For instance, emotional and physical states (e.g., fatigue) affecting crowd performance are influenced by the perception of the task as being simple and monotonous [55]. Crowdsourcing systems differ in terms of level of collaboration between members, amount of time spent, incentives, task complexity, and type of tasks assigned to the crowd [56].

On reading the literature, we come to the view that such tasks are usually categorized into microtasks and macrotasks [51]. Microtask crowdsourcing is characterized by context-free units of work that are simple for individuals to perform. On the other hand, macrotask crowdsourcing is mainly focused on solving challenging and innovative tasks, which require special skills and task dependency while are usually more extensive and less fragmented. However, complex work traditionally conceptualized as macrotasks may also be decomposed into microtasks through decontextualization, a strategy that has been applied to problems in several domains. For example, in Soylent [44], editing a document is broken down into "find", "fix" and "verify" microtasks, in which workers identify review opportunities, generate possible revisions, and vote on them.

4) Motivational Factors

The ways of engaging crowds in work settings can be classified into extrinsic/intrinsic [39]. Extrinsic factors can be monetary (e.g., immediate payoffs) and non-monetary (e.g., acknowledgement). Intrinsic factors include enjoyment and worker status. The rewards reported in the literature range from money to gifts and gamification strategies [25]. Besides the known motivational factors affecting crowd members, a collaboration process design framework for crowdsourcing [41] provided additional dimensions such as shared understanding, feedback, and type of participation (e.g., comment). As argued by Xie and Lui [38], contests are also intuitive ways for motivating crowd members and are frequently adopted in complex crowd work.

5) Quality Control

Quality control is particularly important in dynamic settings to avoid malicious or poorly motivated workers providing biased, low quality outputs. Factors impacting the quality of results include task requirements and size and heterogeneity of the crowd. In this sense, quality control mechanisms are required for detecting low quality work and modeling crowd bias [25]. For instance, worker filtering is a quality control approach widely adopted in crowd work to filter possible unqualified and malicious workers [49]. Worker selection can be open to everyone or performed taking into account factors like reputation and credentials. As Daniel and co-workers [25] put, the assessment process is performed individually (e.g., qualification test, usability check), computationally (e.g., ground truth, task execution log analysis), or collaboratively (e.g., peer review).

6) Context

The motivation of a crowd participant depends on contextual factors such as time, location, and device [49]. We assume that crowdsourcing is highly context dependent and situational information is particularly critical to achieving successful interactions in a crowd-AI working environment. In particular, having contextual data about users and tasks can improve performance by avoiding duplicated efforts. When building a crowd-powered system, the overload of user-generated inputs must be handled in order to extract and process the relevant information properly [32]. Nonetheless, a fundamental problem relies on obtaining an efficient and accurate context detection.

7) Ethical Issues and Privacy

The use of hybrid crowd-AI systems raises a number of legal and ethical issues. A frame into previous works (e.g., [52]) reveals concerns related to low wages, worker rights, unclear task descriptions, rejected work without due cause, poor responsiveness to questions, licensing and consent, and acknowledging crowd contributions appropriately. Other researchers have also reported a preoccupation with the ethical standards, terms and conditions, and compliance with laws [25]. In spite of the aforementioned issues, Amershi and co-workers [21] raise a related concern in relation to the need of avoiding undesirable behaviors and social biases during interaction. To address these shortcomings, system designers must play an important role by taking into account the possible consequences of AI systems and applications on people's lives when designing technical artifacts.

8) Governance

Complex work settings require a dedicated governance strategy instead of a self-governed arrangement [47]. As a crowdsourcing project evolve, rules and guidelines are developed in a social fashion [35] and users may lose access to the platform for bad conduct. Governance (understood as the actions and policies used to manage the crowd) and active control can reduce the dangers of malicious work. When studying crowd work regulation (e.g., [47]), we found that identity and reputation management, privacy (including confidentiality of participant identities), and intellectual property are pivotal concerns in the literature.

9) Computing Platform

Designing for crowdsourcing include factors that range from task design to the use of optimization mechanisms and periodic feedback as incentives for engagement [25]. Technical aspects comprise software components, functions, and data objects (including authentication, user interface, and workflow support). Hetmank [42] goes even further by claiming that a crowdsourcing platform must support actions such as assigning and splitting tasks, setting time period, stating reward, recruiting and evaluating users, submitting contributions and merging submissions, selecting solutions, and paying users. Such systems also support organization and control of computational resources. In complex crowd-AI work settings, crowd members must be able to track the changes made by participants over time to stay cognizant of long-term activities, and the system must answer to the location, content, time, author, actions, and reason of each change accordingly.

10) Reasoning Abilities

Incorporating reasoning abilities into hybrid intelligence systems supports better decisions since machines can learn from crowd behavior. This claim is in agreement with the findings of Enjalbert and Vanderhaegen [36] who called attention to the learning strategies (e.g., trial-and-error, redundancy, cooperative learning) that can be used to reduce errors and increase stability while adapting to (or recovering from) critical situations. We build on Kamar's [1] work to stress the importance of deeper reasoning abilities for computer algorithms in co-evolving synergistic activities. Such approaches can draw conclusions by interpreting complex patterns and changing situations [33]. This offers a lot of possibilities for predicting future events and improves the decision-making process at a large-scale.

11) Training Strategies

Crowd intelligence presents a vast set of possibilities for training AI algorithms. According to Lasecki [19], crowd-powered systems can "train intelligent systems in situ, while deployed, and then, over time, automated to improve faster, cost efficiency, and reliability". Machine inference must be aligned with human problem solving by considering distinct levels of confidence for actions. Humans must "feed" the machine to act autonomously based on crowd-powered data inputs that can work as training samples. In other words, the crowd must be able to configure the level of automation (degree and scope) and to extend the scale of data processing taking into account the system as a whole [5]. This approach includes autonomy regarding criteria of knowledge or skills, availability and possibility to act through human-machine interaction [20]. Undoubtedly, a concern that is steadily growing is the extent to which crowd participants can be trained to obtain new skills and abilities [1].

12) Scalability

Research into machine learning and AI has raised some issues about the study of crowds as leveraging mechanisms to get high-quality training data. This specific area also raises some concerns about the use of machine algorithms to improve crowdsourcing outputs [10]. Hybrid crowd-machine systems explore the complementarity between crowd work and the scalability of machine algorithms to solve complex tasks that are difficult to perform in isolation [7]. A key component of Wang et al.'s [4] conceptual framework for human-centered AI focuses on the in-depth understanding of human behavior as a powerful means to inform the design of AI systems. Hybrid, crowd-machine interaction can close this gap by putting humans "into the loop". Due to its flexibility and scalability, crowdsourcing represents an effective instrument for handling complexity.

13) Hybrid Intelligence

Hybrid human-machine computation has been addressed as an extension of human computation, pursuing the design of systems that "tightly integrate human computation and machine resources" [7]. While human crowds can produce distinct ideas and analyze data with high accuracy, algorithms are useful in handling large volumes of data (with multiple criteria). In spite of the aforementioned arguments, new insights can be obtained from complex decision rules of human intuition for further validation in a human-in-the-loop approach that was not yet captured by interactive, crowd-AI systems and architectures. This raises fundamental questions regarding the design of intelligent systems fully able to "collaborate naturally and effectively with people" [40].

B. Validation Study

We need to understand how human-AI symbiosis can be applied to environments under extreme uncertainty. Thus, a methodologically grounded examination of the possible impacts of hybrid intelligence in multivariate contexts is required. For instance, few attempts have been made in identifying crowdsourcing and AI risks through a deep understanding of their uses and consequences in terms of socio-technical affordances and constraints. To validate the human-centered AI framework discussed above, we performed an analysis based on data presented in Figure 1.

A lens into the literature has revealed some patterns that require further examination, as shown in Table I. While several articles touch on issues of task allocation and training strategies, we have to rethink governance strategies and how to reward contributors in appropriate ways. It is worthwhile to note that most papers did not provide a human-centered AI perspective and some practical and ethical concerns in crowd work (e.g., unfair rejection of work by requesters) remain unsolved. At the same time, there is a need for shared rules, standards, work ethics, and regulations [25]. In addition, the potential risks of malicious behavior and low quality data are often underestimated.

Regarding the design of human-AI interaction systems, some concerns arise about the distribution of intelligent functions and autonomy between human crowds and machine agents and the automated observation of user actions [21]. Therefore we need error-tolerant work systems taking into account the always-growing complexity resulting from the interaction between humans and automated reasoning systems. The design of intelligent agents that are adaptive to highly dynamic, self-adjusting contexts is an important element of crowd-AI hybrid systems.

Table I. Studies mapped according to their main attributes.

Ref.	T1	T2	T3	T4	T5	T6	T7	T8
[1]	X/O	X	X	O	X	X	X	X
[2]	X	X	X	O	X	X	X	X/O
[3]	X	X	X	X	O	X	X	X
[4]	O	X	X	O	X	X	X	X
[5]	X	O	O	X	O	O	X/O	X/O
[6]	X	X/O	X	X	O	O	O	X
[7]	X	X/O	O	O	O	O	X	X
[8]	O	O	O	X/O	O	O	X	O9
[9]	X	X/O	X	O	O	X	X	X
[10]	X	X	X	X	X	X	X	X
[11]	O	X/O	O	X	O	X	X	X/O
[12]	O	O	X/O	X/O	X	X	X	O
[13]	X	X	X	X	O	X	X	X
[14]	X	O	X	X	X/O	X	X	X/O
[15]	X	X	O	X	X	O	O	O
[16]	X	O	O	X	O	O	X	X/O
[17]	X	X	O	O	X	O	X	X/O
Ref.	**T9**	**T10**	**T11**	**T12**	**T13**		**MT1**	**MT2**
[1]	O	X	X/O	O	O		X	X
[2]	O	X	O	O	O		X	X
[3]	X	X	X/O	O	X		X	X
[4]	O	X	X	O	O		X	X
[5]	X	X	O	O	O		X	X/O
[6]	O	X	O	O	O		O	X
[7]	O	X	O	O	O		X	X/O
[8]	X	X/O	O	O	X/O		X	X/O
[9]	O	X	X	O	X/O		X/O	X
[10]	X	X	O	O	X		X/O	X
[11]	O	X	O	X	X		X	X
[12]	O	X/O	X	O	O		X	X/O
[13]	O	X	X	O	X/O		X	X
[14]	O	X	O	O	O		X	X
[15]	X	X/O	O	O	O		X	X/O
[16]	X	X	O	O	O		X/O	X/O
[17]	O	X	O	O	O		X	X

[*] Overall criteria of the qualitative assessment of the human-centered AI framework. Topic (**T**) – Fully addressed (**X**), Not addressed (**O**), Partially addressed (**X/O**)

These adaptive agents "coordinate to retrieve, filter and fuse information relevant to the user, task and situation, as well as anticipate the user's information needs while supporting the decision making process" [37]. As argued by Dellermann et al. [14], "the main idea of hybrid intelligence systems is, thus, that socio-technical ensembles and its human and AI parts can co-evolve to improve over time". In such scenarios, algorithm transparency can be particularly relevant to achieve interpretability [21]. Nonetheless, design implications remain largely unexplored in the context of hybrid intelligence systems and we need more research to putting human crowds into the loop of crowd-AI interaction.

Prior work also addressed the need for more guidance for developers of crowd-AI systems [14]. As argued by Amershi and co-authors [21], future research may aim to improve the potentially ways as humans handle the unpredictable and intrusive behaviors of AI algorithms. The authors also presented a set of human-AI interaction design guidelines that range from mitigating social biases to learning from user behavior. The validity of this extension needs to be examined, particularly when looking at the risks and errors that may result from the increasing complexity of algorithms and failing heuristics. In this context, crowd-AI interaction requires an interdisciplinary theoretical framework for exploring the best of both 'worlds' by augmenting human and machine capabilities. This implies that future systems for supporting hybrid crowd-machine interaction need to be designed taking into account the in-depth examination of the symbiotic relationships between crowds and computational tools in cooperative work settings [43].

III. Conclusion

The work outlined in this paper deals with the efficient understanding of machine-crowd interaction. Our literature review and framework directly inform the design of crowd-AI powered systems through a deep understanding about the challenges that researchers, developers, and end-users face as well as the possible consequences of such technologies. Based on insights we gained from this study, we are able to clarify open issues about the scalability and generality of crowd-AI hybrids. However, we suggest that future research should extend the scope of the review. In particular, further examinations remain to be done when considering problems of massive scale since most studies comprise only small-scale efforts and "scaling up" is still difficult to accomplish. Combining the strengths of human crowds and computer algorithms offer significantly improved performance, even in complex domains. Continuous observation of the evolving relations between machines and humans will produce new insights and actionable recommendations. We hope that gaining more understanding of this symbiotic relationship will influence further efforts in the future towards the development of more intelligent systems.

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